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## CHAPTER 2

### LITERATURE SURVEY

DR is a chronic retinal disorder that develops as a complication of diabetes and remains a primary cause of visual impairment and blindness globally. The condition advances through multiple stages, from mild to severe, potentially resulting in permanent vision loss if not identified and managed promptly.

Timely detection and precise classification of DR stages are crucial for ensuring effective treatment and minimizing the risk of further complications. Nevertheless, manually identifying DR features in retinal images is a labor-intensive process that demands expert knowledge, thereby increasing the demand for automated screening systems [18].

In recent years, DL methods, especially CNN, have demonstrated significant promise in enhancing the detection and classification of DR. These advancements in image processing have enhanced the ability to identify key features such as MAs, HEMs, and EXs, which are critical indicators of DR. Automating these tasks reduces the workload of healthcare professionals while ensuring faster and more reliable diagnoses, particularly in environments where specialist access is limited.

This literature survey explores the key research areas that contribute to the automated detection of DR. Specifically, it reviews studies focused on the detection of MAs, HEMs, and EXs, which are lesions for diagnosing DR. Moreover, it examines the efforts to classify the four stages of DR, from no DR to severe DR, using advanced ML and DL techniques. By using large annotated datasets and pretrained models, researchers have made significant strides in improving classification accuracy, addressing challenges such as overfitting, computational complexity.

The progress in these areas facilitates the way for the development of robust, scalable DR screening systems that can be implemented in clinical practice. These systems offer substantial potential to enhance patient outcomes by supporting early diagnosis and allowing prompt intervention, especially in underserved areas where access to ophthalmologists is restricted.

## 2.1 EXISTING STUDIES

### 2.1.1 Microaneurysm lesion detection

MAs represent one of the initial indicators of DR and appear as small, round red dots with distinct boundaries, usually not exceeding 125 micrometers in diameter. These lesions result from localized dilations in the small retinal blood vessels. When MAs rupture, they lead to HEMs. Research indicates that retinal lesions, including MAs, EXs, and HEMs, were present in approximately 90% of individuals with diabetes who have lived with the condition for 15 years or longer. The following studies offer detailed insights into the detection of MAs within the context of DR.

In MA detection model, the median filter was first applied to the green channel with a filter size larger than the widest blood vessel in the fundus image to perform shade corrective preprocessing [19]. After extracting the Directional Local Contrast (DLC) features from each candidate patch, Naive Bayes was used as a classifier. The reported sensitivity value at an average of 8 False Positive per Images (FPIs) was 0.7. The main drawback of this method is the poor performance of its high-dimensional DLC features. An advanced deep convolutional encoder-decoder framework was used to identify MAs by utilizing modifications in the network's skip connections [20]. A detailed probability map for MA localization was generated using a long-tailed activation function. Comprehensive experiments on the eOphtha database MA and Retinopathy Online Challenge datasets demonstrate that the method achieves accuracy comparable to that of leading techniques, yet operates at just one-hundredth of their computational cost. Visual Geometry Group-19 (VGG-19) and InceptionV3 pretrained CNN models were used in a hybrid feature embedding strategy to achieve early detection of MAs [21]. Using two publicly accessible datasets, "EOphtha" and "DIARETDB1," the performance of the approach was assessed, achieving classification accuracy of 96% and 94%, respectively.

A DL-based computer-aided approach was implemented for detecting MAs in retinal images [22]. The model employs dropout training combined with a maxout activation function in a five-layer deep network architecture. This design enhances the model's robustness and reduces overfitting, contributing to its high accuracy. The technique is validated using publicly accessible datasets, achieving advanced performance in

extracting MA candidates with a notably low false-positive rate. Its superior detection capabilities make it particularly suitable for large-scale DR screening programs, addressing the need for efficient and reliable diagnostic tools.

An automated method for retinal image analysis using a CNN was used which introduces a two-stage framework that utilizes data from two publicly available online datasets [23]. The method addresses the challenge of imbalanced data distribution and significantly reduces training time while maintaining reliable performance. The results demonstrate a competitive sensitivity value of approximately 0.8, with fewer than six false positives per image on average. This innovative technique provides a practical solution for enhancing the efficiency and accuracy of MA detection in DR screening. A novel DL method using a Stacked Sparse Auto-Encoder (SSAE) for MA detection was implemented which consists of multiple SAE layers, enabling the model to learn advanced MA features autonomously [24]. The high-level features extracted by the SSAE are then passed to a softmax classifier to determine whether an image patch contains an MA. This hierarchical learning framework enhances the model's capacity to recognize subtle characteristics linked to MAs, providing an effective approach for retinal image analysis.

A two-step MA detection framework using Deep CNN (DCNN) was used to identify the potential MAs, while the second DCNN focuses on reducing false positives [25]. This hybrid approach integrates Gabor filters, Hessian matrix-based shape indices, and double-ring filters to enhance feature extraction. The methodology was evaluated using the DIARETDB1 database and demonstrated superior performance in terms of sensitivity and precision. The integration of DCNNs in this stepwise approach underscores its effectiveness for accurate and reliable MA detection.

A comprehensive framework for MA detection was employed, encompassing three stages: image preprocessing, candidate MA extraction, and DCNN-based classification [26]. The preprocessing step enhances the image quality, ensuring optimal feature extraction. The DCNN was quantitatively assessed through Free-Response Receiver Operating Characteristic (FROC) curves and compared with alternative methods, showcasing competitive performance. This method highlights the importance of integrating preprocessing techniques with advanced classification models to improve the detection accuracy. An ensemble-based neural network architecture was applied to enhance the

detection of MAs in fundus images [27]. This architecture connects multiple independent DCNNs to facilitate concurrent training, using the strengths of each model to enhance the overall performance. The ensemble approach outperforms individual DCNNs in terms of detection accuracy, addressing challenges such as overfitting and data variability. This model provides a robust solution for detecting MAs, with potential applications in automated DR screening systems.

### **2.1.2 Hemorrhage lesion detection**

HEMs, like MAs, manifest as larger patches on the retina with irregular borders, typically reaching widths of up to 125 micrometers. They are categorized into two types, flame and blot, depending on their depth and surface area. The occurrence and distribution of HEMs serve as indicators of DR severity. The following overview examines the literature on DL methodologies applied to the detection of HEMs in the context of DR.

A system for extracting HM was utilized, comprising three key components: image preprocessing, enhancement of training data, and object detection using a CNN with label smoothing [28]. A novel approach was employed for precise bleeding detection in retinal fundus images [29]. In the third phase, the convolutional sparse image decomposition technique was applied to integrate all the extracted feature vectors. This method was evaluated using 1,509 images drawn from the High-Resolution Fundus (HRF), Digital Retinal Images for Vessel Extraction (DRIVE), Structured Analysis of the Retina (STARE), Methods for Evaluating Segmentation and Indexing Dedicated to Retinal Ophthalmology (MESSIDOR), Diabetic Retinopathy Database 0 (DIARETDB0), and Diabetic Retinopathy Database 1 (DIARETDB1) datasets. The approach outperformed previous methods, achieving an average accuracy of 92.71%.

An automated bleeding detection method based on two-dimensional Gaussian fitting was employed which enhances the image quality [30]. A potential HM candidate undergoes two-dimensional Gaussian adaptation to extract visual features. When tested on 219 retinal fundus images from the DIARETDB1 database, this technique achieved sensitivity, specificity, and accuracy rates of 100%, 82%, and 95.42%, respectively. CNN was applied to develop an algorithm for the automatic identification of EXs and HEMs [31]. Evaluation on the CLEOPATRA database showed that the method attains a sensitivity of 0.6257. A

bleeding detection approach based on a multi-layer neural network framework was applied which reports an average sensitivity, specificity, and classification accuracy of 92.20%, 93.10%, and 94%, respectively [32]. A CNN architecture with nine layers was applied, trained using selective samples for bleeding detection [33]. Despite the limited availability of well-annotated data, the annotation process, especially for pixel-wise annotation, was time-consuming, resource-intensive, and prone to errors, with significant interobserver variability.

### 2.1.3 Exudates lesion detection

EXs, result from fluid leakage from retinal blood vessels and play a critical role in vision loss associated with DR. They are classified into two categories: hard EXs, which present as yellowish spots with clearly defined edges, resulting from plasma leakage, and soft exudates, characterized by swollen nerve fibers that manifest as white, oval-shaped regions with indistinct borders on the retina. The following sections summarize the literature focusing on the application of DL techniques for the detection of these EXs in DR.

A ten-layer CNN was used for exudate detection. However, the model demonstrates only a modest sensitivity of 0.77 [34]. To classify the data, the network was fed the immediate regions surrounding the seed points, enabling pixel-level exudate detection. This approach allows for the more precise identification of EXs in retinal images. Despite its low sensitivity, the method was effective in localizing affected areas. A method requiring manual preprocessing steps, such as optic disc removal and vessel segmentation, was used to detect the exudates [35]. Despite the labor-intensive process, a commendable sensitivity of 0.88 was achieved. DCNNs were applied to identify exudates, and the outputs from the optic disc and vascular detection algorithms were combined with the CNN results to integrate high-level anatomical information about probable exudate regions. Validation using a manually segmented image database yielded an F1 score of 0.78.

CNN algorithms were combined with the circular Hough transform for exudate detection, a key symptom of DR [36]. This combined approach demonstrates superior performance compared to using CNN or image processing techniques alone. The method shows greater efficiency in detecting exudates, highlighting the benefit of integrating both the CNNs and the circular Hough transform. This strategy proved to be more successful compared with the traditional standalone techniques. A CNN-based method for exudate

detection was applied, beginning with data preprocessing to standardize the exudate patches [37]. Region of interest (ROI) localization was applied to identify exudate characteristics. TL was employed with pretrained CNN models, including Inception-v3, ResNet-50, and VGG-19, to extract features. The experimental results indicate that the pretrained CNN-based system excels over the current exudate detection methods, demonstrating its superior ability to identify EXs in retinal images.

An automated U-Net method for hard exudate segmentation was applied to assist ophthalmologists in the early detection of DR [38]. The experimental findings indicate that the pretrained CNN-based system surpasses conventional techniques in detecting exudates. The approach provides a more accurate and reliable way to segment hard exudates, offering significant support for ophthalmologists in diagnosing DR. The results emphasize the effectiveness of the U-Net architecture in retinal image analysis. Another study in which both supervised and unsupervised classifiers, along with a variety of DL algorithms, were employed for exudate detection [39]. Tests were conducted on the e-Ophtha and DIARETDB1 public image databases. ResNet-50 combined with a Support Vector Machine (SVM) classifier outperformed other networks, achieving an impressive performance of 98% accuracy and 0.99 sensitivity. This approach demonstrates the effectiveness of using a pretrained ResNet-50 model with SVM for exudate detection in retinal fundus images.

#### **2.1.4 Machine learning Techniques in DR Detection**

ML is a dynamic area within computer science and engineering, recognized as a subset of AI for its capability to enable computers to extract patterns from data and perform designated tasks in a human-like manner. By using algorithms that rely on sample data, known as training data, ML develops predictive models without explicit programming. For instance, when a ML algorithm is applied to a dataset (e.g., fundus images) along with relevant information (e.g., blood vessel features), it acquires knowledge by analyzing patterns and relationships within the training data to make predictions. If the algorithm improves its performance by optimizing parameters to correctly diagnose more test cases, it is considered to have effectively learned the task.

ML applications extend across a wide range of domains, such as speech recognition, robotics, pattern recognition, natural language processing, data mining, stock market

forecasting, Computer-Aided Diagnosis (CAD), autonomous driving, and recommendation systems. Numerous tasks once considered unattainable are now achievable owing to significant progress in ML methods. In the case of DR, early detection remains a major challenge, primarily because the disease presents no noticeable symptoms during its initial stages.

Traditionally, physicians rely on retinal imaging features to classify DR cases and predict eye disease. However, ML simplifies this process by using training and test data to predict various disease forms. The following papers are expertise-driven ML approaches applied to DR detection.

Researchers conducted a cross-sectional study to analyze DR using ophthalmological examinations and retinal scans [40]. Specialized retinal images were classified using OPF and Restricted Boltzmann Machines (RBM) models, where the classification relied on the presence or absence of DR-associated features. The study used RBM and OPF to extract 500 and 1000 features from the images, supporting disease identification following system training. Fifteen experimental series were conducted, each repeated 30 times. A total of 73 diabetic patients (122 eyes) were included, with an approximately equal gender distribution and an average age of 59.7 years. The findings show that RBM-1000 achieves the highest overall diagnostic accuracy at 89.47%, while RBM-500 exhibits optimal sensitivity, detecting DR signals in fundus images with 100% accuracy. In terms of specificity, both RBM-1000 and OPF-1000 correctly classify all images without DR signs. The study underscores the effectiveness of the RBM model as a ML technique for automated DR detection, demonstrating its strong diagnostic performance, sensitivity, and practical relevance for DR screening.

The structure of the veins in retinal images serves as an essential indicator of diseases such as glaucoma, DR, and hypertension [41]. The accuracy of the retinal vessel segmentation significantly impacts the retinal image analysis, which plays a key role in ophthalmic diagnostic procedures. Contrast enhancement plays an important role in retinal vessel segmentation methods. Researchers assessed the performance of a newly developed spatially adaptive contrast enhancement technique aimed at improving the quality of retinal fundus images for vessel segmentation. This enhancement method was applied using a modified form of the Tyler Coye algorithm, which was further refined through a vessel

reconstruction approach based on the Hough line transformation. This method was assessed using two publicly available datasets, STARE and DRIVE. Retinal blood vessels were extracted using the Tyler Coye algorithm, and after segmentation, the extracted vessels were fed into various ML algorithms to detect DR. The approach aims to facilitate the early detection of DR, allowing individuals to take preventive measures to avoid permanent vision loss.

Glaucoma, often associated with DR, affects the optic nerve system and leads to vision loss. The fractal dimension was widely used in retinopathy research because of its ability to characterize the retinal vasculature. Researchers explored the use of fractal dimension analysis to differentiate between healthy individuals and DR patients, as well as to evaluate disease severity [42]. Using the MESSIDOR dataset and a Random Forest (RF) classifier, the study shows that fractal dimensions were effective in distinguishing healthy cases from those with DR. However, this method falls short in accurately classifying the different severity levels of the disease. Future work aims to incorporate additional features, including univariate and multivariate statistical measures, and to improve red lesion detection to enhance the performance in DR severity classification.

The researchers use Artificial Neural Networks (ANN), specifically a Multi-layer Perceptron (MLP), trained using Levenberg-Marquardt (LM) and Bayesian Regularization (BR) methods for DR classification [43]. Nineteen features were extracted from the fundus images and fed into the neural network as input. This study investigates varying numbers of hidden nodes to identify the optimal configuration. The results reveal that the MLP trained with BR delivers higher classification accuracy - 72.11% for training and 67.47% for testing—compared to the LM approach. These findings indicate that BR is effective in enhancing the performance of neural network-based DR classification models.

This paper explores a DL-based approach that integrates feature extraction with an SVM classifier. High-level features from the final fully connected layer of a CNN were extracted using TL and used as input for the SVM classification[44]. This strategy considerably decreases the computational time relative to the CNN fine-tuning methods while preserving the classification accuracy. The method was assessed using retinal images from the Messidor database, achieving accuracy rates of 95.83% for base 12 and 95.24% for base 13 .

### **2.1.5 DL Techniques in DR Detection**

DL in medical imaging is poised to be a transformative technology with far-reaching implications. This approach uses DNN models, which offer a closer approximation to the human brain's functioning compared to simpler neural networks.

Many researchers predict that DL applications will significantly transform healthcare within the next 15 years. Intelligent systems powered by DL are expected to perform diagnostic tasks, predict diseases, prescribe medications, and even guide treatment plans. Beyond assisting in feature selection and extraction, DL facilitates the development of new features essential for accurate diagnosis. The ability to capture and interpret medical images accurately is crucial for identifying diseases, but traditional approaches often fall short due to significant variability in patient data.

In recent years, DL has made substantial progress, enabling the handling of complex and large datasets. This advancement has gained traction across various domains, particularly in medical image analysis. The field is projected to generate over half a trillion dollars in revenue by 2024, outpacing the entire analytics sector's funding in 2020. Consequently, DL is expected to receive increased funding for medical imaging research.

This remarkable progress has inspired researchers to explore DL algorithms for DR detection [45]. The following studies employ DL methods for DR detection, showcasing the field's potential. This study proposes a DL-based method for DR classification and lesion localization. The system categorizes retinal images into five stages-no DR, mild, moderate, severe, and proliferative DR-while simultaneously identifying the affected lesions on the retinal surface. It incorporates two models: CNN512 for image-level DR stage classification and an adapted You Only Look Once Version 3 (YOLOv3) model for lesion detection and localization. CNN512 attains classification accuracies of 88.6% and 84.1% on the DDR and APTOS Kaggle 2019 public datasets, respectively, surpassing existing state-of-the-art techniques. YOLOv3 achieved a mean Average Precision (mAP) of 0.216 for lesion localization on the DDR dataset. The combined use of CNN512 and YOLOv3 further boosts the overall performance, achieving a classification accuracy of 89%, with 89% sensitivity and 97.3% specificity, indicating notable improvements over earlier models.

An advanced red-lesion extraction approach was employed to improve the accuracy of DR diagnosis [46]. The method initially detects boundary pixels associated with blood vessels and red lesions, followed by the extraction of discriminative features to distinguish red lesions from other boundary pixels. It utilizes prominent intensity variations across multiple directions within fundus images by employing specialized neighborhood windows around the identified boundary pixels. This approach was evaluated on three datasets—Diaretdb0, Diaretdb1, and Kaggle—with results indicating strong performance, achieving sensitivity and specificity values of 0.87 and 0.88 for Diaretdb1, 0.89 and 0.90 for Diaretdb0, and 0.82 and 0.90 for the Kaggle dataset. Moreover, the method demonstrates an efficient processing time for red-lesion extraction, positioning it as a promising solution for automated DR analysis.

MAs represent some of the earliest indicators of DR, and their accurate detection is vital for early diagnosis [47]. An automated method for detecting MAs in fundus retinal images was used, employing the E-optha database, which includes 100 images for performance assessment. The methodology comprises several stages: pre-processing, segmentation, post-processing, feature extraction, and classification. During the pre-processing phase, image filtering and contrast enhancement techniques were applied to improve the image quality and facilitate subsequent analysis. Segmentation was performed using the H-maxima and thresholding techniques, followed by morphological operations to refine the images. Feature extraction and MA candidate detection were then carried out. The detected MAs were classified using a Multi-Layer Perceptron (MLP) into three categories: background (B), MAs, and Retinal Blood Vessels (RBVs). The classification performance was assessed based on accuracy, sensitivity, and specificity. The MLP classifier outperformed the SVM, achieving the highest accuracy of 92.28% under condition 2. The result shows that the methodology effectively classifies MAs, B, and RBVs, while also being computationally efficient for real-time implementation .

A deep CNN comprising 18 convolutional layers and 3 fully connected layers was employed for the automatic analysis of fundus images [48]. The model classifies DR into three categories: no DR (controls), moderate DR (a combination of mild and moderate NPDR), and severe DR (including severe NPDR and proliferative DR). It achieves a validation accuracy between 88% and 89%, sensitivity between 87% and 89%, specificity

ranging from 94% to 95%, and a Quadratic Weighted Kappa Score of 0.91–0.92, based on 5-fold and 10-fold cross-validation. Prior to training, the pre-processing stage included image resizing and class-specific data augmentation. This approach offers a dependable and objective method for diagnosing and grading DR, thereby reducing reliance on retina specialists and enhancing access to retinal care. The system supports early diagnosis and objective monitoring of disease progression, enabling timely medical intervention to prevent vision loss .

This study proposes a DNN that integrates an enhanced pre-processing technique with multilevel and multiscale Deep Supervision (DS) layers to improve the accuracy of retinal vessel segmentation [49]. The architecture utilizes the first four layers of the VGG-16 model, augmented with vessel-specific Gaussian convolutions initialized at two distinct scales. These layers produce activation maps that capture vessel-specific features across varying scales, depths, and levels. The receptive fields of these activation maps were extended to refine vessel probability maps, effectively minimizing interference from the optic disc, boundary artifacts, and non-vessel background noise. The model's performance is assessed using several retinal imaging datasets, including DRIVE, STARE, HRF, and real-world clinical datasets. It achieves sensitivity scores of 0.8282 on DRIVE, 0.8979 on STARE, and 0.8655 on HRF, along with robust specificity and accuracy, confirming its effectiveness in segmenting retinal blood vessels.

The performance of the two DL architectures, InceptionV3 and Xception, was compared for classifying DR using the Waggle dataset [50]. The study utilized the complete dataset, consisting of 35,126 retinal images, reserving 20% for testing the algorithm's performance. The focus was on comparing the last two blocks of both architectures for fine-tuning, using two optimizers with different learning rates. To improve the model's robustness, image augmentation techniques were applied, including horizontal and vertical flipping, image shifting, and rotation. The evaluation metric used was accuracy, yielding a result of 87.12% for the InceptionV3 architecture and 74.49% for Xception, indicating that InceptionV3 performs better in the classification task .

Two CNN architectures were employed for this task: a pre-trained VGG16 model and a custom CNN comprising five convolutional layers, five max-pooling layers, and one fully connected layer were used for detecting DR red lesions. These models were trained

using the DIARETDB1 dataset and evaluated for patch-level classification to distinguish red lesions from non-red lesions across multiple datasets, including DDR, IDRiD, Messidor-2, Messidor, Kaggle, and DIARETDB0 [51]. Following classification, a probability map was constructed to determine whether an image was categorized as DR or non-DR. The method achieves a high sensitivity of 0.94 and an AUC of 0.912 on the Messidor dataset, highlighting its effectiveness in detecting DR-related lesions .

A DL algorithm was applied and validated for the detection and classification of different DR stages using retinal fundus images [52]. The study, published in JAMA, focuses on designing a CNN capable of identifying five stages of DR: no DR, mild NPDR, moderate NPDR, severe NPDR, and proliferative DR. Trained on a large annotated dataset, the algorithm achieves an AUC of 0.95, accurately recognizing both the presence and severity of the disease. This study underscores the potential of DL to improve diagnostic precision and support healthcare professionals in the effective management of DR .

A comprehensive review on AI applications in DR was published, discussing the development and performance of various AI technologies, particularly DL algorithms, for DR screening and diagnosis [53]. The review focuses on AI systems that use retinal fundus images to detect and stage DR, emphasizing their ability to reliably identify the disease. It also explores advancements in AI-based screening tools, comparing their efficacy with traditional methods and assessing their capability to enhance diagnostic efficiency and broaden accessibility. The study underscores the growing importance of AI in DR screening, highlighting how these technologies integrated into clinical processes to enhance early detection and disease management .

An AI-based grading system for DR was assessed to determine its effectiveness in identifying and classifying different stages of the disease, ranging from no DR to severe NPDR and proliferative DR, using retinal fundus images [54]. The evaluation revealed that the system achieved high staging accuracy and exhibited strong concordance with expert human graders. These outcomes underscore the potential of AI to improve DR screening by delivering reliable staging results and boosting diagnostic efficiency, particularly in primary care environments. The study concludes that AI-driven solutions play a crucial role in advancing the accuracy and speed of DR diagnosis.

A systematic review examines recent advancements in AI techniques for DR detection, highlighting the progression of ML and DL models in enhancing diagnostic accuracy and reliability [55]. The review analyzes a range of studies employing diverse imaging modalities, including fundus photography and OCT, to detect early indicators of DR such as MAs and exudates. These findings emphasize the growing role of AI in facilitating earlier and more precise DR diagnosis across various clinical contexts. Challenges in deploying AI systems, including data quality issues, model interpretability, and generalization across diverse patient populations, were also discussed. The review highlights the importance of standardized protocols and large, annotated datasets for developing robust AI-based screening tools for DR .

An intelligent recommendation-based framework enhances DR grading using a fine-tuned EfficientNetB0 architecture [56]. The study aims to improve DR classification accuracy by utilizing TL techniques to adapt a pretrained model for DR grading. The process involves fine-tuning the EfficientNetB0 model on a diverse dataset, incorporating various data augmentation strategies to improve robustness and overall performance. This framework not only facilitates the classification of DR stages but also offers clinical recommendations, thereby bridging the gap between AI-generated outputs and practical decision-making in clinical settings. The results demonstrate significant improvements in classification accuracy and efficiency over traditional methods, highlighting the potential of integrating DL with intelligent recommendation systems for more effective DR screening . Early detection was critical for effective treatment, yet DR often presents no symptoms or only mild ones in its initial stages, making manual diagnosis by ophthalmologists challenging accuracy of 86%, demonstrating its potential for supporting early and accurate diagnosis of DR [57]. To address this, recent work proposes an automated classification approach using a hybrid DL model that combines DenseNet121, Xception, and EfficientNetB3. The method begins with a preprocessing step to enhance retinal image quality, followed by parallel feature extraction using the three pretrained models. The extracted features were then concatenated and passed through a classification submodel to determine the severity of DR. Evaluated on the APTOS dataset, the model achieves an.

## **2.2 SUMMARY**

AI and DL techniques significantly contribute to the detection and classification of DR through retinal imaging. These methods enable the accurate identification of key

lesions, including MAs, HEMs, EXs, which serve as critical indicators of DR progression. However, distinguishing between No-DR, Mild-DR, and Moderate-DR remains challenging due to their visual similarities.

Existing AI models for DR classification face several limitations, including challenges related to accuracy and computational complexity. These factors often impede their ability to reliably classify all DR stages, particularly in real-world clinical settings where variations in image quality and dataset availability are common. To mitigate these constraints, subsequent research should explore on the following key areas:

A promising direction involves developing lightweight or hybrid models that merge traditional ML techniques with DL methods. These models balance high accuracy with computational efficiency, making them suitable for clinical environments with limited resources. By using the strengths of both approaches, hybrid model that reduce processing power requirements, enhancing their feasibility in restricted computational infrastructure.

Overfitting is a persistent challenge in DL models, particularly when training on small or specialized datasets. Incorporating regularization techniques, such as dropout, weight decay, and data augmentation which enhances generalization across diverse datasets. These strategies confirms that models perform reliably on unseen data, which is crucial for real-world applications where image distributions may differ from training datasets.

Addressing these limitations will be essential for developing robust, accurate, and scalable AI models for DR screening. These advancements will enable early detection and precise stage classification, facilitating timely intervention. Ultimately, improved AI models will enhance patient outcomes by providing more efficient and accessible tools for diagnosing and monitoring DR, particularly in regions where specialized ophthalmological services are inaccessible or insufficient.