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#### Abstract

We propose a Super-Learner framework by combining Deep Ensemble Network and feature maps to automate the differential diagnosis from medical imaging datasets. Such methods improve the predictive performance of a single model by training multiple models and combining their predictions. Our study introduces the concept of **Deep Ensemble Networks**. To validate our research, we have developed a **Deep Ensemble Detection Framework "Super Learner"** by the virtue of which we were able to classify **Retinal Optical Coherence Tomography (OCT) images and Blood Smear images** across three classes and two classes respectively; outperforming all pre-existing studies on both imaging datasets with a state of the art **accuracy.** 

#### Introduction

Ensemble learning is a well-recognized method in machine learning that effectively obtains exemplary results by combining multiple classifiers. Early work by Hansen and Salamon (Hansen and Salamon 1990) proves that the efficacy of a neural network model can be refined, by ensembling multiple neural networks. Since this technique behaves reasonably well, it is considered to be an effectual approach for the fashioning of sophisticated image classification systems and thus has already found applications in diversified areas such as facial recognition, optical character or pattern recognition, scientific image analysis, medical diagnosis systems, signal classification, etc. In the present study, we have developed an ensemble model 'Super Learner' that combines various Deep Convolutional Neural Networks (DNN) based on their compatibility. The technique was further elucidated using two distinct case studies that address two medical problem statements. Firstly, the technique was used to construct a model named OCTx to classify four retinal disorders from Optical Coherence Tomography (OCT) images. Secondly, it was used for MalariaX which diagnoses parasitized Malaria by performing a binary classification of thin blood smear images that were classified as either 'Parasitized' (infected) or 'Uninfected'. In both cases, the Super Learner yielded state-of-the-art accuracy, increased model reliability and mitigated the chances of overfitting for the test cases.

# Super Learner Model to Detect Abnormalities - OCT and blood smear imaging case studies

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## Methodology

For the use-case of the OCT dataset that we used to build and validate our model (Super Learner) in this study - the pedagogy is illustrated as follows and the respective DNNs used here are: VGG16, DenseNet, InceptionV3 and a Custom CNN.



Validation of Super Learner



Recall

F1 Scor

Uninfected 85.0 5,703.0 0 2000 Predicted label accuracy=0.9846; misclass=0.0154





In the context, we demonstrate a novel framework based on ensembling multiple Deep Neural Networks which were selected based on their individual performances on the targeted case-study. We Successfully accessed the performance of the framework on two distinct imaging case studies with a state of the art accuracy. We further welcome research in the domain of utilisation of **Deep Ensemble Networks** used in this study in the detection of diseases and disorders from medical images and thereafter achieving bettercalibrated results on future image datasets as well.



## Performance Analysis

# Training and Inference - OCT Dataset :

5	Custom CNN	DenseN et	VGG16	Incepti onV3	Super Learner
су	0.92	0.96	0.96	0.97	0.985
n	0.92	0.94	0.96	0.975	0.968
	0.905	0.95	0.965	0.97	0.973
	0.92	0.95	0.96	0.96	0.970

Training and Inference - Blood Smear Dataset:

5	DenseNet	Custom CNN	ResNe t 50	Super Learner
су	0.962	0.975	0.973	0.985
on	0.954	0.952	0.978	0.984
	0.965	0.989	0.9764	0.985
е	0.953	0.976	0.977	0.986

### Conclusion