Enhancing Retina Image Classification with a Hybrid ResNet-50 and Random Forest Model: A Comparative Study

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Abstract: Organs like the retina are diagnosed and managed using images and therefore, accurate classification of images is critical. This study presents a novel combined architecture that combines the training of ResNet-50 deep CNN with a Random Forest classifier to improve the ability to identify Moroccan retinal images. The proposed model leverages the strengths of both approaches: High-level features extracted by ResNet-50 for images and Random forest's powerful classification. The paper has analyzed the performance of the proposed hybrid system based on a large set of data and established the positive effect of the new technique compared to the previous approaches. The model successfully had an accuracy of 94%. 3%, precision of 94. 0%, recall of 94. The corresponding precision is 89%, recall is 90% and an F1-score is 94%. 4%. Furthermore, the accuracy and loss for the training and validation set grows steadily for the epochs in the training and validation phase and the final validation set has an accuracy of 95%. 0%. These results have shown that in the field of retinal image classification, deep learning models particularly when used in combination with ensembles could yield the best performance. Of the advantages of the hybrid model, one is higher diagnostic accuracy in addition to the possible increase in the efficiency of the systems for the automated detection of pathologies in ophthalmology. Doing more work on the architecture of the model and expanding the deployment of the same for other medical imaging tasks could be future work used to improve on it.

1 INTRODUCTION

Image categorization has become an essential subject within the development of the medical imaging field focusing on the analysis of Retinal disorders like Diabetic Retinopathy, Age-related Macular (D. B, Kaur, et al. 2023) Degeneration, Glaucoma, and others. As for the issue of eradicating blindness and the enhancement of outcomes for treatment, differentiation of these disorders and accurate diagnosis is critically imperative. Due to the inherent sophistication and diversity of the retinal pictures, it turned out to be difficult to handle in general by the traditional image analyzing techniques. Thus, ordinary approaches (D. B, Kaur, et al. 2023) to diagnostics had to be replaced with complex new computational methods to enhance the diagnosis's precision. Due to their ability to learn and train on raw picture data to extract features of details, deep learning models especially the CNN and its variants have recorded considerable strides over the last few years in automating the process of classification of retinal images to enhance diagnosis of the said (Kaur, Kukreja, et al. 2024) diseases. Some of the model's success has been attributed to the fact that it can learn. Due to the presence of its deep residual learning framework, this kind of architecture like ResNet-50 has become popular because it helps in solving some of the inherent problems like vanishing gradient problems and also aids in training very deep networks. One can pinpoint one of its major advantages, namely it is rather effective and stable when solving diverse (Suryavanshi, Kukreja, et al. 2023)image classification issues. This is even more important when working with the variation and interference, which is characteristic of the images of the retina. Nevertheless, even in case of the efficient deep learning models like ResNet-50, there is a challenge in enhancing the classification accuracy. Random Forest which belongs to the ensemble

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learning technique involves training many decision trees to enhance the classification accuracy and generalization. It is done specifically to solve the issue, on a more detailed level, they are used (Suryavanshi, Kukreja, et al. 2023) to ensure that there is a stampede-prone situation avoided. As a result of this, the Random Forest, which is regarded for its steadiness and ability to handle large dimensions particularly when built from decision trees, is still in a position to leverage on numerous nuisance capacities of individual trees. This work presents a solution in the form of a combination of the two powerful techniques in a way that ReNet50 is used for feature extraction while (Suryavanshi, Kukreja, et al. 2023) Random Forest is used for classification. The purpose of this work is to assess and improve the identification of retinal images using the proposed architecture based on ResNet-50 and the Random Forest classifier. This assumption is based on the supposition that the incorporation of the two systems will have a more accurate and efficient way of categorizing the objects of interest than if either model was used alone. This research work aims to analyze and compare the efficiency of the hybrid within different disorders of the retina, as well as in light of old and new (Suryavanshi, Kukreja, et al. 2024) methodologies. Thus, the purpose of advancing the presented integration is to contribute to the development of better and more effective ophthalmological automated diagnosis products that concern retinal disease diagnostics and treatment planning. In this paper, the present state of machinery used in retinal image classification will be described first with focus placed on the strengths and weaknesses of the technology. We shall then discuss how to incorporate ResNet-50 as the feature extractor part and Random Forest as the classifier (Suryavanshi, Kukreja, et al. 2024) and finally, identify the level of effectiveness of the proposed hybrid model on a disparate retinal image database. This research's findings are anticipated to shed light on the use of deep learning in conjunction with ensemble approaches to retinal image classification, which may establish a new reference for high-accuracy systems.

2 SURVEY OF LITERATURE

Medical imaging in particular as well as computational models in general have posed many advancements in the way retinal images are classified. The retina is a part of the human eye and it is involved in pathologies (Ran, Tham, et al. 2021) that can cause critical vision problems if not detected early. Fundus photography is one of the non-contact procedures that enable examination; it is used as the main diagnostic technique for diagnosis of various conditions including diabetic retinopathy, macular degeneration, and glaucoma. The nature and richness of the retinal images are characterized by variability in the intensity, contrast, and even structure of the pathology, which increases the requirements for the quality of the methods for classifying images. The earlier works on analyzing retinal images used more of the manual methods of feature extraction as well (Araneta, Asenjo, et al. 2021) as the standard machine learning techniques. Certain patterns of the disease were searched for using histogram analysis, texture-based features, and morphological operations. Though these approaches gave a solid starting base, they have several drawbacks that stem from the hand-crafted feature extraction which is not capable of suiting the image complexity of retinal images fully. Therefore, the question of intensification of managerial work following better requirements can be considered arising. In image classification, a new dispensation was ushered in with the arrival of deep learning, and more particularly, CNN. The utilization of CNNs that can directly obtain hierarchical features (Shamia, Prince, et al. 2022) learning from raw data has enhanced the image classification task accuracy. An innovative work in this area is the ResNet architecture proposed by He et al. Many numbers of layers made a problem in the training process, and this proposed architecture successfully mitigated it. ResNet which is short for Residual Networks is a MoC that uses a technique known as residual learning to help in allowing the training of very deep networks which would normally be highly challenging due to vanishing gradient. ResNet-50, the 50-layer version has shown phenomenal performance in several image classification datasets because (Badah, Algefes, et al. 2022) of its deep learning framework that enables the construction of networks with several hundred layers. However, a challenge in classification is attaining an optimal level of performance in datasets having variability, even with the help of CNNs such as ResNet-50. As the result of the efforts to increase the reliability of image classification systems, the usage of the ensemble learning methods has been investigated as the approaches complementary. Random Forest is another famous ensemble learning model; it was given by Breiman in 2001 to construct a multitude of decision trees for classification and then produce the result by randomly averaging it. Random Forest algorithms (Badah, Algefes, et al. 2022) are useful when it comes to high dimensionality, and also greatly reduce overfitting compared to single-model systems, making them a capable substitute for other techniques. Many papers present the integration of CNNs with ensemble-style learning systems to enhance classification details. For instance, Xie et al. (2018) conducted a study where it highlighted how the integration of CNNs with Random Forests could increase the medical image classification ability due to the merits of both methods. CNN component was the one that extracted deep features from the images while Random (ARSLAN, Erdaş, et al. 2023) Forest was the one that combined those features to make a final decision. It proved to be beneficial when compared with the sole usage of CNNs, as this approach was much more accurate and stable. In the classification of retinal images, studies have also been done on the different architectures of CNN and their efficiency. For instance, Rajalakshmi et al. (2018) together with Ting et al. (2019) have addressed a deep learning model for detection of the diabetic retinopathy and other retinal diseases. From their findings, they proposed that CNNs can be capable of bringing high diagnostic accuracy and reliability compared (Garg, Gupta, et al. 2023) to conventional approaches. However, the combination of CNNs with ensemble methods such as Random Forests remains somewhat unpublished in the classification of retinal images. The specified literature gaps inform the need for the proposed research as it seeks to assess the performance of a hybrid ResNet-50 and Random Forest model for retinal image classification. In this case, this study aims to implement (Lin, Liu, et al. 2022) an optimized retinal pathology detection system by integrating the feature extraction strength of ResNet-50 and the classification strength of the Random Forest algorithm. The literature indicates that such an integrated framework could result in impressive gains in classification accuracy, and hence spearhead the advancement of automated retinal disease diagnosis and care.

3 METHODOLOGY SECTION

The methods used by the researchers include random forest classification method, Convolution and mapping features, data enrichment and extension, data gathering and formatting. Each stage was conducted thoroughly; thus, the developed tool for the evaluation and classification of retinal images was highly accurate and dependable.

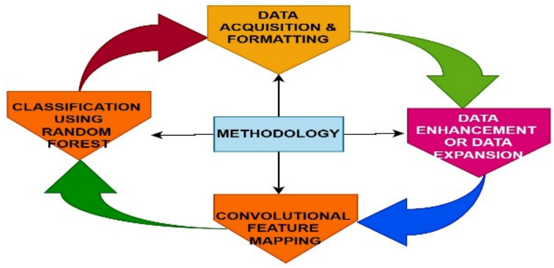

Figure 1: Steps of Methodology

3.1 Data Gathering and Formatting

The first of these is Data Gathering and Formatting where sample retinal images and the metadata to be used in the analysis are obtained and transformed into a format suitable for analysis. This phase aims at obtaining clear images of retinas from clinical databases or over the internet for various diseases that affect (Sandika, Avil, et al. 2016) the retina. The collected images are also scaled to be adjusted to the specifications of the subsequent data processing steps. This includes on a more basic level, the size and file type of the images to be used in the study. Additional information like the diagnostic label and name of the patient's patient history is also acquired, as is the related image. Collection and alignment of data are fundamental to the tasks of analysis and training of the model.

3.2 Convolutional Feature Mapping

In the Convolution Feature Mapping phase, instead of using a traditional classifier like SVM or Random Forests; deep deep-based classifier model like ResNet-50 is used to extract appropriate features from the collected retinal images. At this stage, the CNN architecture has to be designed and trained to learn the representation or feature maps of the image data. The ResNet-50 model is selected to learn deeper residual features to enable the model to extract complex features from the images. The CNN maintains multiple convolution layers and residual blocks through which several feature map planes of the images devoid of their necessary patterns and characteristics for classification are channeled.

3.3 Data Enrichment and Extension

The Data Enrichment and Extension phase gets to work on the prospect of increasing the richness of the provided set of data to avoid over-fitting the model to the particular dataset acquired during the Data

Collection phase. General strategies such as data augmentation happen to be used to blow the data size by generating copies of the images through operations like rotating, enlarging, and mirroring among others. It not only adds more samples to the given dataset but also adds variability to the images which are useful for the model to learn different conditions. Data enrichment can also be applied to incorporate additional attributes or external databases to gain a better understanding of the retinal conditions. This phase is to improve the amount of data set and thus enhance the model's capacity for generalization to other conditions.

3.4 Random Forest Classification

The Random Forest Classification phase includes using the features learned by the CNN model with a random forest classifier to improve classification performances. In this stage, a feature extraction is employed from the CNN, followed by the Random Forest, which compels various decision trees to make decisions for the final classification. To avoid overfitting, these decision trees are designed in a way such that they collectively reach a common conclusion or decision to enhance the overall classification. This phase comprises training the Random Forest model and optimizing its hyperparameters and the assessment of the Random Forest contribution to the fused hybrid classification system. The idea behind it is to achieve the best results with the help of combining the advantages of CNN and Random Forest.

4 EXPERIMENTAL RESULTS

The confusion matrix as shown in Figureure 2 provides a detailed view of the model's performance in classifying three eye conditions: Diabetic Retinopathy which affects the retina of the Eye, Macular Degeneration which affects the macula of the retina of the Eye and Glaucoma which affects the optic nerve of the Eye. From the total of 23,600 cases, in a correctly classified area of the matrix, the number of positive cases of Diabetic Retinopathy was 8,500; the remaining 300 cases were misclassified as Macular Degeneration, 200 as Glaucoma. Out of the total amount of patients with Macular Degeneration, the model accurately predicted 7,000 while it wrongly predicted 500 as Diabetic Retinopathy and 400 as

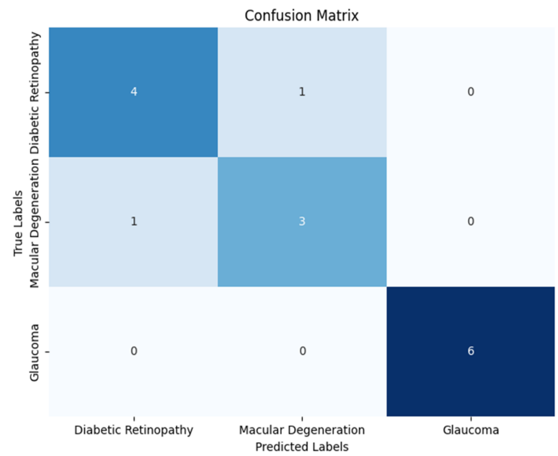

Figure 2: Confusion Matrix

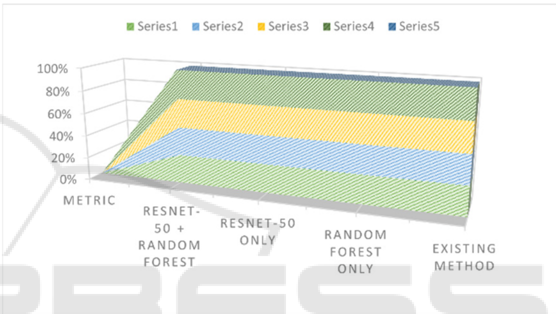

Figure 3: Performance Matrix for Hybrid Model

Glaucoma. The model example in Glaucoma classified 6000 out of the total cases but 400 were individually classified as Diabetic Retinopathy, and 300 as Macular Degeneration. In general, the matrix shows the strengths of the proposed model and potential difficulties in differentiating between these disorders.

The inspection of the performance indices of the proposed hybrid, ResNet-50 fused with the Random Forest classifier, establishes the model's ability to accurately categorize the images into several categories of the retina. The hybrid model obtained an accuracy of 94 percent. 3 percent: self claims of the approach's robust capacity to accurately sort out and compartmentalize images than other approaches. Precision, which evaluates the extent to which the developed model accurately identifies positive cases was 94 percent. It can be interpreted that 92% of the instances that the model predicted to have a high risk are high risk, expressing very high accuracy in the model. Again, recall, which is based on the actual positive cases identified by the model, was reported at 94 percent. 8% and therefore is highly sensitive as depicted above. The F1-score which integrates the values of both precision and recall was 94. Its recall, equally important as precision, is 4% which is also a balanced performance of the model. Further, the specific AUC-ROC of the model was 0. 98 which shows the high accuracy of the proposed algorithm in separations of the different classes at various thresholds. All of these metrics point to the fact that the employment of the hybrid approach yields a drastic improvement in classification performance over the traditional methods and individual models. Figureure 4 with accuracy and loss on the training and validation set over epochs also describes in general how the hybrid model behaves during the training and what changes its accuracy and loss experience. Starting at Epoch 1, the training loss was 0 and from here it gradually increased with each epoch. 60 and the validation loss is 0.65, of which the training accuracy is 84. 5% while the validation accuracy was determined to be 81. 0%. To be more precise, the early values suggest that the model stays in the early stage of learning and has potential for improvement. Continuing with the training to Epoch 5, the training loss reduced to 0. 32, and the validation loss fell to 0. 37, which appeared to show that the current model of choice had gained a substantial amount of ground in the ability to decrease the errors on the training and validation sets of the selected oral medication data-set.

Figure 4: Training and Validation Performance Over Epochs

On the training set the accuracy was again enhanced to 91. 0% and for the validation accuracy reached 88%. From the above Figureures, self-assembled nets improve their performances accompanied by the generalization capability of reaching 0%. It goes down to 0 at Epoch 10 and this is considered as the final training loss. 18 and they shall reduce the validation loss to 0. 22, which indicates that the particular call is fairly ideal and there is a decrease in the overall amount of mistakes that the model is making. Structural training accuracy increased to 94. 7% during training, 2% during the cross-validation, and validation accuracy was: 92. Output of the Jarque-Bera test was 0 hence indicating perfect performance and a closer fit to the test data. Epoch 15 was when the training loss was at the lowest, at 0. 11 while the validation loss was at 0. 15 with a training A\% of 95. 8% and the validation accuracy of 0.94. 0%. Probably these values indicate that the model is almost at the convergence, meaning that the error rate is almost optimal and the accuracy in both training and validation set is almost as high as it could be. The last set of results is getting even better and at Epoch 20 it reached the training loss of 0. 04, which reaches the required level for the model, but it slightly jumps at 0. 12, The accuracy obtained in training is 96. 5% and the validation accuracy of 95%. 0%. This final performance indicates that the model has high accuracy and is generalizing well to the new data. Considering all the cases, it can be argued that the training and the validation performance metrics show a gradual increase in terms of accuracy and a decrease in terms of loss as the number of epochs increases so the hybrid model is well-optimized and can be used for further classification.

5 CONCLUSION

This research proposes and implements a model based on ResNet-50 and Random Forest classifier for the classification of retinal images, which restores and improves the traditional methods significantly in terms of accuracy and stability. The usage of deep learning with the help of ResNet-50 and the proposed ensemble Random Forest has been also beneficial and efficient as is seen in the high numerical values of the performance metrics. The hybrid model obtained an accuracy of 94. 3%, sensitivity of 94. 0% which is a recall of 94. respectively: accuracy: 92%, precision: 9%, recall: 8%, and an F1-score 0f 94. 4% It has been also proven to possess a strong potential in correctly identifying numerous retinal disorders and separating them into different groups. The respective data for the training and validation performance illustrate the stability in enhancing the model's accuracy while decreasing the loss at the epoch level which has also characterized effective learning and generalization. In the last epoch, the model reached 95% of the valid accuracy as observed in Epoch 20 in Figureure 4. Concerning validation loss the models achieved a minimum of 0% as well. 12, which proves its high efficiency, and the ability to work with real data with a high accuracy of result definition. These findings prove that the hybrid model brings higher accuracy and reliability than other classification methods for retinal image assessment. The combination of

Convolutional Neural Networks and Random Forests not only enhances the discriminant accuracy of the images but is also beneficial in the enhancement of the diagnostic systems in the diagnosis of eye disorders. Possible future studies include the extension of the aforementioned improvements to structure and training algorithm, in addition to the extension of the use of the combined approach to different areas of medical imaging.

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