**Research Papers Literature Review**

**Title: Opti-EN-net: Optimize ensemble deep neural network for the classification of Retinal Detachment \***

**Problem Statement**

Fundus imaging is crucial for detecting retinal detachment (RD), but manual diagnosis is laborious and requires specialized expertise. This project aims to develop an automated deep learning (DL) framework to streamline the RD diagnosis process. By leveraging DL techniques, the proposed framework will analyze fundus images to identify and classify RD efficiently, potentially improving diagnostic accuracy and reducing the burden on ophthalmologists.

**Proposed CNN**

They utilize ResNet50 extracts features, which are then optimized using a genetic algorithm. The ResNet50, integrated with ELM (Extreme Learning Machine) and RVFL (Random Vector Functional Link) classifiers, is trained with frozen earlier layers. Then, majority voting ensembles the classifier outputs for improved performance.

ELM is a training approach designed for single layer feedforward neural network(SLFN).

**PreProcessing**

The proposed work preprocesses images using CLAHE and WPT (Wavelet packet transform) to improve quality and reduce noise/blurring.Feature extraction is then performed on the processed images for further analysis.

**Data Augmentation**

To enhance classification accuracy , we implemented data augmentation by vertically and Horizontally flipping and rotating training and validation images. This increased dataset diversity and mitigated overfitting. Images were then scaled to 299x299x3 and normalized to match the model’s input requirements.

**Dataset**

**A dataset of 1800 RD fundus images and 1800 healthy fundus images was created from publicly available sources. This dataset is intended to facilitate future research and improve the diagnosis of retinal detachment.**

**Title: Retinal Disease Diagnosis Using Deep Learning on UFI (Ultra-Wide-Field) Fundus Images \***

**Problem Statement**

Manual diagnosis of eye diseases using fundus images is time-consuming, prone to human error, and often inaccessible in remote areas due to limited access to specialists.Essentially, the challenge lies in developing a system that can accurately and efficiently diagnose eye diseases using fundus images, while also improving accessibility to specialized care.

**Proposed CNN**

They use various deep learning models for eye disease classification. ResNet152, ViT, Inception-ResNet-v2, RegNet, and ConVNext. ResNet152 uses residual blocks to overcome training challenges in deep networks, while ViT leverages attention mechanisms to process image patches. Inception-ResNet-v2 combines Inception modules with residual connections, RegNet dynamically optimizes network dimensions, and ConVNext modernizes ResNet by integrating transformer-inspired design principles.

**Pre Processing**

They utilized preprocessing techniques like data augmentation (flips, rotations), image enhancement (histogram equalization, brightness, and contrast adjustments), resizing images to 512 × 512 pixels, and normalization to standardize pixel intensities.

**Data Augmentation**

They utilized data augmentation techniques like random flips, rotations, and brightness/contrast adjustments, expanding the dataset to over 21,000 images.

**Dataset**

They does not explicitly mention the specific dataset used for the study. They only describes the preprocessing steps applied to their dataset, which was expanded to over 21,000 images through data augmentation and prepared for medical image classification task.

**Title: Age-Related Macular Degeneration Detection in Retinal Fundus Images by a Deep Convolutional Neural Network \***

**Problem Statement**

The problem is the early detection of age-related macular degeneration (AMD), a leading cause of vision loss. Currently, detecting AMD from fundus images is challenging and often relies on manual examination, which can be time-consuming and prone to errors. The need for this solution arises from the growing prevalence of AMD, particularly in aging populations, and the importance of early detection to prevent severe vision impairment.

**Proposed CNN**

The proposed CNN for this study is Xception, a 71-layer model with 22.8M parameters, leveraging depthwise separable convolutions for efficiency . Using transfer learning, only the fully connected layers were fine-tuned, with minor adjustments near these layers. Training employed SGDM, a learning rate of 0.001, minibatch size of 10, 30 epochs, and 10-fold cross-validation.

**Pre Processing**

The preprocessing techniques likely involved resizing images to match the Xception model's input size (e.g., 299x299), normalizing pixel values, and using data augmentation (e.g., flipping, rotation, cropping) to enhance dataset diversity and reduce overfitting. Labels were likely encoded numerically, and the dataset was split into training, validation, and test sets for effective model evaluation.

**Data Augmentation**

They used data augmentation techniques including rotations (0° to 180°), scaling (up to a factor of 1.5), and translations (up to 200 pixels) to enhance the training dataset by increasing its variability and robustness.

**Dataset**

They utilizes two datasets the **Ocular Disease Recognition Dataset** from Kaggle, containing diverse retinal images labeled with diagnoses like AMD, diabetic retinopathy, and glaucoma, and the **SAMRH Project Dataset**, comprising 150 images from public repositories and an ophthalmology specialist, focusing on various retinopathies. A combined dataset of 250 images (180 from Kaggle and 70 from SAMRH) was created, with 128 images of AMD-affected patients and 122 of healthy individuals.

**Title: Combining convolutional neural networks and self‑attention for fundus diseases identification \***

**Problem Statement**

The problem addressed in this research is the challenge of accurately classifying multiple fundus diseases from color fundus images. Traditional convolutional neural networks (CNNs) struggle with global feature modeling and multilabel classification tasks, where a single image may contain multiple fundus diseases. Additionally, the lack of sufficient training data and image noise hampers the performance of CNN models.

**Proposed CNN**

They proposed MBSaNet, a model that combines Convolutional Neural Networks (CNNs) and Self-Attention (SA) mechanisms for the classification of multiple fundus diseases. The CNN component, using the MBConv block, captures low-level features, while the SA mechanism captures global relationships within the image, enhancing feature modeling. The model also includes a multiscale feature fusion stem, which extracts and fuses features from different scales to improve accuracy.

MBSaNet outperforms traditional CNN-based and hybrid models, particularly in handling imbalanced datasets and smaller sample sizes. Its ability to combine CNN's local feature extraction with SA's global dependency modeling results in superior performance.

**Data Augmentation**

They employed data augmentation techniques to address the challenge of overfitting, particularly with the limited number of fundus images. By transforming the training images, they effectively expanded the dataset, which helped the model generalize better.

**Dataset**

They utilize the of dataset " Ocular Disease Intelligent Recognition," sponsored by Peking University. It contains real patient data from hospitals in China, including 3,500 patients' ages, color fundus images, and diagnostic keywords. The data is divided into training and test sets, with a balanced test set created by sampling 400 images from the training set. The fundus images were captured using various cameras and include eight categories: normal, diabetic retinopathy, glaucoma, cataract, age-related macular degeneration, hypertension, myopia, and other diseases/abnormalities. The dataset is multilabel, with some images showing multiple conditions, and includes a variety of image qualities.

**Title: A systematic review of retinal fundus image segmentation and classification methods using convolutional neural networks \***

**Problem Statement**

The problem addressed in this research paper is the challenge of manual diagnosis of eye diseases, such as glaucoma and diabetic retinopathy, using retinal fundus images. The study explores the use of Convolutional Neural Networks (CNNs) to automate the segmentation and classification processes, aiming to improve accuracy, reduce clinician workload, and enhance diagnostic efficiency.

**Proposed CNN**

They proposed several CNN-based methods for retinal fundus image segmentation and classification. These include encoder-decoder networks for optic disk and optic cup segmentation, using feature detection and cross-correction sub-networks. They also employed a modified U-Net and bi-directional LSTM for diabetic retinopathy detection. Additionally, attention-based CNNs and multi-scale feature extraction were used for multi-component segmentation, improving accuracy in detecting retinal features like arteries, veins, and optic discs.

**Pre Processing**

The preprocessing techniques used in retinal vessel segmentation include methods like image normalization, data augmentation, and vessel enhancement. Various CNN-based models, such as DCCMED-CNN, MPC-EM, and UNet, leverage these techniques along with multi-scale features and attention mechanisms for improved accuracy. Advanced methods like VSSC Net and MPS-Net, as well as reinforcement learning approaches, further enhance segmentation performance.

**Data Augmentation**

They does not mention data augmentation techniques. However, it discusses the use of various datasets and CNN-based methods for segmenting and classifying retina fundus images.

**Dataset**

They utilize datasets such as DRIVE, STARE, CHASE-DB1, HRF, MESSIDOR, and several others for retinal fundus image segmentation and classification.

**Title: CLASSIFICATION OF MULTIPLE EYE DISEASES USING RETINAL FUNDUS IMAGES \***

**Problem Statement:**

This research addresses the challenges of improving image classification using Convolutional Neural Networks (CNNs), focusing on issues like overfitting, data imbalance, and the need for effective preprocessing. Their goal is to enhance model accuracy and generalization for real-world applications like medical image analysis and object recognition.

**Proposed CNN:**

They proposed CNN architecture that uses multiple convolutional and pooling layers to extract hierarchical features, with techniques like dropout and batch normalization to prevent overfitting and improve training stability. Transfer learning with pre-trained models such as ResNet or VGG is also utilized to boost performance, especially with limited data.

**Pre-Processing:**

The Preprocessing in this study involves resizing images to a fixed size, scaling pixel values to a range of [0, 1], and normalizing colors to reduce variations in lighting and orientation. These steps ensure the data is consistent and ready for the CNN, improving model accuracy and efficiency.

**Data Augmentation:**

Data augmentation is used in this research to artificially expand the training dataset by applying transformations like rotation, flipping, and zooming. This helps improve the CNN’s generalization ability, reducing overfitting and making the model more robust to variations in real-world data.

**Dataset:**

The dataset used in this study is the RMiFD, which contains 3200 retinal images, including those from diabetic patients with varying stages of retinopathy and healthy individuals for comparison. Among the 45 types of abnormalities in the dataset, three were selected: Diabetic Retinopathy, Optic Disc Cupping, and Age-related Macular Degeneration. Initially, the dataset had 1,177 images, but after augmentation techniques, the number of fundus images increased to 1600. The dataset is diverse and covers various retinal conditions to ensure robust model performance.

**Title: Early detection of glaucoma , feature visualization with a deep convolutional network \***

**Problem Statement:**

This research addresses the challenges of early glaucoma detection, a leading cause of irreversible blindness, by focusing on subtle indicators like optic disc cupping and retinal nerve fiber layer thinning that require specialized expertise. Traditional diagnostic methods, including optic nerve evaluation, visual field testing, and intraocular pressure measurements, often fall short in timely diagnosis. By leveraging Convolutional Neural Networks (CNNs), this study aims to develop an automated system for accurate glaucoma detection using fundus images.

**Proposed CNN:**

They proposed a deep CNN model for glaucoma classification with four convolutional layers and two dense layers, featuring intermediate visualization for enhanced interpretability. The model processes preprocessed and augmented fundus images, enabling automated feature extraction and classification while offering insights into the decision-making process.

**Pre-Processing:**

The preprocessing in this study starts with resizing the fundus images to the required dimensions and resolution. Additionally, data augmentation techniques were applied to increase the number of images, ensuring the dataset was optimized for input into the deep CNN model.

**Data Augmentation:**

This study used data augmentation to increase the number of images for training and testing the model due to the smaller size of the dataset. The augmentation techniques applied include horizontal flipping, vertical flipping, and rotating the images by 90°, 180°, and 270°. These transformations were applied to all classes of the glaucoma image dataset. Additionally, dropout layers and normalization terms were included in the architecture.

**Dataset:**

The dataset used in this study consists of 295 normal fundus images and 120 glaucomatous images from a project conducted by L.V. Prasad Eye Institute in Hyderabad, India. The normal fundus images are categorized into large, medium, and small optic discs with counts of 96, 100, and 99, respectively. Glaucomatous images are classified into mild, moderate, and severe categories based on the severity of damage, with 10, 23, and 29 images in each category, respectively.