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AI-Driven Early Prediction of Eye Disorder

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Session #5
Applications and services for sustainable development

Introduction

- What is DR and how it occurs [1]?
- What WHO says?
- Why detection is important [2]?
- What are issues with conventional methods?
- How AI can solve the problem?

Methodology

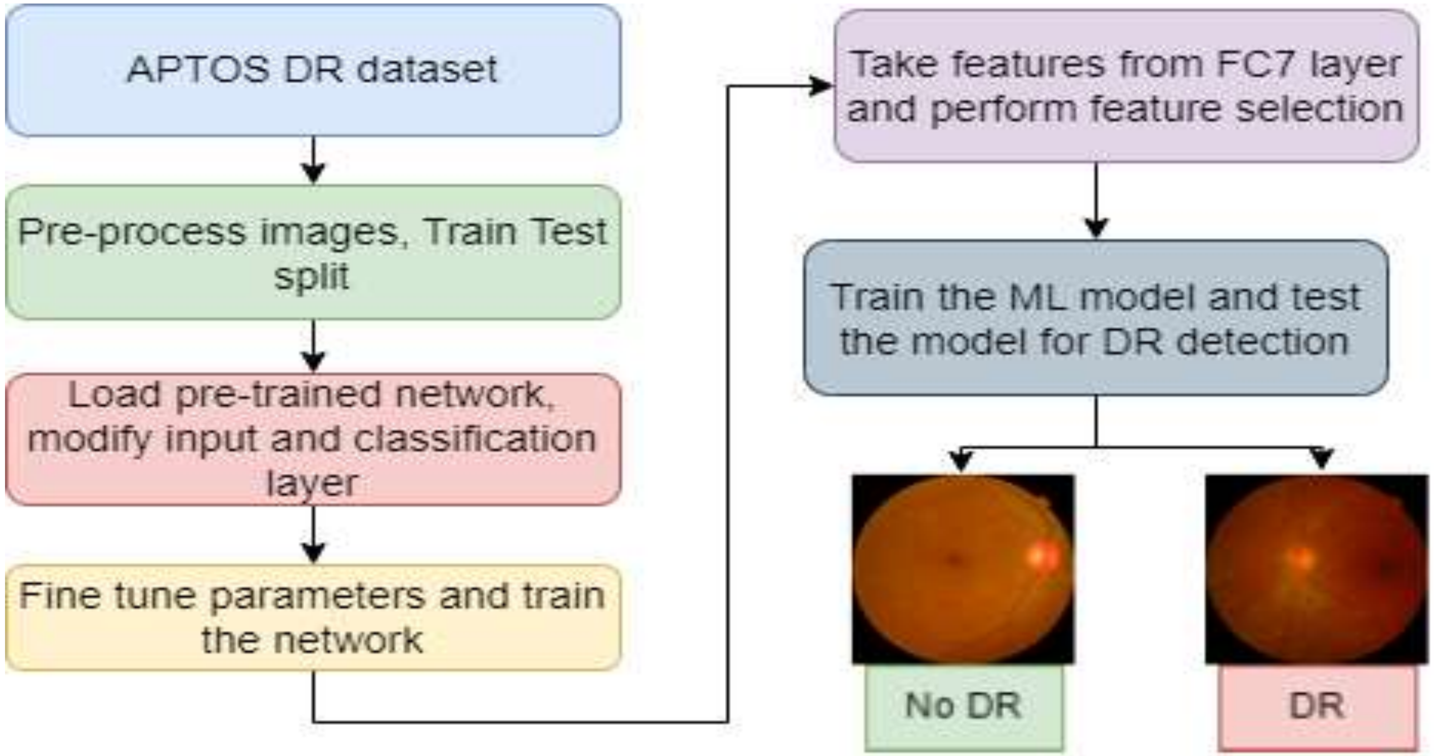
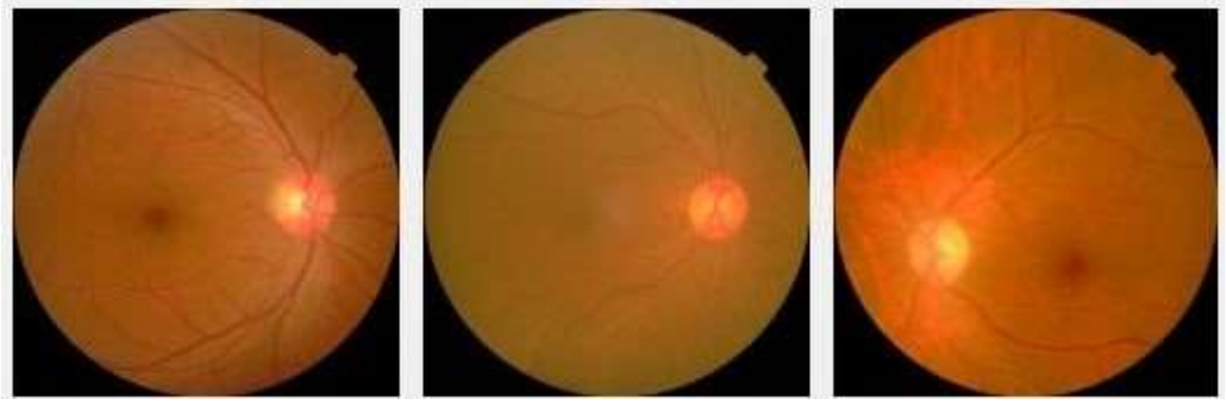


Fig. 1 Block diagram of the proposed method

Comparison

Example images from DR class →

Example images from Normal class →



Dataset

APTOS consists of retinal images captured by a fundus camera operated by Aravind Eye Hospital in a rural setting [7]. Among these images, 2930 were allocated to the training set, while 366 were designated for the validation and test set each. All images in the dataset have a resolution of 3216×2136.

Pre-processing

- To accommodate the requirements of CNN networks, all images are resized to a standard size of 224x224x3.
- Additionally, subtraction of the mean across all images from each image in the training dataset is done.

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Convolutional neural networks (CNN)

Transfer learning is employed to fine-tune two distinct CNN networks, VGG16 and ResNet18 [8,9]. Since all these networks are pre-trained on the ImageNet dataset, customization of the classification layer is necessary to adapt them to our specific application.

CNN Training Parameters

- HYPER-PARAMETERS FOR TRAINING
  - Batch Size 20
  - Epochs 20
  - Learning rate 0.0001
  - Optimizer stochastic gradient descent

Feature selection

- Kruskal-Wallis (KW) test [10] is employed to identify the most significant features. This test serves to reduce dimensions and enhance classification performance in a non-parametric manner.
- KW test determines p-values. These p-values signify the probability of observing the data under the null hypothesis. Features with higher p-values are considered less significant, whereas smaller p-values indicate rejection of the null hypothesis.
- In this study, features with p-values less than 0.05 are selected for further analysis.

Classification

- After feature selection, retinal images are classified using three machine learning classifiers, namely, k-nearest neighbor (kNN), decision tree (DT) and support vector machine (SVM).

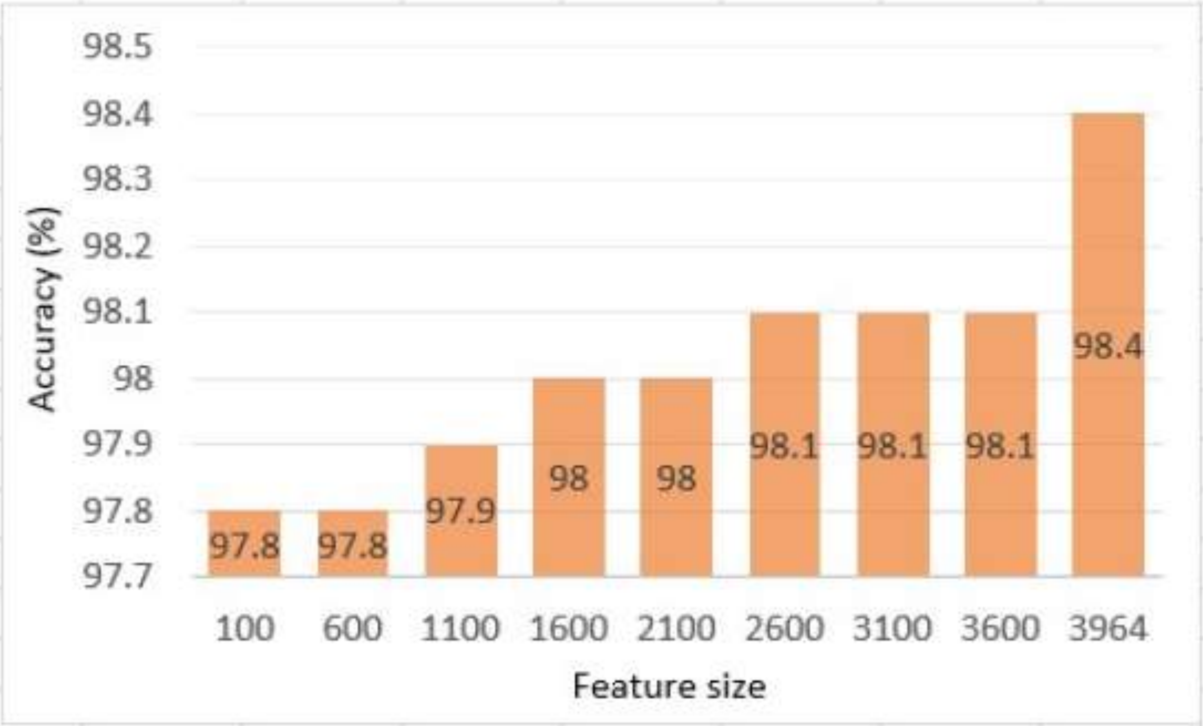

Fig. 4 Accuracy versus feature length for modified VGG

Result and Discussion

Table-I - Performance comparison of using different classifiers

Classifier	Accuracy (%)	
	Validation	Testing
kNN	99.1	97.5
DT	99.5	97.5
SVM	99.9	98.4

Table-II - Performance comparison of Modified VGG16 and VGG16

Classifiers	Accuracy (%)	Precision (%)	Recall(%)	F1-score (%)
Modified VGG16	**98.4**	**98.2**	**98.2**	**97.6**
VGG16	97.3	98.1	95.8	97.0

Result and Discussion

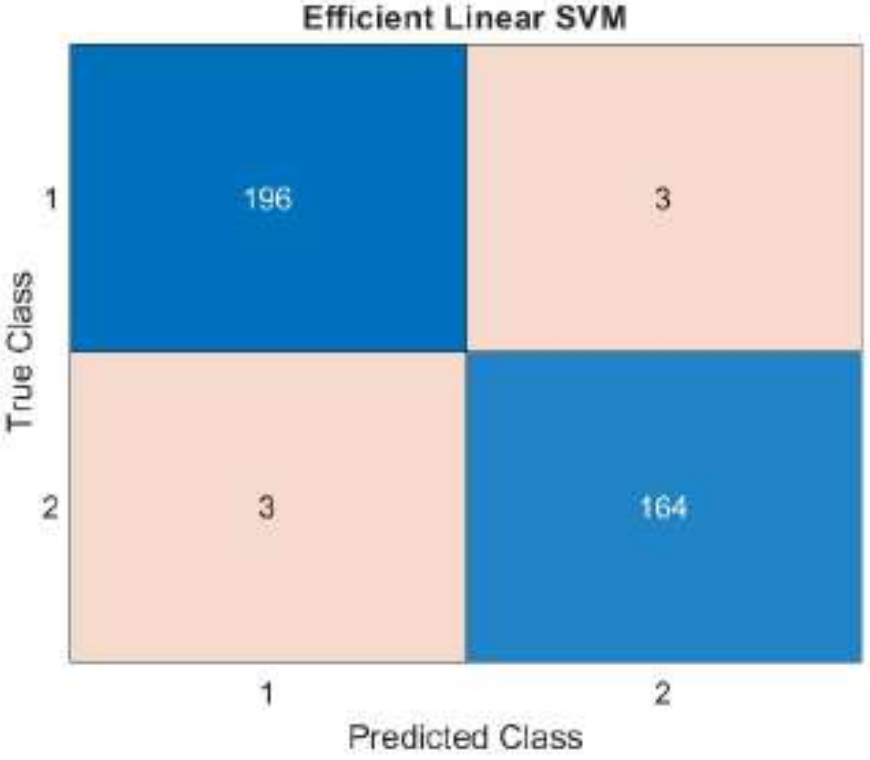

Fig. 5 – Confusion matrix of SVM using test data.

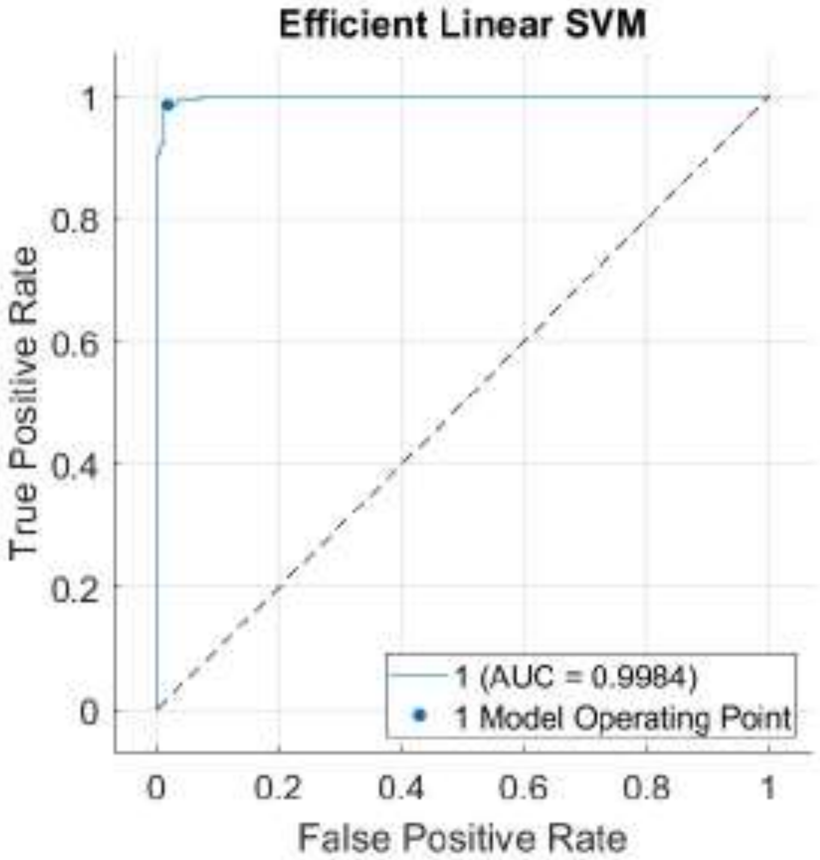

Fig. 6 – Region of convergence (ROC) curve of SVM using test data.

Result and Discussion

- Performance Comparison of Different Models

Methods	Accuracy (%)
VGG16	97.3
ResNet18	95.3
Deshpande et al. [6]	81.6
Lahmar et al. [3]	93.0
Lahmar et al. [4]	88.8
Kassani et al. [5]	83.0
Proposed method	**98.4**

Conclusion

- Leveraging transfer learning in medical image analysis, our study presents a refined VGG16 network tailored for DR detection, integrating a feature selection technique.
- Through meticulous parameter tuning and feature selection, our approach achieves a notable performance boost.
- Notably, our modified VGG16 network outperforms both the standard VGG16 and ResNet18 networks, attaining an impressive accuracy of 98.4% on a benchmark DR dataset.
- This underscores the potential of our approach in enhancing automated DR detection systems for clinical use.
- The boom in telecommunication network and enhanced data rate owing to 5G and 6G technology, AI can further enhance tele-ophthalmology services, making eye care more accessible, especially in remote areas

References

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Thank you!

Literature Survey

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Thank you!