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Optimized Inception-Based Architecture for the Detection of Macular Degeneration

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Abstract:- This paper introduces Fusionception, a hybrid deep learning model for the classification of retinal Optical Coherence Tomography (OCT) images [22]. The paper starts with a comparative analysis of three convolutional neural network (CNN) models- InceptionV1, InceptionV3 and InceptionResNetV2 on [42] three publicly available datasets- OCTID, Retinal OCT Images (Kermany et al.), and the Age-related Macular Degeneration OCT dataset. Among these models, InceptionV3 and InceptionResNetV2 resulted in better accuracy and generalization. Based on these, Fusionception combines the strengths of both models by extracting the deep features of each model. These features are then combined using global average pooling and concatenation followed by a custom-designed dense classification layer [23]. We applied fine tuning and data augmentation to ensure its robust performance across different datasets. Fusionception demonstrates potential to be an effective tool in Ophthalmology with a powerful ability to recognize complex patterns and give reliable classifications across different OCT images.

Keywords: *Macular Degeneration, Convolutional Neural Networks, Inception V1, Inception V3, Inception ResNet V2, Retinal Image Classification, Medical Image Analysis.*

1. Introduction

Macular degeneration, the eye disease that affects the central part of the retina [24], is common in people who are over the age of 50, therefore results in gradual central vision loss. Nowadays Macular Degeneration has become one of the leading causes of permanent blindness, impacting millions of individuals every year [1], [25]. Early detection can lead to a significant slowdown or halting the progression of this disease. However, due to the subtle nature of retinal changes, it is difficult to identify macular degeneration at an early stage using the traditional diagnostic tools [9]. To solve this challenge, scientists used artificial intelligence and image-based diagnostics.

Convolutional Neural Networks (CNNs) is known to be a powerful tool for medical imaging. These deep learning models automatically learn to detect the important features in retinal scans, hence making them efficient in diagnosing eye diseases like macular degeneration and diabetic retinopathy [2], [4], [8]. CNN has proven to be more efficient and highly accurate in retinal image classification by performing better than traditional methods [9].

Among the CNN architectures, GoogLeNet, which is also known as the inception family has proven effective in medical imaging applications. These models extract features at multiple scales and offer a balance between computational efficiency and performance. In our research, we focused on three inception versions, InceptionV1 [5], InceptionV3 [6] and InceptionResNetV2 [7]. Each model has different features like InceptionV1 is lightweight and efficient, InceptionV3 is better in learning complex features and InceptionResNetV2 involves residual connections which improves training speed and accuracy.

To understand the strengths and limitations of these models, we evaluated them across three different OCT datasets. Though all performed well, they also had certain challenges- such as handling class imbalance, overfitting or high computational demands etc.

To overcome these issues, we proposed a hybrid architecture called Fusionception. This architecture combines the best features of three inception variants resulting in higher accuracy and better generalization. The main goal is to create a robust and practical tool to support early diagnosis of macular degeneration [3], [10], [11].

Problem Statement:

Although deep learning has made significant advancements in retinal disease detection, existing CNN designs like Inception- v1, v3, and ResNet-v2 are still plagued by irregular accuracy, overfitting, and poor generalizability across different datasets. A robust and effective model that combines the best from these architectures is essential to improve early and accurate macular degeneration detection.

2. Related Work

In [5] The inception model shown in equation 1 proposed a new architecture that we can scale in different filter sizes in one module, and we can get features of different scales from the network at the same time. To make the computation cheaper, they added 1x1 convolutions at the beginning to decrease the dimension before applying larger filters. [7] They added residual connections to the inception architecture and obtained inception v4 and inception-ResNet. They mixed the expressive power of inception modules in one network and residual learning, and obtained optimization efficiency, and successfully applied them to train deeper networks. The gain from shortcut connections helped accelerate convergence and improve generalization on unseen data. In their paper, authors implemented models and the architectures they proposed on imageNet benchmark multiple times, and they found their models are better than previous models. They also found some choices in the model design that not only make the models can converge faster, but also make them perform better in general. Saidi et al., in [11], extended this work and applied deep learn- ing model on OCT images classification and retinal disease detection (AMD, DME,). On Duke dataset, OCTorch-Net obtained 99.68% accuracy, which is also superior to other models, Inception-ResNetV2 The authors also emphasized the importance of transfer learning and fine-tuning part of medical images. Preprocessing, model design, part of medical images data augmentation and training methods are also be emphasized in this paper. This research has a great significance in for us to implement automated ophthalmic diagnosis.

BERT, proposed by Devlin et al. [13], is an impressive transfer learning model. Its bidirectional transformer architec- ture pre-trained on a large corpus obtained remarkable results on several natural language processing tasks. Although BERT is a model targeting on text, the design of its success, i.e., contextual embeddings and task-specific fine-tuning, inspire the development of image models, Vision Transformers have played a significant role in narrowing the gap between natural language processing (NLP) and computer vision tasks.

Unlike [7], Szegedy et al. [6] proposed improvements over the inception architecture by adding more efficient versions of certain layers such as factorized and asymmetric convo- lutions as well as auxiliary classifiers. These improvements are included in Inception-v3, which are more computationally efficient at the expense of some accuracy degradation. For example, they obtained top-1 error of 17.3% on ILSVRC 2012 validation set which is popular benchmark and is believed to provide a good trade-off between performance and computa- tion cost.

Amaladevi [12] have compared the performance of GoogLeNet and VGGNet on the problem of classification on retinal images, which are used in detection of dia- betic retinopathy and AMD. VGGNet performed better than GoogLeNet, achieving 96% accuracy and 99% specificity. While GoogLeNet had comparatively lower results. It was also shown that pre-trained CNN models are a great help in medical images, especially in cases when training data is scarce.

Ji et al. [10] propose optimized and light-weight CNN models on top of Inception-v3, ResNet50 and DenseNet121 for macular disease identification from OCT images. Firstly, they have performed extensive evaluation on large-scale OCT datasets and then they have proposed pruning and simplifying architectures for macular disease identification in healthcare application up to 99.80% accuracy.

3. Methodology

A. Proposed Architecture

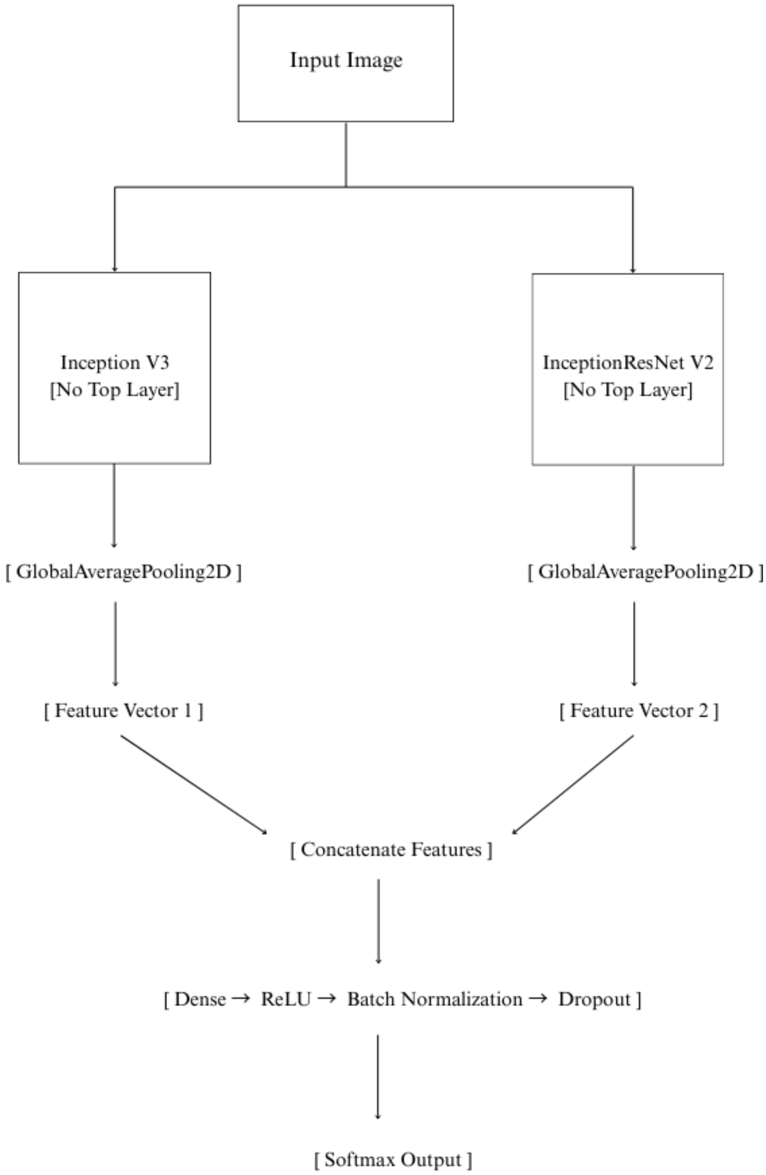


Fig. 1: Architecture of Fusionception

In this work, we present a hybrid deep learning model [26] by combining the strengths of two CNN architectures—InceptionV3 and Inception-ResNetV2 to improve binary classification of images. Instead of choosing just one architecture, we run both models in parallel, which allows them to independently extract features from the same input image [27].

Both models are pre-trained on the ImageNet dataset and are used to extract features [35] alone, as we remove their fully connected (top) layers. The input image, which is resized to 224 × 224 pixels with three color channels, is fed simultaneously to both models. Each model, based on its unique architecture, processes the image differently and captures patterns and features in its own way.

To combine the outputs of these models and convert them into one-dimensional feature vectors, we first apply a Global Average Pooling (GAP) layer to the final output [36] of both models. These vectors are then normalized using Batch Normalization to stabilize learning. We concatenate them and combine both sets of features into a single, complete feature set.

Then, this combined vector goes through a custom classification block. First, it passes through a dense layer of 256 neurons [37] and a ReLU activation function to introduce non-linearity [28]. Then, a batch normalization layer helps to stabilize and speed up training. To prevent overfitting, a dropout layer with a 50% rate is applied. Finally, the output goes into a final dense layer that has two output units and a SoftMax activation function [38] for binary classification.

To train our model more effectively, we use the Adam optimizer with a learning rate of 0.0001 and the categorical cross-entropy loss function [20]. We apply data augmentation so that the model generalizes better and becomes more reliable. This includes randomly rotating, shifting, zooming, and flipping images during training, which simulates the changes that the model might encounter in real-world [23] data. We then split the dataset into training and validation sets in a ratio of 80:20 [21]. This helps to monitor the performance of model on unknown data [29] during training. We trained the model over several epochs, and continuously calculated accuracy and loss to measure how well the model was learning. To make our hybrid approach extract a wider and more detailed set of features from the images [30], we combined the strengths of two different CNN architectures at the feature level. As a result, it is likely that it may perform better than models that rely on just a single network.

B. Comparative Analysis of Inception Models

For our project, we used three deep learning models from the Inception family: Inception V1 (GoogLeNet), Inception V3, and Inception-ResNetV2 to determine how well they can identify retinal diseases on the basis of OCT (Optical Coher- ence Tomography) images. We used three different datasets:

- OCTID – Optical Coherence Tomography Image Database [17]
- Retinal Optical Coherence Tomography Images Dataset [22]
- Age-Related Macular Degeneration Retinal Optical Co- herence Tomography Images Dataset [19]

These datasets include labeled OCT scans of different eye conditions which makes them perfect for model testing.

The images were resized and normalized before being fed to the models to maintain consistency and improve performance. We also applied data augmentation on the datasets such as flipping, rotation, and zooming images to make the [25] models generalize better and prevent overfitting. We divided the three datasets into training, validation, and test subsets.

We then used transfer learning for all three models, starting with those models that were already trained on ImageNet dataset and then adapted them to our task [39] by fine-tuning the final layers. We trained the models with the Adam optimizer and the categorical cross-entropy loss function [34] for classification. We calculated metrics such as accuracy, precision, recall, F1-score, and observed confusion matrices and ROC curves to observe the [40] performance of each model. We also monitored the training and validation performance. Finally, we compared the [41] outputs of all three models and datasets to see which combination performed best at detecting retinal disease from OCT images.

C. New Architecture

After analyzing the results from our previous models, we observed that although Inception V1 was fast and lightweight, it still didn't perform well in terms of accuracy and didn't generalize the data well. It was unable to distinguish among different retinal diseases, so we decided not to include it in our new model design.

Instead, we focused on the models that performed best on these datasets, i.e. Inception V3 and Inception ResNetV2. The former showed good accuracy, and the latter provided stability during training due to its residual connections. By combining the strengths of both these models, we created a hybrid model that benefits from the feature extraction of Inception V3 and the training efficiency of Inception-ResNetV2. Using this approach, we captured high-level features from the OCT images while keeping the training process smooth and reliable.

We used the same three OCT datasets—OCTID, Retinal OCT Images, and the AMD dataset. We resized and normalized all images, and then applied data augmentation techniques. We split the datasets into training, validation, and testing sets [31].

We built the hybrid model using transfer learning. We initialized both the networks with pre-trained weights from ImageNet then we fine-tuned the [32] final layers for our specific classification task. To train the model, we used the Adam optimizer and categorical cross-entropy loss function. To prevent overfitting and for an effective training process, we [20] applied techniques like early stopping i.e., the training is automatically stopped when the model stopped improving and learning rate reduction which is used to fine tune the learning.

After training, we planned to compare the hybrid model's performance with the performances of the original Inception V3 and Inception-ResNetV2. Based on the complementary strengths of these architectures, we expect that the hybrid model might achieve improvements in both accuracy and efficiency, making it a more practical choice for real-world applications [33] in diagnosing OCT-based retinal diseases.

4. Experimental Results

Inception-Based Models Performance

In our project, we tested the idea of combining two strong deep learning models (InceptionV3 and Inception-ResNetV2) into a single hybrid design called Fusionception. Early comparisons with existing models on retinal OCT datasets suggest that this approach may be able to capture richer features and give more reliable results. While we have not yet done large-scale or clinical testing, these initial findings support our hypothesis that Fusionception could perform better than using a single model alone.

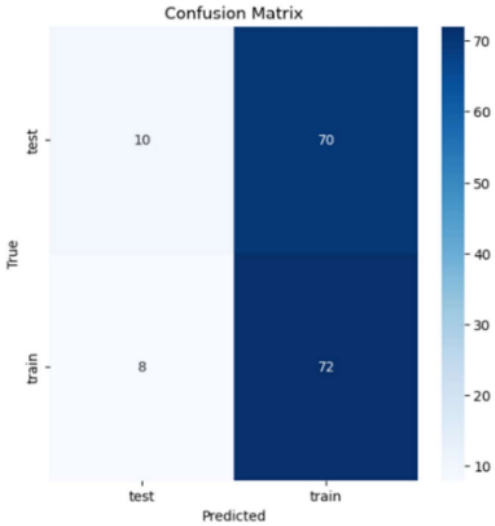
Table 1 shows the comparative performance of Inception V1, Inception ResNetV2 and Inception V3 across three datasets. It highlights the strengths and limitations of these models, especially in handling imbalanced data.

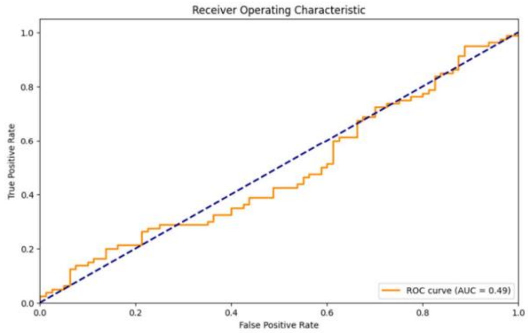
Table 1: Tabular visualization of Inception-based models across datasets.

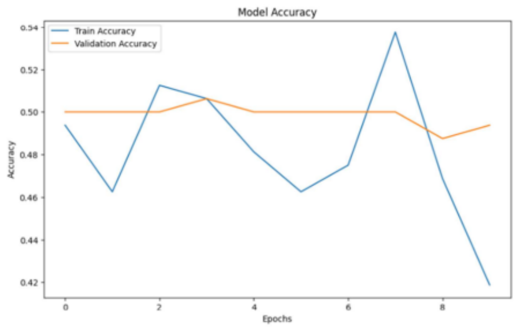
Model	Dataset	Accuracy	Precision	Recall	F1 Score	AUC	Key Issues
Inception V1	Dataset 1	~50%	50.7%	40%	44.8%	48.6%	Moderate performance, some overfitting
Inception V1	Dataset 2	~50%	50%	100%	66.7%	53%	Model bias, predicting only majority class
Inception V1	Dataset 3	~83.6%	83.5%	100%	91.0%	49.3%	Severe class imbalance, trivial classifier
Inception V3	Dataset 1	~90%	36%	64%	46%	53%	Poor discriminative ability despite high accuracy
Inception V3	Dataset 2	~88%	48%	47%	48%	49%	Near-random classification
Inception V3	Dataset 3	~83.5%	84%	100%	91%	50%	Severe class imbalance, trivial classifier
ResNetV2	Dataset 1	~95%	26.7%	32%	29.1%	43%	Worse than random chance
ResNetV2	Dataset 2	~96%	96.1%	100%	98%	48.3%	High metrics but poor discrimination
ResNetV2	Dataset 3	~93.5%	83.6%	100%	91%	50%	Severe class imbalance, trivial classifier

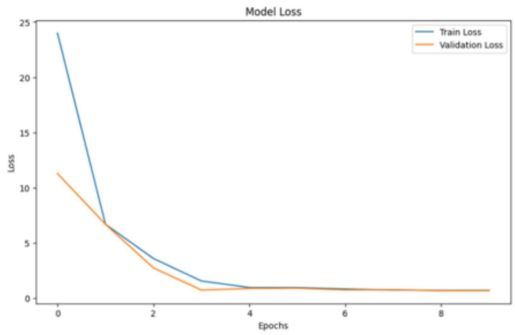
Inception V1

Dataset 1

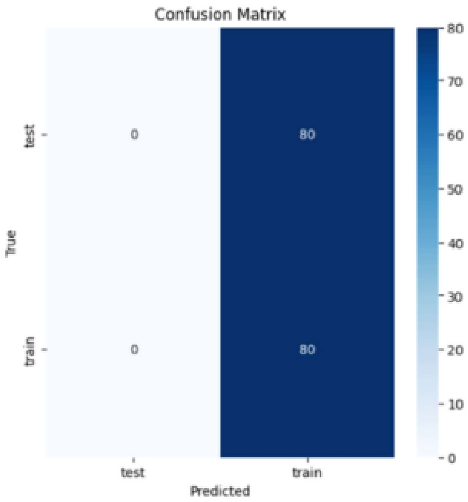


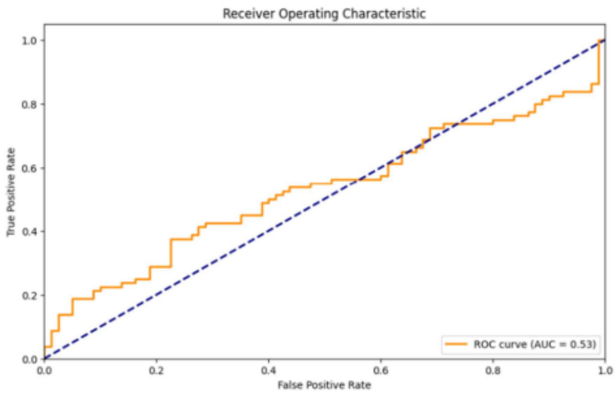


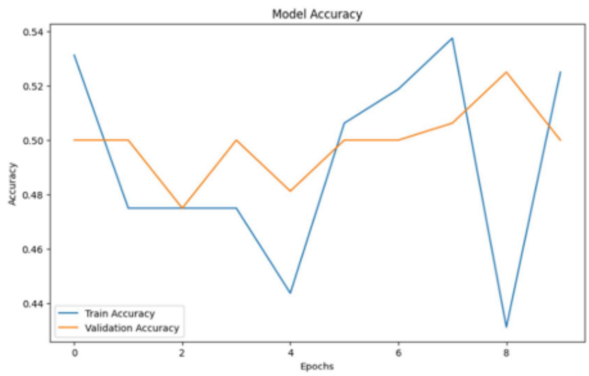


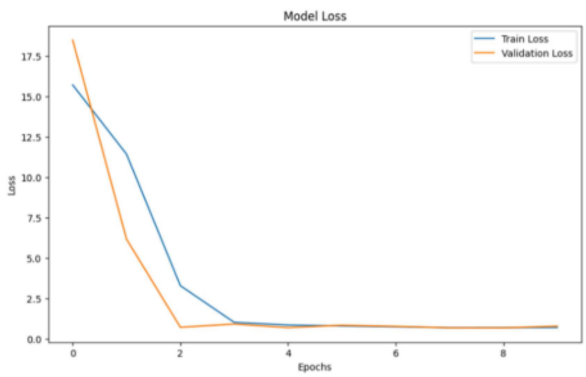


Dataset 2

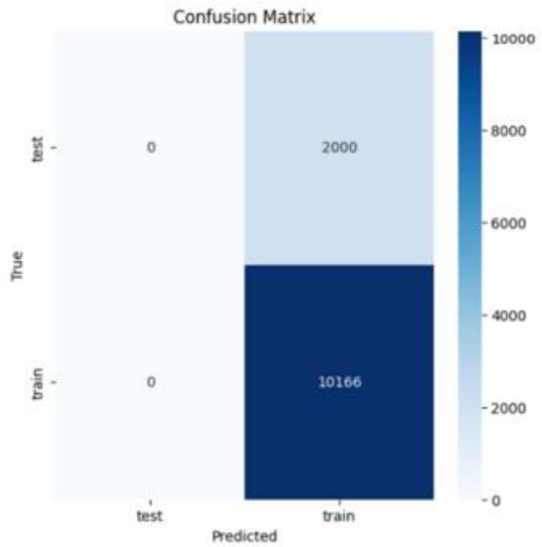

Confusion Matrix
test
train
True
Predicted
0
80
0
80
0
10
20
30
40
50
60
70
80

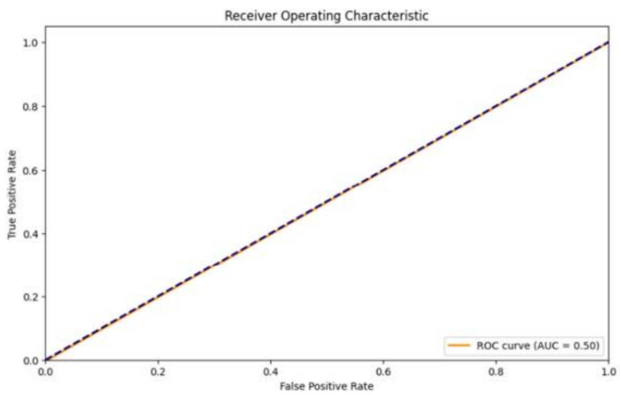

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.53)
0.0
0.2
0.4
0.6
0.8
1.0

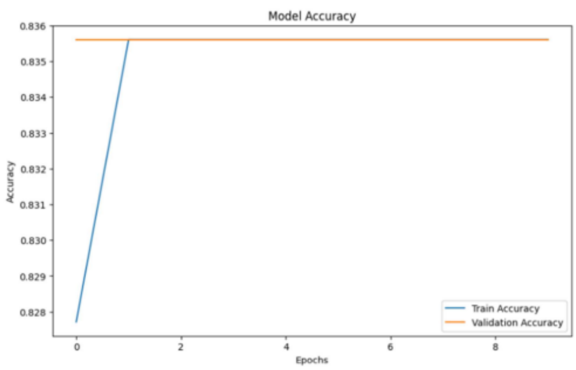

Model Accuracy
Accuracy
Epochs
Train Accuracy
Validation Accuracy
0.44
0.46
0.48
0.50
0.52
0.54
0
2
4
6
8

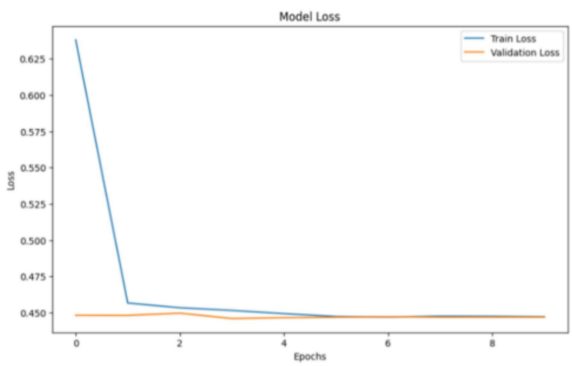

Model Loss
Loss
Epochs
Train Loss
Validation Loss
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
0
2
4
6
8

Dataset 3


Confusion Matrix
test
train
True
0
2000
0
10166
test
train
Predicted
10000
8000
6000
4000
2000
0

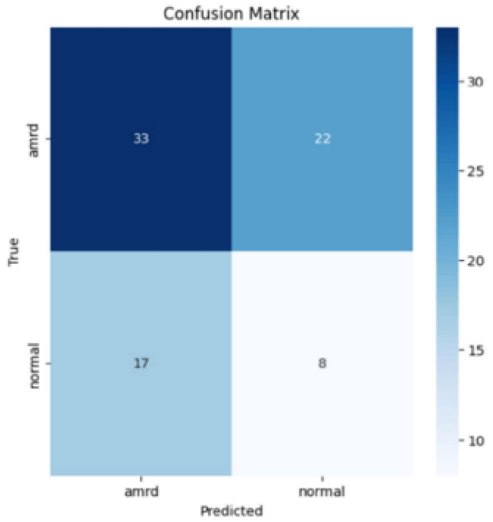

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.50)

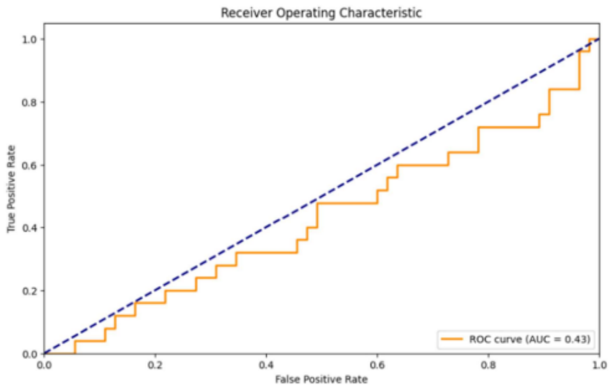

Model Accuracy
Accuracy
Epochs
Train Accuracy
Validation Accuracy

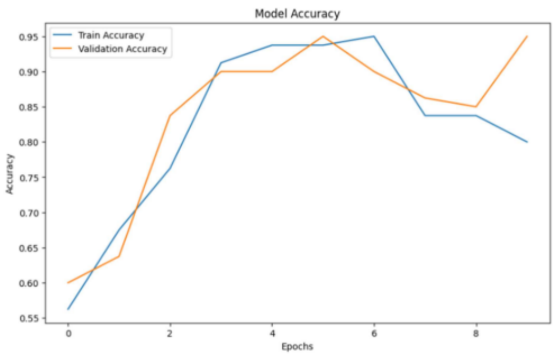

Model Loss
Loss
Epochs
Train Loss
Validation Loss

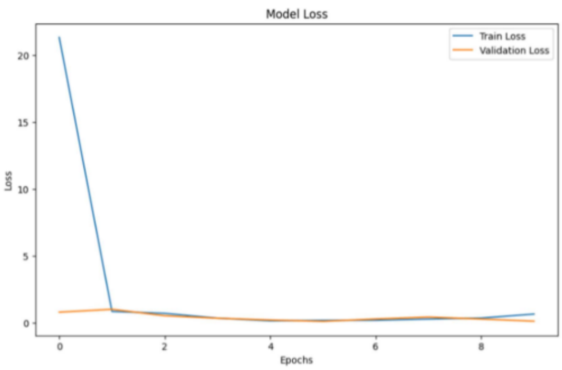
Inception ResNet V2

Dataset 1

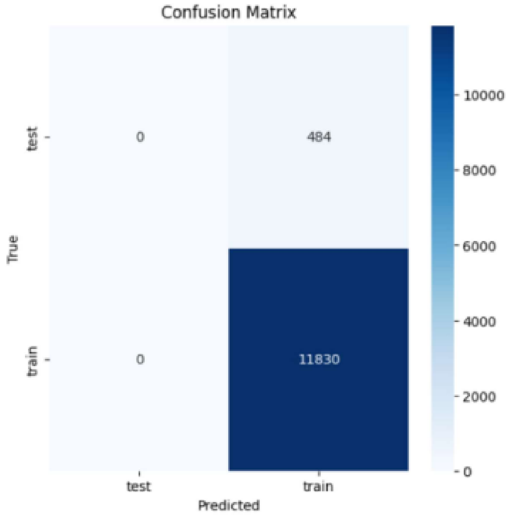


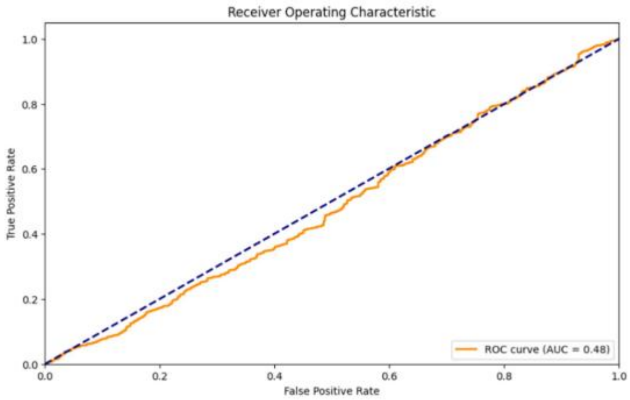


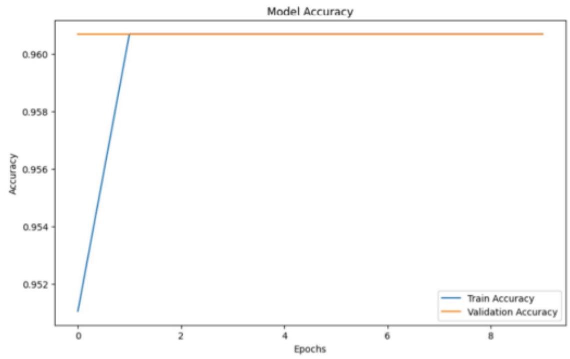


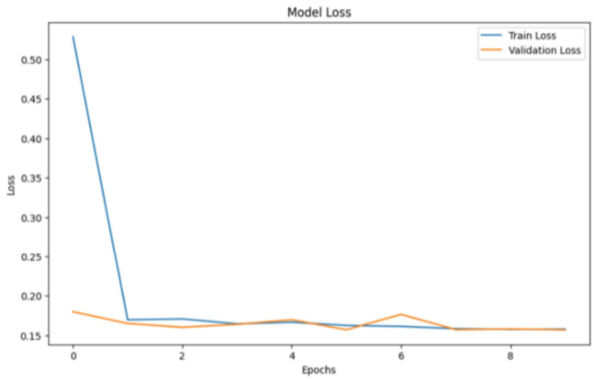


Dataset 2

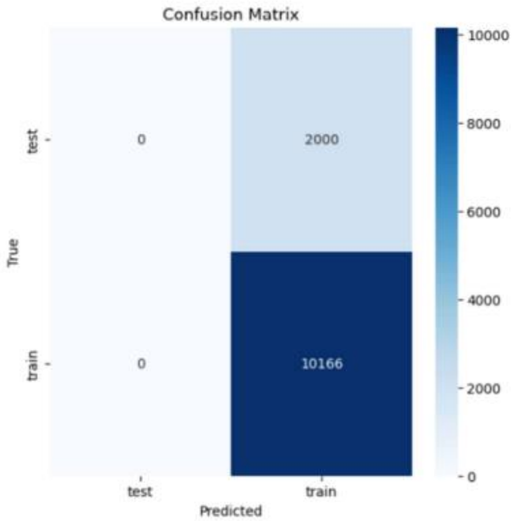

Confusion Matrix
True
Predicted
test
train
0
484
11830
10000
8000
6000
4000
2000

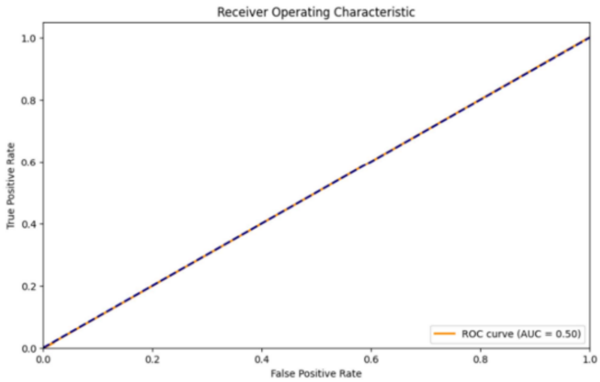

Receiver Operating Characteristic
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.48)

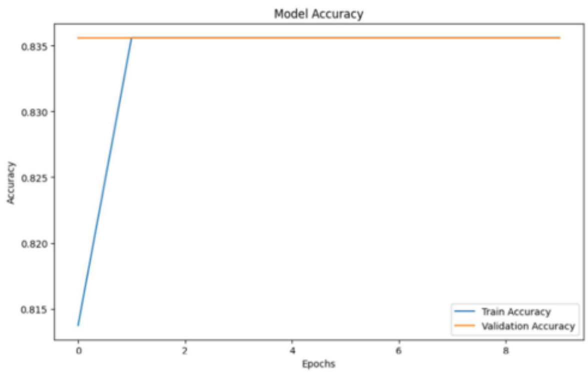

Model Accuracy
Accuracy
Epochs
Train Accuracy
Validation Accuracy

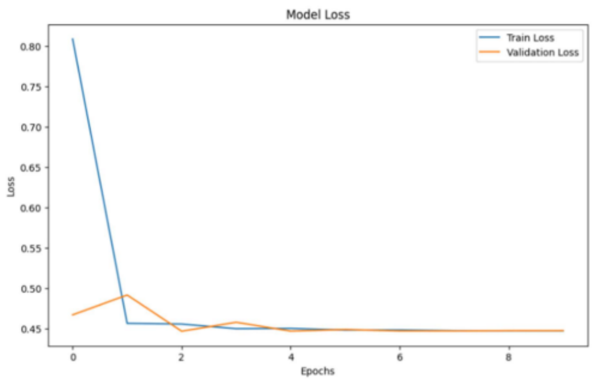

Model Loss
Loss
Epochs
Train Loss
Validation Loss

Dataset 3


Confusion Matrix
True
Predicted
test
train
0
2000
10166
10000
8000
6000
4000
2000


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.50)


Model Accuracy
Accuracy
Epochs
Train Accuracy
Validation Accuracy


Model Loss
Loss
Epochs
Train Loss
Validation Loss

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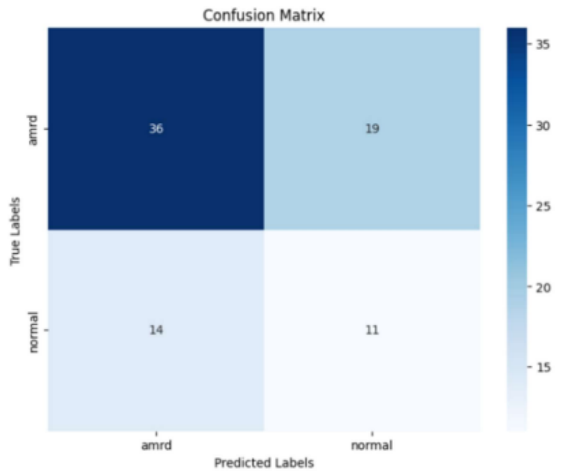
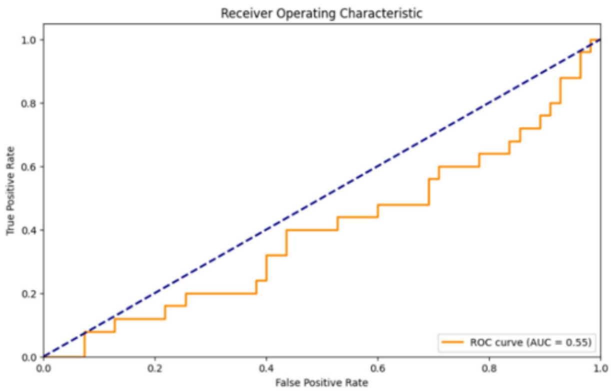
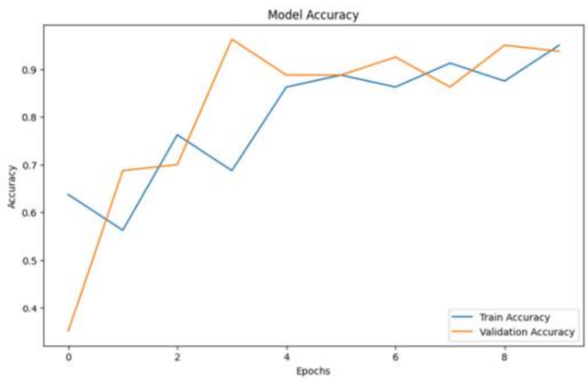
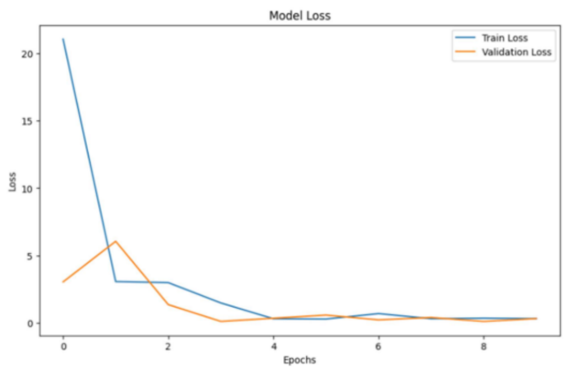
Inception V3

Dataset 1

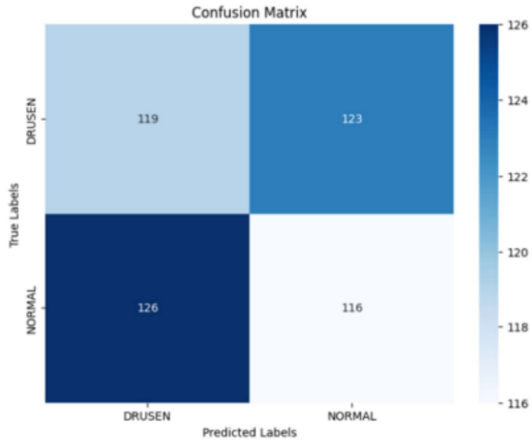


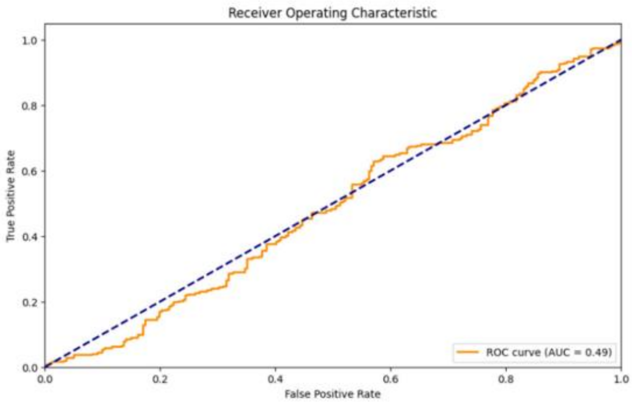


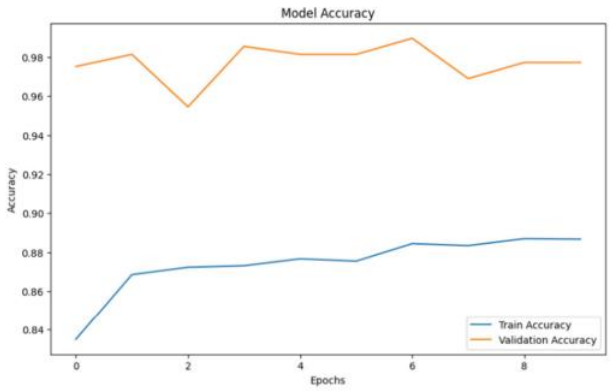


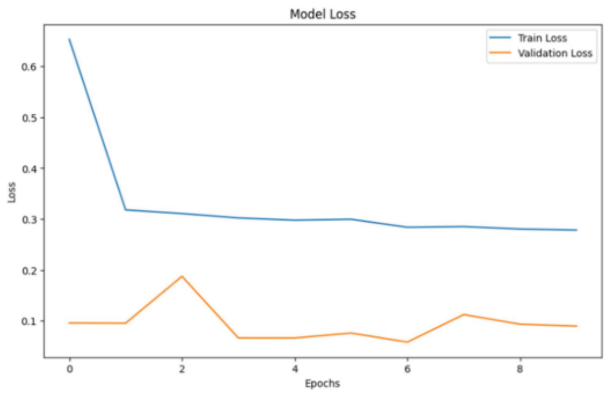


Dataset 2


Confusion Matrix
DRUSEN
NORMAL
True Labels
119
123
126
116
DRUSEN
NORMAL
Predicted Labels
126
124
122
120
118
116


Receiver Operating Characteristic
True Positive Rate
False Positive Rate
ROC curve (AUC = 0.49)
0.0
0.2
0.4
0.6
0.8
1.0


Model Accuracy
Accuracy
Epochs
Train Accuracy
Validation Accuracy


Model Loss
Loss
Epochs
Train Loss
Validation Loss

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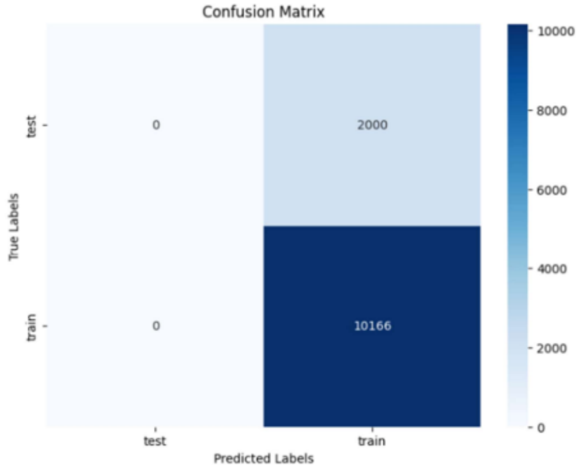
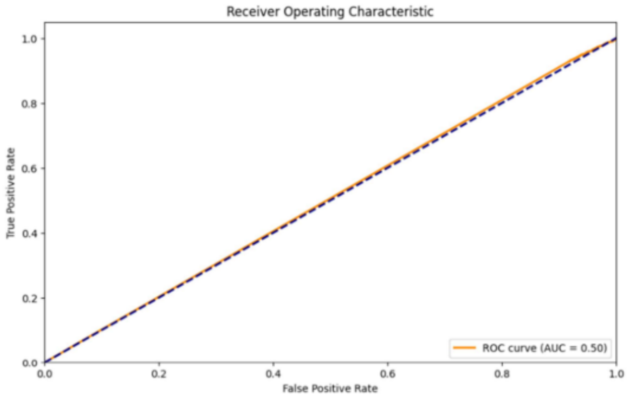
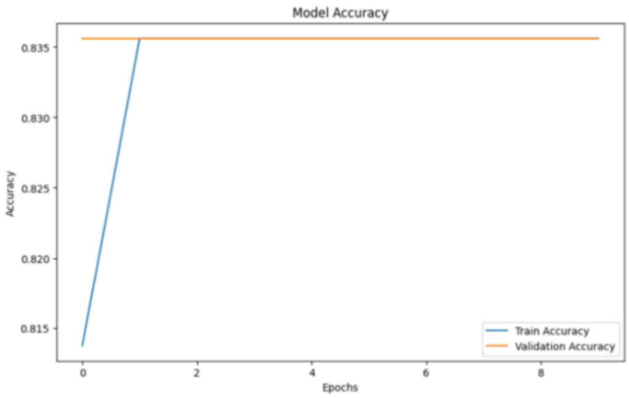
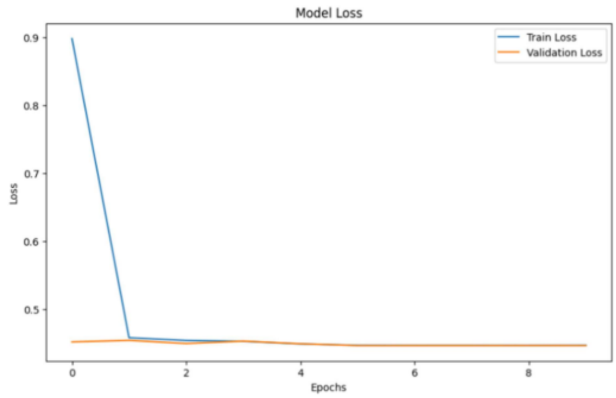
Dataset 3









5. Conclusion

In this study, we propose Fusionception, a deep learning hybrid architecture which combines the good [43] features of InceptionV3 and InceptionResNetV2 in order to classify retinal OCT im- ages more efficiently. We choose the best architectures and amalgamate them together by comparing and evaluating the three deep benchmark datasets independently; OCTID, Retinal OCT Images, and Age-related Macular Degeneration OCT dataset in the meantime. At the [44] same time, with a richer representation, the model passes input images through both networks, takeout high-level features, and merge them at the feature level. The results of thorough experimentation and re- search indicate that Fusionception may outperform individual CNN models in terms of accuracy, robustness and general- ization. The results suggest that [18] fusing features via ensemble methods can potentially improve how well medical images are analyzed. So as to help ophthalmologists to diagnose retinal disorders as soon as possible, future studies will attempt to elaborate this approach to multi-class classification and attention mechanism base and apply the model in clinical decision making system.

6. Future Work

In the near future, we can see the following. If we use a large set of OCT images from different types of various resources as the validation part for the model. It will be possible to validate the model in the laboratory and clinical environment. It will also be an interesting step if we can increase the clarity of the model, in other words, what parts of the image should we focus so that we can get a better conclusion. So that the doctors can trust and realize the predictions as a result. Also, we can enhance the model more for more accurate by tuning some parameters like dropout setting or learning rate. We can also tune or simplify the model to be evaluated on smaller portable computers. At last, it will also be good to include images along with basic patients' data to make the predictions more clinical and personalized.

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