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Research Article

Detection of Multiple Eye Disorder using Deep Learning Techniques

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ABSTRACT

The global impact of vision impairment, affecting an astonishing 2.2 billion individuals, imposes a significant burden on public health, with a notable proportion of cases being preventable. Retinopathy, characterized by retinal vascular disease, stands as a leading cause of preventable blindness. Early detection is challenging due to asymptomatic early stages, necessitating the adoption of automated diagnostic approaches. Here, we used 3220 labelled fundus images from RFMID dataset to create a AI-powered neural platform that can identify several fundus diseases (39 classes). This study conducts an extensive review of deep learning architectures employed by researchers, encompassing models such as VGG-19, DenseNet-121, and Efficient Net- B0. This work introduces the development of a deep neural network model explicitly designed for classifying the RFMID dataset. Initial models displayed suboptimal accuracy, prompting efforts to reduce trainable parameters. Despite enhancements in computational efficiency, a notable increase in accuracy remained elusive. Subsequently, transfer learning was employed, involving model training on a diverse dataset before evaluating its performance on RFMID dataset. To address overfitting, dropout techniques were strategically applied, resulting in a final model showcasing improved accuracy.This study emphasizes how transfer learning and dropout strategies can improve the effectiveness and precision for diagnosing retinopathy. The consequences of these findings extend to the broader goal of leveraging advanced technologies to address global vision impairment and proactively prevent cases of avoidable blindness.

Keywords: Convolutional Neural Network, Ocular Disease, Rare Pathologies, Transfer Learning

INTRODUCTION

Vision impairment has become a burden on global health. The sheer number of approx. 2.5 billion people havingeither close or far vision impairmenthas alarmed the medical fraternity to the core. Retinopathy is a type of retinal vascular disorder, which is when irregular blood flow damages the retina [2]. This is a major cause of blindness. If someone has dark or empty patches of vision, fluctuating eyesight, or blurred vision, the person may be suffering from retinopathy [3]. The disease can be treated using methods like injectable medications, Laser Therapy, Vitrectomy to name a few. Corrective measures can be taken if the problem can be able to be identified early. This is challenging as it requires regular screening, is costly and due to the scarcity of ophthalmologists. The above factors necessitate the use of automated retinopathy detection using deep neural networks. Many researchers have employed deep learning architectures to diagnose different types of retinopathies using imaging dataset [4]. Kaur et al. [6] employed an extensive approach, applying different CNN approach for DR severity levels. Akram et al. [7] conducted a similar study, applying K-NN, SVM models to detect lesions. Amin et al. [9] worked on the classification method of diabetic retinopathy especially on lesion detection including exudates. Author use SVM technique to classifying images according to their severity in DR. Latha et al. [11] offer a neural network-based framework for advanced DR detection, with a focus on accurately segmenting exudates, one of the key indicators of DR progression. The authors developed an integrated approach for adopting a deep convolutional learning approach model, tailored to identify and segment exudates from ophthalmic images, aiming to support early diagnosis of DR.

In this paper, a CNN model was constructed for classifying some of classes in the RFMID dataset. However, this initial model did not perform well in case of accuracy. The overall learnable attributes of the model was 11,180,206. Subsequently, an attempt was made to make the model efficient by decreasing the count of trainable parameters. The overall learnable parameters of the second model were 2,790,222. This was achieved by decreasing the count of kernels in the convolutional layers. However, despite of being computationally efficient as these changes aimed at reducing model complexity, there was no significant improvement in accuracy observed in the second model. Finally, it was decided to use the transfer learning to accomplish the task. In transfer learning the model is trained with another dataset having ample training samples and once it is trained, its performance is measured with the given dataset [24]. Furthermore, the overfitting of the model is controlled by employing techniques such as dropout. The final model works well for most of the classes.

The core contributions of the work are summarized as follows:

1. Designing CNNs for the classification of retinopathy.
2. Optimizing the so created models to efficiently and effectively accomplish the task, by hyper-parameter optimization.
3. Using transfer learning to classify the given classes.
4. Optimizing the transfer learning models.

The structures of this document are as follows: Materials and methods are covered in the next section, the experiments and results are described in the III section, and the conclusion and future is given in the IV and last section.

MATERIALS AND METHODS

In this section, we provide a deep learning (DL) approach for fundus image-based retinal disease detection. The RFMID databases provided the data used in this investigation [30].

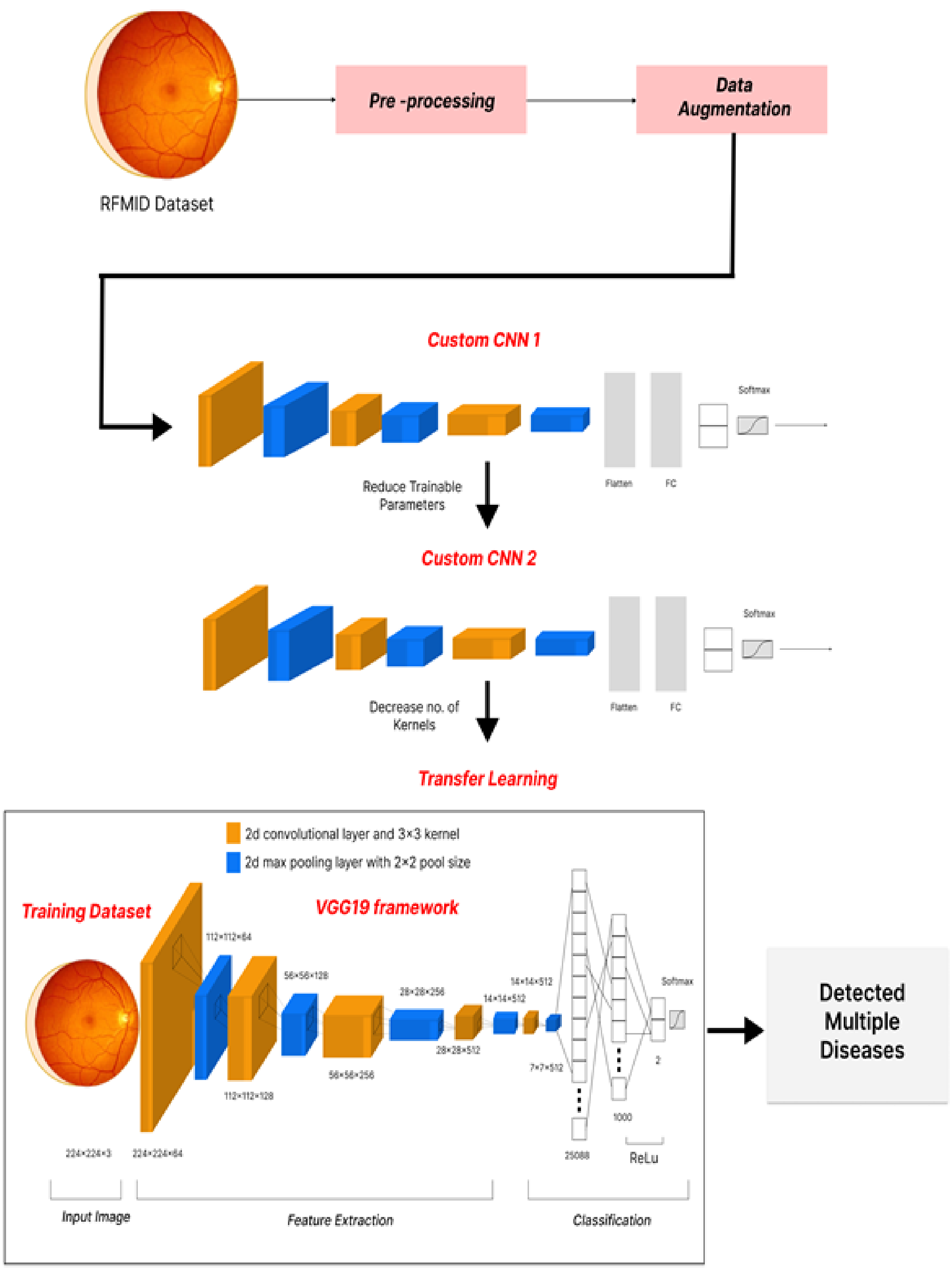

Figure 1. Proposed Framework of Multi-disease Retinopathy Detection

Both single-labeled and multi-labeled photos are included in these databases. Then we carried out pre-processing steps after obtaining the dataset, as indicated in Figure 1. Since each image in the dataset varied in size, we used data augmentation during preprocessing to balance and enlarge the dataset, clip the undesirable part, and then recreate the images to the actual size. The dataset has been separated into segments for testing, validation, and training. To further identify various retinal disorders, we utilized VGG 19 in conjunction with transfer learning. The accuracy of the statistical results was discussed and accuracy, loss, and confusion matrix results are displayed graphically.

DATASET DESCRIPTION

The RFMID, a publicly available dataset that containing the count of 3,200 images interpreting 39 retinal conditions and expert annotations, is used in this work [15]. Of these 39 conditions, 11 conditions have been identified. RFMID is a publicly available dataset that includes a wide range of disorders that are prevalent in typical clinical settings. In contrast to earlier attempts that concentrated on identifying particular disorders. But this dataset is a multi-label dataset. The total number of single-labeled retinal images in datasets is displayed in Table 1.

DATA PREPROCESSING

To get the RFMID dataset ready, firstly every image is in PNG format or changes them to be. Then, change the size of all the pictures to be 224x224 pixels so they're all the same. Next, adjust the brightness by dividing each value by 255. This makes the range from 0 to 1, which helps the computer learn better. Also, mix up the data a bit to make the dataset more varied. This helps the computer model learn better and work well in different situations.

THE PROPOSED ARCHITECTURE FOR RETINAL FUNDUS MULTI DISEASE CLASSIFICATION

In this section, the proposed algorithm was able to classify the multiple classes by implementing modified CNNs using transfer learning. This article has been provided an overview of how each technique was applied to enhance performance. The proposed model has been improved with 19 layers and uses fixed size 3x3 filters for detecting features. This model takes input images that are 224*224 pixels. Most of the convolution layers in VGG19 use 3x3 filters with a stride value of 1, though max pooling layers are used regularly to down sample the feature maps by factor 2, effectively reducing their spatial dimensions. After extracting features from the input image using the convolution layers, the feature maps are typically flattened before being passed to the fully connected layers for classification. Flattening the feature maps involves reshaping them into a one-dimensional vector. After the feature maps are flatten, they are passed through one or more fully connected (dense) layers. The remaining hidden layers are commonly called Dense layers and are fully connected to all the neurons from the previous layer. In the case of our proposed architecture, there are two fully connected layers (dense and dense_1 in our proposed architecture), which perform the final classification based on the extracted features. Usually, we would do a SoftMax to the raw scores outputted by the last fully connected layer to finally get the probabilities. These probabilities represent the likelihood of the input image belonging to each class in the classification task. The detailed pseudo code (Algorithm 1) is shown as below.

Algorithm 1: Transfer Learning for Multi-class Classification

```
BEGIN
        Initialize input_layer with input_shape (224, 224, 3)

        FOR i = 1 TO n DO
                Add convolutional_layer with filters=f_i and kernel_size=k_i
                Apply activation_functionReLU
                Add max_pooling_layer with pool_size (2, 2)
        END FOR

        Add dense_layer with units=1000
        Apply activation_functionReLU
        Add dense_layer with units=Number_of_Classes and activation=softmax
        Compile model with optimizer=Adam, loss=categorical_crossentropy, and
metric=accuracy
        Set hyperparameters with learning_rate=lr, batch_size=batch_size, and
epochs=num_epochs
        Apply transfer_learning using model VGG16 with freeze_layers_except_last=True

        If fine_tuning is required THEN
                Unfreeze specific layers
        END IF

        Add dropout_layers with dropout_rate
        Test model on RFMID_testing_dataset
        Calculate performance_metrics
END
```

By conducting these analyses, one can thoroughly evaluate the performance of a model in diagnosing retinopathy using retinal fundus images, ensuring its effectiveness and reliability for clinical use. The model undergoes adjustments based on various factors such as epochs, hidden layers, nodes, activation functions, dropout rates, learning rates, and batch sizes as shown in table 2.

Table 2. Configuring parameters for model training

Parameter	**Description/Values**
Base Model	VGG19 pre-trained on ImageNet
ConvolutionalLayers	16
MaxPoolingLayer	5
Flattening Layer	Flattens the 3D output to 1D
Dense Layers	Two dense layers with 1000 and 11 units
neurons' output weights	0 to 0.5
Epochs	20(each 60 iteration)
ActivationFunction	'relu' for dense layers, 'softmax' for output layer
ImageSize	224x224x3
Optimizer	Adam
Trainable Layers	Layers in base model set to non-trainable

The table 2 shows hyperparameter and configurations utilized in training a neural network model, particularly one built on the VGG19 architecture, modified for a specific classification task. The base model is VGG19, which providing a robust starting point. In this configuration, however, the layers of the base model are frozen (i.e., their weights are not updated during training), and only the weights of the added layers are trained.

A flattening layer is added to convert the multidimensional output from the convolutional layers into a one-dimensional array, which can be used as input for the dense layers. We then add two dense layers and the first one consisting of 1000 units and a 'relu' activation function, and the second layer acts as the output layer with 11 units (the number of classes) and a 'softmax' activation function. When training the model, we use the Adam optimizer, which is widely used for this purpose as it allows for an adaptive learning rate and thus helps the model to converge quicker. It employs categorical crossentropy as a loss function (useful for multi-class priors) and accuracy as a metric for assessing model performance.

RESULT AND DISCUSSION

Here, we provide the results and discussion on our **research** of "Transfer Learning for Multi-disease Classification" of the RFMID dataset in many classes. This algorithm takes advantage of transfer learning to classify a multiclass and multilabel dataset. We used the systematic processing described in the Methods section above. The results of our experiments showed that the algorithm was able to classify classes from the RFMID dataset with relatively acceptable performance. Importantly, using transfer learning greatly outperformed CNNs trained from scratch, indicating the power of leveraging pre-trained models.Using a VGG19 model via Transfer Learning, the top 9 classes out of 39 classes were classified as [DR, ARMD, MH, MYA, BRVO, TSLN, ODC, RT, RS]. We first loaded the VGG19 architecture pre-trained on ImageNet excluding the top layer that produces a classification output. Next, we froze all the layers of the base model because we already want to keep all the knowledge from the pre-trained model, then added to it a Dense layer of 1000 with ReLU activation, as well as an output Dense Layer of 10, which matches the number of classes, and finally, this Dense Layer had SoftMax activation. For our classification task, starting with two out of nine classes and gradually increased the number of classes and fine-tuned the model accordingly.The iterative process of fine-tuning the model on the RFMID dataset allows the model to learn from the training examples specific to the dataset, further improving the classification performance. With the introduction of dropout layers in the architecture, the over fitting was appropriately addressed and ensured better generalization on the testing data.Fine-tuning the model on the RFMID dataset enables it to adapt to the special characteristics and nuances of the dataset, ultimately enhancing classification accuracy. The incorporation of dropout layers effectively mitigates overfitting, ensuring that the model doing well to unseen data.

COMPARATIVE ANALYSIS OF DEEP LEARNING MODELS ON RETINAL FUNDUS IMAGES FOR 2-CLASS CLASSIFICATION USING RFMID DATASET

Here, we present a comparison of our model versus to two other powerful deep learning models, EfficientNetB0, and DenseNet121—on the Retinal Fundus Multi Disease Image Dataset (RFMID). Providing a diverse and complex set of valuable ophthalmic images, the RFMID dataset has served as a difficult benchmark for image classification, proving effectiveness of various convolution neural networks (CNNs). By trying to figure out the best model for accurate and efficient retinal diseases 2 class classification, this analysis could provide some good knowledge for further research in automated eye disease diagnosis.

For RFMID dataset, different custom classification head was added on top of pre trained weights on image net and each such model has been trained. The baseline model is VGG-19 having a simple architecture with additional dense layers for binary classification. We have customized the EfficientNetB0, a well-known architecture that provides high accuracy with less number of parameters, with Global Average Pooling and Dropout Layers to improve its classification performance on our subset. Similarly, a more complex architecture called DenseNet121, which utilizes densely connected layers, has been adapted for this task.

All three models were trained for 10 epochs with Adam optimizer and categorical cross-entropy loss. The learning process has been monitored on the training and validation datasets and recording performances like accuracy and loss after each epoch. We have compared the performance of these models using accuracy, validation accuracy, loss, and validation loss plots. These diagrams demonstrate how good the models learn the data and validate their utility for these tasks. Below we have the chart mentioned in figure. 2 showing the training and validation accuracy over 10 epochs.

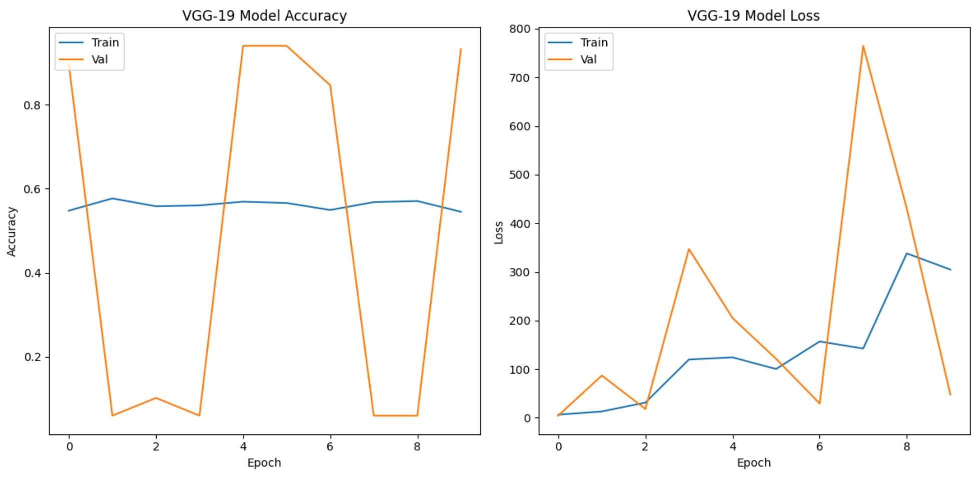

Figure 2. Model accuracy and error rate of VGG19 on RFMID dataset

The VGG-19 model yielded acceptable accuracy for the validation data and therefore was a good model to start with for the retinal images classification task. However, it has also shown signs of over fitting as evident from the disparity between training and validation accuracy. Similarly, when looking at the validation loss curve, the model appears to not generalize to new, unseen data, another common limitation with reasonableness inferences when employing simpler architectures against a fairly obscure dataset such as RFMID. This suggests that VGG-19 is potentially limiting as a pre-processing or a base model for more challenging tasks with limited resources.

The EfficientNet-B0 achieves better validation accuracy than VGG-19. All layers in EfficientNetB0 are scaled in a compound manner, which ensures that the network is deep, wide, and represents high-resolution input images while keeping the computational costs relatively low. It is a great option when high accuracy with computational efficiency is required. The performance of its respective architectures is best in class for practical applications in medical image analysis, especially if the resources are limited as shown in Figure 3.

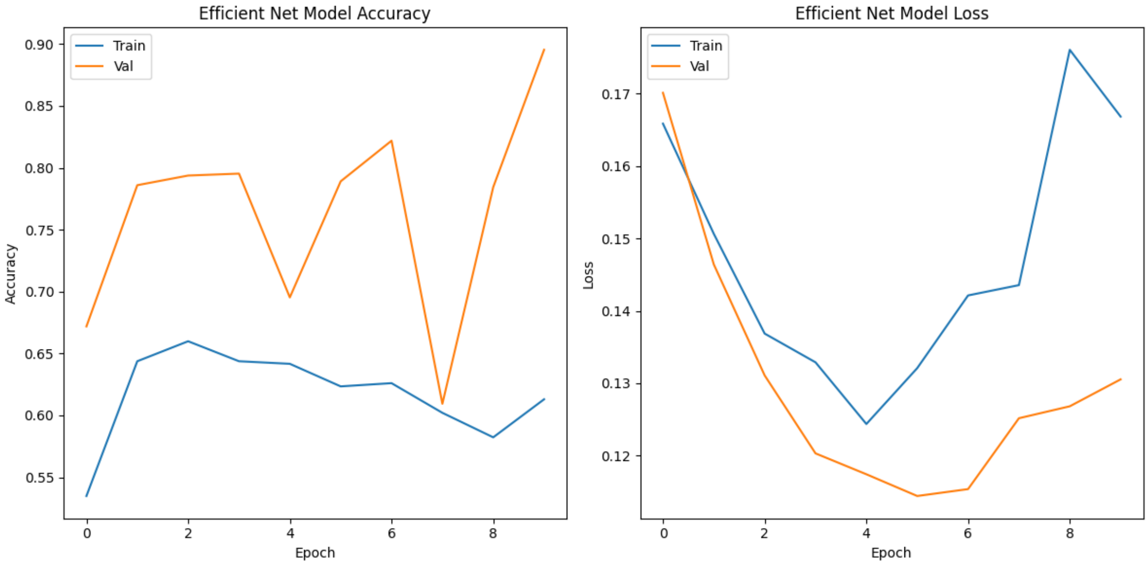

Figure 3. Model Accuracy and Loss of EfficientNetB0 on RFMID dataset

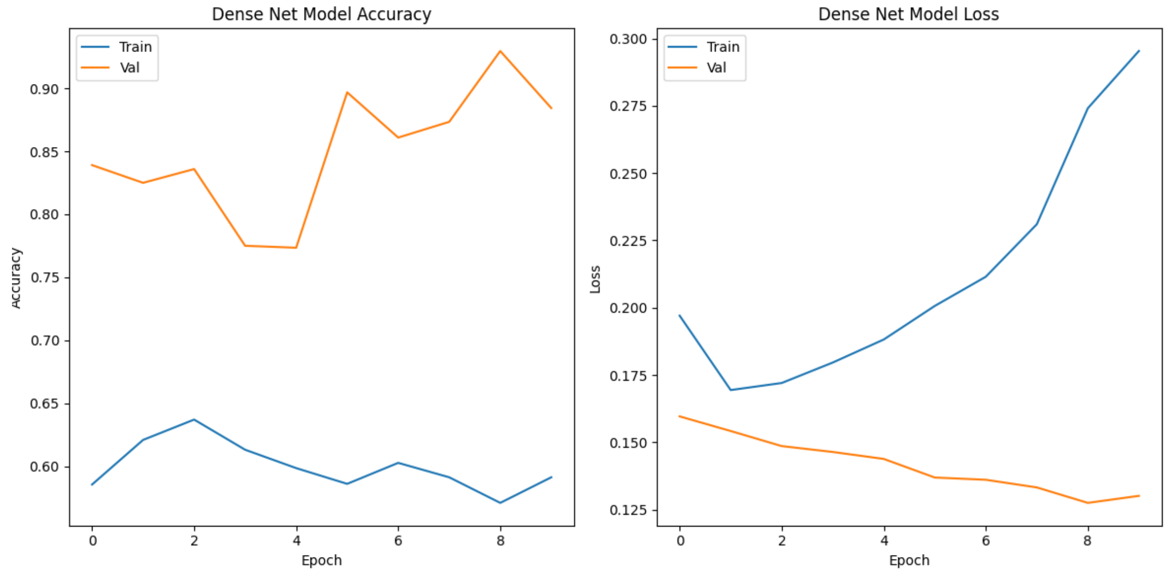

Figure 4. Model accuracy and error rateof DenseNet-121 on RFMID dataset

Out of the three models used, DenseNet121 has the highest potential for accuracy, where classification performance is better than both VGG-19 and EfficientNetB0 as shown in Fig. 4. Its densely connected topology provides efficient reuse of features, a critical advantage when learning complex patterns in the RFMID dataset. Though its validation accuracy has been pretty high during training, the model is really computationally expensive and takes too long to train and consumes a lot of resources. Nevertheless, this is important in cases where you care about getting the best accuracy you can, and the computational strain is worth it.

Among them EfficientNetB0 has achieved the best balance between accuracy and computational efficiency when applied to the RFMID dataset. It is a good compromise between computational cost and performance suitable for cases where computational performance is crucial; The DenseNet121 performs over the RFMID dataset shows the best accuracy out of the three models comparing, since, with its dense connection architecture, it can learn more complex patterns in data. This model is the most computationally heavy, though, as it has the longest training period as well as the most resources used. Its best use case is applications where accuracy is the primary concern, but computational resources are not an issue.

Although VGG-19 can be used as a baseline, we can see that both EfficientNetB0 and DenseNet121 outperformed it so we could favor either of those two over VGG-19 for our classification use case due to accuracy and efficiency. The results appeared promising in comparison with the state of the art as shown in Table 4.

Table 4. Performance of different deep learning models.

Reference	Year	No of Classes	Model/Technique	Performance
Li et al.	2022	4	DenseNet121	Accuracy = 88.4%
Wisaeng et al.	2023	4	EyeDeep-Net	Validation accuracy = 82.13 %
Maysanjaya et al.	2023	4	Deep Convolutional Ensemble (DCE)	Mean accuracy = 72.7%
R. Pires et al.	2024	2	ResNet152	89.17
			Vision Transformer	87.26
			InceptionResNetV2	88.11
			RegNet	88.54
			ConVNext	89.08
Proposed Approach	**2024**	**2**	**VGG 19**	**94.12%**
			Dense Net-121	**91.02%**
			Efficient Net B0	**93.52%**

CONCLUSION

Retinopathy is a medical condition that impacts the eye and can result in severe vision loss. The situation can be handled with timely and accurate diagnosis. Traditional techniques used for detecting retinopathy often need the manual review of retinal images by skilled ophthalmologists. Although these methods have demonstrated some effectiveness, they are hindered by subjectivity, the lengthy process involved, and the cost associated with them, and the scarcity of trained professional. In contrast, Deep Learning methods present several advantages over these conventional methods. Deep Learning methods are employed from scratch and using transfer learning, have demonstrated better performance in retinopathy detection as compared to the state of the art. Our study involved incrementally increasing the number of classes for retinopathy detection, starting with a few classes, and gradually expanding to include more. The extended work will employ newer models with the increased number of classes and will use one vs. all method for multiclass classification. The extended model will also use Graphical processing Units for possibility of parallel processing, hence effectively and efficiently classifying the given data.

FUTURE WORK

To facilitate the results more accurately and reliably, we can improve detection and classification of retinal diseases in future work. Next challenges could be to ensure a better generalization. To facilitate the models generalize well to a diverse range of images across populations. By training on larger, more diverse datasets and leveraging transfer learning approaches, the models may be better suited to adaption to new environments and other types of data. Another important aspect is its ability to process in real-time. In the future, optimization of the models might provide rapid and accurate outcomes in clinical practice.

CONFLICT OF INTEREST

There was no conflict of interest declared by the authors.

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