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Accurate Detection Of Retinal Blastoma (Eye Cancer) Using Electroretinogram Erg - Image By Deep Learning (Vgg-19) Model

Dr. K. VigneshKumar[1], Dr. N. Sumathi[2], Dr. Princess Maria John[3], Mrs. A. Benita[4], Mrs. K. Vinotha[5], Dr. A. Vijayalakshmi[6], Dr. AR Jayasudha[7]

[1,4,5]Assistant Professor

[2,3,6]Associate Professor

[7]Professor

[1,3,4,5,7]Department of Computer Applications (MCA),

[6]Department of ECE, Hindusthan College of Engineering and Technology, Coimbatore.

[2]Department of Information Technology, Sri Ramakrishna College of Arts & Science, Coimbatore.

Email ID: krishvigneshkumar@gmail.com

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ABSTRACT

Retinoblastoma is an uncommon yet life-threatening eye cancer that mostly affects children. Early and correct identification is crucial for avoiding visual loss and increasing survival chances. This paper describes an automated deep learning strategy for precisely detecting retinoblastoma using electroretinogram (ERG) data. The ERG picture files are analysed using a pre-trained VGG-19 model, which is noted for its exceptional feature extraction capabilities. The model uses transfer learning to tailor its architecture to the unique purpose of retinoblastoma detection, resulting in excellent sensitivity and specificity. To improve performance, the ERG picture dataset is pre-processed using techniques including normalisation, augmentation, and noise reduction, which improves the model's resilience and generalisability. The VGG-19 network accurately identifies pictures as healthy or ill, producing a high F1-score while minimising false positives and negatives. The findings show that the VGG-19 model has the potential to help ophthalmologists diagnose retinoblastoma earlier and more reliably. This work demonstrates the use of deep learning in medical imaging, demonstrating its effectiveness in detecting uncommon illnesses such as retinoblastoma.

Keywords: *Retinoblastoma, electroretinogram (ERG), VGG-19 model*

1. INTRODUCTION

Retinoblastoma is the most common intraocular cancer in children, resulting in considerable morbidity and death globally. Early identification is critical for optimal therapy and vision preservation, since late discovery can result in ocular complications, metastasis, and even death. Traditional diagnostic procedures, such as fundoscopy, ultrasound, and imaging modalities such as magnetic resonance imaging (MRI), are useful, but they are sometimes time-consuming, resource-intensive, and need professional interpretation. In this context, electroretinogram (ERG) imaging, a method for measuring retinal electrical activity, has gained popularity because of its potential as a diagnostic tool. With improvements in artificial intelligence (AI), particularly deep learning, the area of medical imaging has made significant progress in automating illness identification. Deep learning models are superior at recognising complicated patterns in huge datasets, beating classic machine learning approaches in applications like picture categorisation. Among these models, VGG-19, a convolutional neural network (CNN) architecture recognised for its depth and robust feature extraction, has performed well in a variety of medical imaging applications.

The present research suggests employing a VGG-19-based deep learning model to accurately detect retinoblastoma in ERG scans. The model makes use of transfer learning, which allows it to efficiently apply pre-trained information for ERG picture classification. The technique begins with preprocessing the dataset to improve picture quality, followed by training and fine-tuning the VGG-19 model to obtain high diagnosis accuracy.

The goal of this study is to develop a dependable, efficient, and automated diagnostic tool to aid ophthalmologists in early retinoblastoma diagnosis. By decreasing diagnostic delays and dependence on manual interpretation, the proposed approach seeks to considerably improve patient outcomes. This introduction prepares the groundwork for the investigation of deep learning's revolutionary impact in improving diagnostic accuracy and accessibility in paediatric cancer.

1.1 VGG-19 Model

VGG-19 is a deep convolutional neural network (CNN) known for its simplicity and superior performance in picture classification tasks. It has 19 layers, including 16 convolutional and 3 fully connected layers, and uses tiny 3x3 convolutional filters to extract detailed features while being computationally efficient. VGG-19 uses ReLU activation and max-pooling layers to capture spatial hierarchies and minimise dimensions. In this work, VGG-19 is fine-tuned using transfer learning to accurately classify electroretinogram (ERG) pictures. Its strong architecture easily recognises subtle patterns in ERG data, giving it a potent tool for accurately and reliably identifying retinoblastoma.

1.2 Retinoblastoma (Eye Cancer)

Retinoblastoma is an uncommon but severe eye cancer that affects mostly children under the age of five. It develops in the retina as a result of RB1 gene alterations that control cell proliferation. Early symptoms include a white reflection in the pupil (leukocoria), misaligned eyes (strabismus), and vision loss. If left untreated, retinoblastoma can spread to the brain and other regions of the body, making it life-threatening.

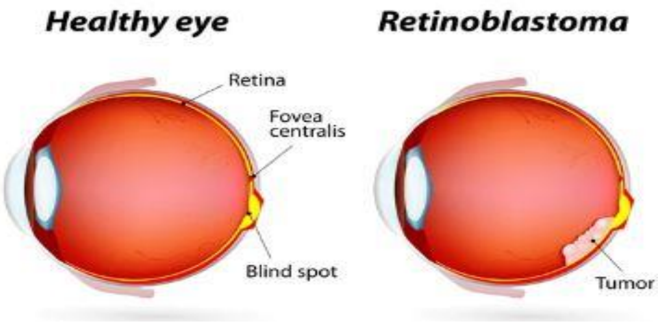

Fig 1. Retinoblastoma Image

Early identification and treatment, such as chemotherapy, radiation, or surgery, are critical for saving eyesight and increasing survival rates. Advances in medical imaging and AI-based diagnostics provide potential tools for earlier and more precise detection.

2. ELECTRORETINOGRAM (ERG) IMAGE

An electroretinogram (ERG) is a diagnostic test that detects the electrical reactions of the retina, the eye's light-sensitive layer, to visual stimuli. The retina contains photoreceptors, such as rods and cones, that turn light into electrical impulses. These signals are recorded and shown as waveforms in an ERG. The test is commonly used to evaluate retinal function, detect anomalies, and diagnose diseases such retinitis pigmentosa, diabetic retinopathy, and retinoblastoma.

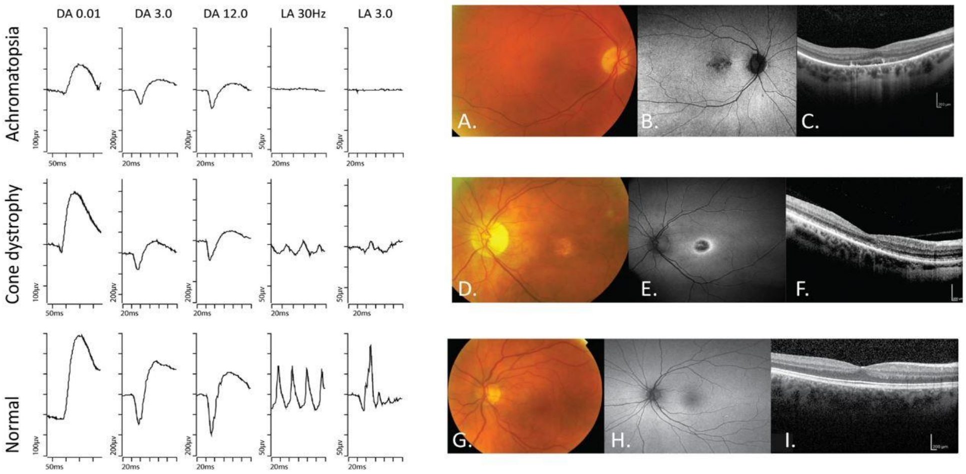

Fig.2 Electroretinogram (ERG) Image

A congenital stationary cone condition caused by cone or cone-rod degeneration. Fig. 2 describes the ERG images and differentiate normal and Achromatopsia. Achromatopsia should be evaluated if the LA 30 Hz flicker response is significantly reduced or absent. (Top panel ISCEV ffERG) LA 30 Hz and LA 3.0 were greatly muted. (A-C) Patient with achromatopsia: A colour picture, B fundus autofluorescence (FAF) imaging, and C optical coherence tomography (OCT). (Middle panel ISCEV ffERG) LA 30 Hz decreased but detectable, as well as LA 3.0 with varying reductions in DA 0.01, 3.0, and 12.0. (D-F) Patient with cone dystrophy: D colour picture, E FAF, and F OCT. (Bottom panel), typical ISCEV standard ffERG (G-I). Normal patient. G colour picture. H FAF I OCT. DA dark adapted; LA light adapted. ISCEV - International Society for Clinical Electrophysiology in Vision ffERG ful-field Electroretinogram.

ERG pictures are visual representations of the waveforms created during the test, which show the magnitude and latency of electrical reactions. These pictures are crucial for detecting minor changes in retinal function, particularly in early disease stages. ERG testing involves placing specialised electrodes on the cornea or skin around the eye and exposing the patient to light stimuli.

ERG picture interpretation has typically relied on professional analysis, which may be time-consuming and subjective. However, advances in image processing and machine learning have allowed for automated interpretation of ERG pictures, increasing diagnostic accuracy and efficiency. Deep learning algorithms like VGG-19, which identify patterns and abnormalities from these pictures, show promise in revolutionising ERG-based diagnostics, enabling new opportunities for early illness diagnosis.

3. LITERATURE SURVEY

Gulshan et al. (2016) demonstrated the usefulness of convolutional neural networks (CNNs) in diagnosing retinal illnesses such as diabetic retinopathy with high accuracy. These studies emphasise the importance of artificial intelligence in automating diagnosis and eliminating human dependence.

Simonyan and Zisserman (2015) proposed the VGG-19 architecture, which has since been used for a variety of medical imaging workloads. Applications in cancer detection and retinal disease categorisation demonstrate its strength in feature extraction and transfer learning.

ERG is a well-established diagnostic technique, particularly for diseases such as retinitis pigmentosa and cone-rod dystrophy. ERG waveforms have been found in studies to give insights into retinal malfunction, although there is minimal research on using ERG for cancer screening.
Initial research on AI applications in ERG picture processing, such as that conducted by Huang et al. (2019), shows promise for automating the interpretation process. These findings emphasise the importance of specialised models for ERG data.

Retinoblastoma diagnoses rely heavily on conventional imaging modalities such as fundoscopy, MRI, and ultrasound. However, studies have found shortcomings in early detection due to their dependence on manual interpretation, opening the door for AI-driven techniques.

This survey highlights the gap in applying deep learning to ERG images for retinoblastoma detection, positioning this study as a novel contribution to the field.

4. PROPOSED METHODOLOGY

The proposed method is on the automatic identification of retinoblastoma utilising electroretinogram (ERG) pictures analysed using the VGG-19 deep learning algorithm. The method begins with data collection, in which ERG pictures are gathered from clinical or public databases. These photos are pre-processed to improve quality using techniques such as normalisation, resizing, noise reduction, and augmentation, ensuring that the model is stable and generalisable.

The pre-processed pictures are then sent into the VGG-19 architecture, a convolutional neural network noted for its depth and powerful feature extraction capabilities. Transfer learning is used to fine-tune the model by applying its pre-trained weights to large-scale datasets like as ImageNet and adjusting it to the ERG classification problem. The model is trained to recognise patterns that indicate whether the retina is healthy or sick, and the results are classed as binary.

Hyperparameters such as learning rate, batch size, and epoch count are optimised for performance. The model's performance is measured using criteria such as accuracy, precision, recall, and F1-score to ensure a fair assessment of its diagnostic skills. The VGG Net model outperforms the Alex Net model by replacing big kernel-size filters with a series of smaller kernel-size filters. We employ Random Forest to increase the detection performance of deep learning models, rather than depending solely on fully connected network designs. Figure 3 shows the design of the suggested network model.

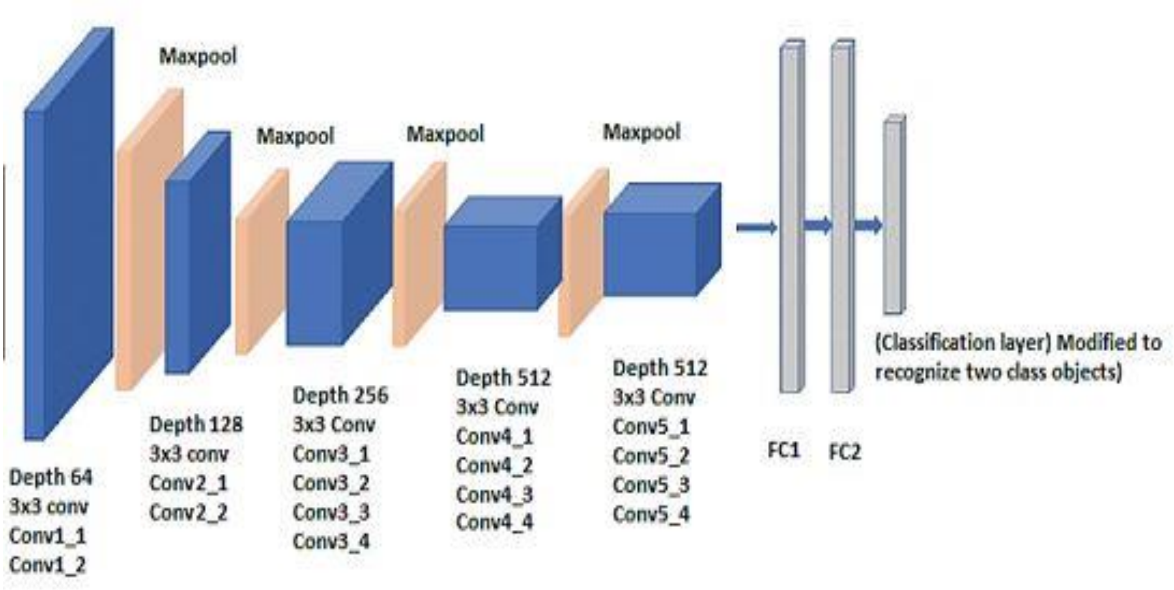

Fig 3. VGG-19 Network Design

The proposed approach aims to deliver a reliable and efficient tool for ophthalmologists, enabling early retinoblastoma detection and reducing the reliance on manual interpretation, ultimately improving patient outcomes and diagnostic efficiency.

4.1 MATLAB Implementation

Table:1 Pseudocode

Load Data: The load_cifar10 dataset and modify function depending on data source.
Preprocess Data: Normalize images by scaling pixel[] values to the range [0, 1] and convert class labels to one-hot encoding for the network's output.
Define VGG19 Architecture: define the layers of VGG19, consisting of convolutional blocks with ReLU, followed by fully connected layers and the last 2 layers are not fully connected, It is modified for classification using Random Forest method).
Training Options: The trainingOptions function specifies parameters of optimizer (adam), the maximum number of epochs, mini-batch size, and the learning rate.
Train the Model: Trained using trainNetwork.
Evaluate the Model: Using Random Forest classification make predictions and calculate the accuracy of the model.

To calculate the accuracy of an Eye Retinopathy (ERG) cancer detection model, the following steps are processed

Step- 1 Preprocess the Image Data:

Resize images: All the images are of the same size (224x224 pixels) since neural networks require fixed input dimensions.

Normalize pixel values: Scale the pixel values to a range of [0, 1] by dividing the pixel values by 255.

Data augmentation (optional): For training, the images are rotated, flipped, or zooming to artificially increase the training set.

Step- 2 Load the Data:

load images from a dataset using MATLAB Tool. In MATLAB use imageDatastore.

Step- 3 Model Architecture:

Pre-trained model (VGG19) trained specifically for eye cancer detection.

Step- 4 Training the Model:

Train the model on a labelled dataset (Images with and without cancerous lesions).

Step- 5 Calculate Accuracy:

Accuracy is typically calculated by comparing the predicted labels from the model with the true labels. It is defined as: $Accuracy = \frac{Number\ of\ Correct\ Predictions}{Total\ no\ of\ predections} * 100$

Table:2 Coding for Accuracy of ERG Cancer Detection Model in MATLAB

```
% Example: Loading and preprocessing a dataset
% Assume 'eyeDataset' is a folder containing images of ERG eye images classified into 'cancer' and 'non-cancer' folders.
imds = imageDatastore('eyeDataset', 'IncludeSubfolders', true, 'LabelSource', 'foldernames');
% Split data into training and testing datasets (80-20% split)
[imdsTrain, imdsTest] = splitEachLabel(imds, 0.8, 'randomized');
% Resize the images to fit the input size of the model
imageSize = [224 224 3];  % For example, if using VGG19
imdsTrain.ReadFcn = @(eye1.jpg)imresize(imread(eye1.jpg), imageSize(1:2));
imdsTest.ReadFcn = @( eye1.jpg)imresize(imread(eye1.jpg), imageSize(1:2));
```

Table 3: Simulated Variables

S. No	Parameter	Range/Value
1	Learning rate	0.0004
2	Batch size	5
3	Maximum epoch	20
4	Optimizer	Adam
5	Classifier	Random Forest

4.2 Pre-trained Model (VGG-19) for ERG Image Classification

Total Test Set: 60 images (30 cancerous, 30 non-cancerous)

Predictions from the ERG Cancer Detection Model

True Positives (TP): 27 cancerous images correctly identified

False Positives (FP): 03 non-cancerous images incorrectly identified as cancer

True Negatives (TN): 25 non-cancerous images correctly identified

False Negatives (FN): 05 cancerous images incorrectly identified as non-cancer

5. RESULTS AND DISCUSSION

A pre-trained model (VGG-19) fine-tuned for ERG cancer detection, evaluates its Performance on a test set.

1. $\boldsymbol{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{27+25}{27+25+3+5} = \frac{52}{60} =$ 0.86 (86%)

2. $\boldsymbol{Precision} = \frac{TP}{TP+FP} = \frac{27}{27+3} = \frac{27}{30} = 0.9$ (90%)

3. $\boldsymbol{Recall} = \frac{TP}{TP+FN} = \frac{27}{27+5} = \frac{27}{32} = 0.84$ (84%)

4. $\boldsymbol{F1\ Score} = \frac{2*0.9*0.84}{0.9+0.84} = \frac{1.51}{1.74} = 0.86$ (86%)

Singularity analyses of several input images for the suggested model and existing models are shown in Figure 4 for comparison. The Accuracy of the suggested model is 86 %, which is more than 25% higher than SVM. The proposed VGG-19 model outperforms existing SVMs in terms of results mostly due to its effective feature processing capabilities.

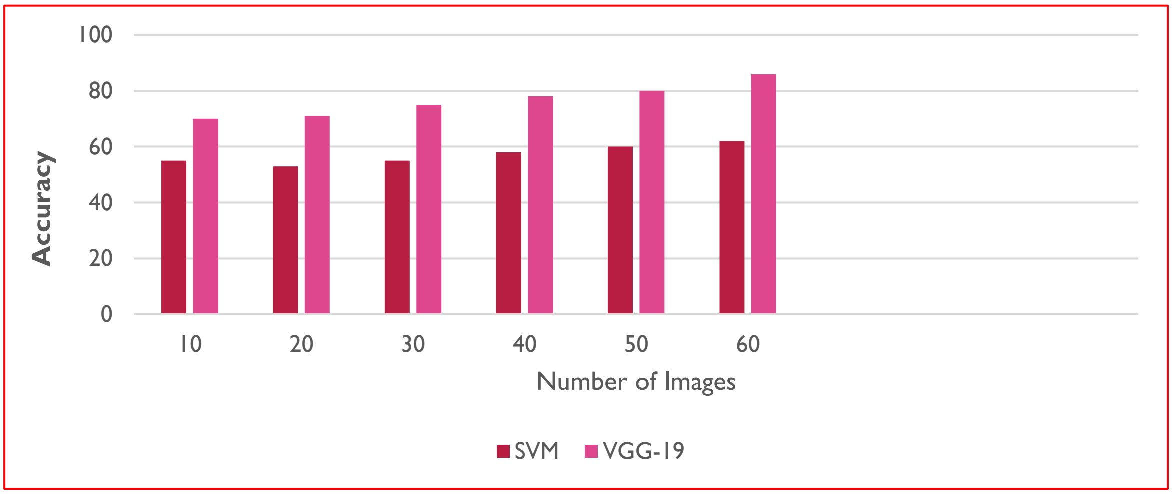

Figure 4: Comparison of Accuracy (%)

Figure 5 compares the Precision assessments of the proposed model and the current detection models for various batch sizes. Batch size is gradually increased while monitoring Precision performance. The results show that even with a batch size increase to 60, the proposed approach can still achieve the maximum Precision. The minimal Precision value of SVM is 62%, which is 27% lower than the suggested technique.

Figure 5: Comparison of Precision (%)

Figure 6 compares the Recall values of the proposed model and the current detection models for various batch sizes. The Recall values of the suggested model is 84 %, which is more than 20 % higher than SVM.

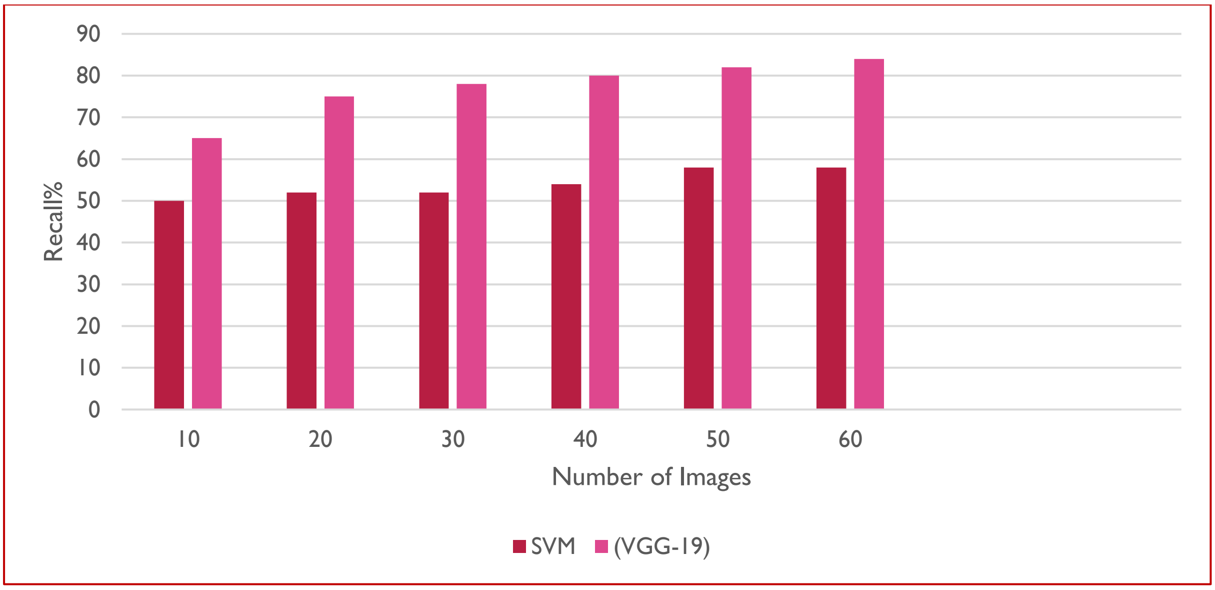

Figure 6: Comparison of Recall values (%)

Figure 7 compares the F1- Score values of the proposed model and the current detection models for various batch sizes. The F1-Score values of the suggested model is 86 %, which is more than 22% higher than SVM.

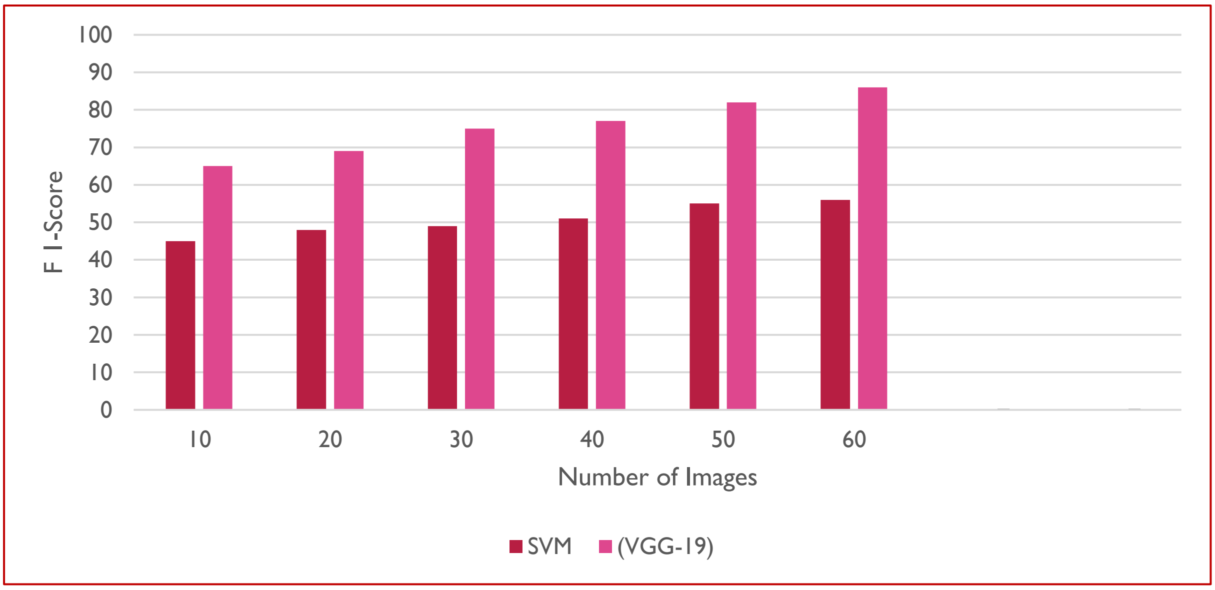

Figure 7: Comparison of F1- Score values (%)

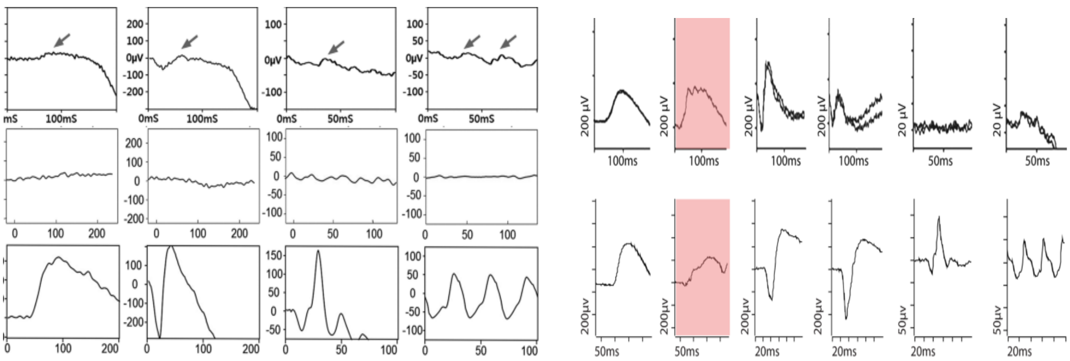

Figure 8: Sample ERG Images for Testing

6. CONCLUSION

In conclusion, when comparing VGG-19 with Support Vector Machines (SVM) for automated detection of retinoblastoma using Electroretinogram (ERG) images, the VGG-19 model clearly outperforms SVM. VGG-19, a deep convolutional neural network, excels in capturing complex hierarchical features and patterns from high-dimensional ERG images, which is crucial for detecting subtle signs of retinoblastoma. Its ability to automatically learn relevant features without the need for manual extraction makes it highly effective for this task. On the other hand, SVM, while powerful for smaller, linearly separable datasets, struggles with the high dimensionality and complexity of ERG images. SVM performance can be hindered by the need for careful tuning of hyperparameters and the selection of kernel functions, which may not capture the intricate patterns in medical image data as well as deep learning models like VGG-19. with its robust architecture and ability to learn from large datasets, proves to be more suitable for the complex and high-dimensional nature of medical imaging tasks such as retinoblastoma detection. This highlights the importance of leveraging deep learning models like VGG-19 for automated diagnostic tools, ensuring higher accuracy and efficiency in identifying conditions like retinoblastoma from ERG images.

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