2024 Second International Conference on Emerging Trends in Information Technology and Engineering (ICETITE) | 979-8-3503-2820-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/IC-ETITE58242.2024.10493693

OcuVision:CNN powered Analysis of Retinal images for Disease Diagnosis *

Yoshita Vemparala
Dept. of Information Technology
(of Chaitanya Bharathi Institute of Technology)
Chaitanya Bharathi Institute of Technology
(of Osmania University)
Hyderabad, India
vemparalayoshita@gmail.com

Niveditha Manne
Dept. of Information Technology
(of Chaitanya Bharathi Institute of Technology)
Chaitanya Bharathi Institute of Technology
(of Osmania University)
Hyderabad, India
nivedithamanne1@gmail.com

Sruthi Katapally
Dept. of Information Technology
(of Chaitanya Bharathi Institute of Technology)
Chaitanya Bharathi Institute of Technology
(of Osmania University)
Hyderabad, India
katapallysruthi@gmail.com

Jayaram.D
Dept. of Information Technology
(of Chaitanya Bharathi Institute of Technology)
Chaitanya Bharathi Institute of Technology
(of Osmania University)
Hyderabad, India
jayaramcbit1974@gmail.com

Ramakrishna Kolikipogu
Dept. of Information Technology
(of Chaitanya Bharathi Institute of Technology)
Chaitanya Bharathi Institute of Technology
(of Osmania University)
Hyderabad, India
krkrishna.cse@gmail.com

***Abstract*—In numerous areas of the world, retinal disorders are a major factor in vision loss and blindness. Early recognition and detection of various conditions, including diabetic retinopathy,macular degeneration, and glaucoma, are essential for avoiding irreversible vision loss.We intend to develop a multi-class retinal illness diagnosis method utilizing deep CNNs that is effective. Convolutional neural networks (CNNs) are utilized by the suggested EyeDeep-Net multi-layer neural network to extract pertinent information from fundus images and make diagnostic assessments.The technology holds promise for utilization in telemedicine scenarios,healthcare settings and point-of-care gadgets with limited resources, enabling the prompt identification of diseases and rapid intervention.The accuracy of the model is evaluated using multiple statistical criteria, showing better performance in both disease diagnosis and classification when compared to many modern baseline models. In order to train and assess the suggested deep learning model, this study makes use of the RFMiD dataset, a useful resource. What sets this work apart is the systematic analysis of different optimizers applied to the EyeDeep-Net architecture, which aims to enhance the model's performance and accuracy. The optimization process is vital in tailoring the model to achieve superior results in retinal disease diagnosis.**

***Index Terms*— Retinal disease diagnosis, CNN-based disease detection, automated retinal screening, deep learning in opthalmology, image classification for retinal diseases.**

I. Introduction

Retinal ailments have emerged as a growing and progressively significant issue, impacting individuals across a diverse range of age groups. The retina, situated at the rear of the eye, plays a central role in the intricate process of converting incoming light into neural signals, which are subsequently conveyed to the brain for the intricate task of visual recognition.Age-related macular degeneration[1], notably prevalent among individuals aged 50 to 60, stands as a substantial contributor to vision impairment. Remarkably, in the United States, for instance, AMD afflicts roughly 35% of individuals in the 80-year age group.

The precise diagnosis of retinal disorders remains a formidable challenge due to their complex and multifaceted nature, often requiring the expertise of experienced ophthalmologists. Nevertheless, the emergence of computer-aided diagnostic systems (CAD) presents a promising pathway for early detection and treatment of retinal disorders, potentially diminishing the need for specialists. Technological advancements, particularly in the domain of Automatic Disease Detection (ADD), hold the potential to reshape global eye care. ADD applications, inclusive of those focusing on the analysis of retinal symptoms, hold the promise of enriching the societal healthcare system and democratizing advanced solutions for eye care on a global scale.

The unfolding evolution of machine learning (ML) and deep learning (DL) models has ushered in a new era of possibilities for the classification, segmentation, and identification of retinal disorders. Nevertheless, it is imperative to recognize that significant challenges persist, primarily in the realms of data collection and annotation, acting as substantial impediments in the seamless deployment of ADD systems. A wide array of ML and DL models, encompassing the likes of RNN[2], CNN[3], AlexNet[4], ResNet[5], VGG[6], and others, have come to the forefront as potent tools in simplifying the diagnosis and categorization of these intricate ocular conditions.

In a sincere effort to confront and overcome these significant challenges and, simultaneously, to enhance the diagnostic process for retinal disorders, our research introduces an inventive approach. Our primary focus revolves around the robust classification of multi-class retinal disorders. We achieve this by harnessing a CNN model deeply entrenched in the fundamental tenets of deep learning. As our research unfolds, our emphasis primarily centers on the importance of early and accurate detection, all while showcasing a deft and nuanced approach to the management of memory consumption. This sophisticated maneuver is engineered to circumvent the intricacies that have historically acted as limiting factors for prior methodologies.

The profound significance of early detection and precise classification of retinal disorders cannot be overstated. Timely diagnosis and the categorization of retinal disorders frequently hold the key to preventing irreversible vision loss. This research aims to make substantial contributions to the development of automated systems designed to aid in the early diagnosis of these disorders, thereby ensuring that eye care is not constrained by geographical boundaries or the availability of specialists.

Our research objectives are clearly articulated: firstly, to propose and evaluate a ConvNet model tailored for the classification of retinal disorders, with a primary focus on utilizing the RMFID dataset[19].Secondly, we aim to demonstrate that the performance of our proposed CNN model surpasses current cutting-edge techniques while effectively managing memory consumption.Lastly, we intend to provide compelling and incontrovertible evidence of our model's enhanced performance through a rigorous process of experimental evaluation, conducted primarily on the multi-class RMFID dataset.

As our journey continues, the structure of our paper adheres to a logical and structured framework. In Section II, we delve into a comprehensive review of related works within the domain of retinal disease detection, thereby offering a necessary context for our research. Section III serves as the platform for the unveiling of our proposed CNN model, accompanied by in-depth insights into the RMFID dataset, underlining its suitability for our research efforts. Subsequently, in Section IV, the spotlight turns to the unveiling of the results derived from our rigorous experimental evaluation.This section offers a clear view of the impressive performance of our CNN model, which stands as a testament to the ingenuity and innovation of our approach. Section V takes on the mantle of critical analysis and discussion, exploring the broader implications of our findings, the practical significance of our work, and the potential directions that may shape the future of retinal disease diagnosis. Finally, in Section VI, we draw our research to a conclusion, emphasizing the paramount need for sustained efforts and continued exploration in the quest for early and accurate diagnosis of retinal disorders.

II. LITERATURE REVIEW

In recent years, the landscape of medical image analysis has undergone a significant transformation, primarily driven by the integration of advanced deep learning techniques[21].This change has been especially noticeable in the field of eye care, where CNNs have become a useful tool for diagnosis for a variety of eye conditions by analysing retinal images.In this comprehensive examination, we delve into a series of deep learning models employed in the diagnosis of eye diseases, with a particular focus on their unique attributes, constraints, and potential applications.

Our exploration commences with a CNN-based approach applied to retinal images that have been preprocessed using Gaussian smoothing techniques, with a specific emphasis on the detection of diabetic retinopathy[7]. The results are intriguing, as the model attains a training accuracy of 86%, showcasing its ability to discern intricate patterns within the retinal scans. However, the validation accuracy, standing at 69.8%, suggests a certain degree of overfitting, possibly associated with the chosen learning rate of 1e-4. Nevertheless, the model's proficiency in detecting diabetic retinopathy underscores the promising role of CNNs in the realm of ophthalmic diagnosis.

Building upon this foundation, we embark on a journey to explore innovative amalgamations of CNNs with various machine learning algorithms. The amalgamation of CNNs with Support Vector Machines (SVM)[8] emerges as a standout, producing remarkable results with a training accuracy of 99.34% and a validation accuracy of 71.07%. This confluence of deep learning and traditional machine learning techniques accentuates the effectiveness of this hybrid approach. Similarly, when CNN is amalgamated with Decision Trees[9], a training accuracy of 99.34% is achieved, although the validation accuracy slightly lags at 65.72%. This divergence in accuracy raises questions regarding potential overfitting challenges inherent to the Decision Tree model.

The integration of k-Nearest Neighbors (KNN) alongside CNN unveils significant promise[10], yielding a training accuracy of 86.74% and a testing accuracy of 74.47%. This hybrid model capitalizes on KNN's aptitude for capturing local patterns within the data, thus complementing the CNN's proficiency in feature extraction. However, it is imperative to acknowledge that KNN's performance is intricately linked to the choice of the parameter k, a facet that necessitates further scrutiny. Conversely, the experimentation involving CNN and Gaussian Naive Bayes (CNN-NB)[9] encounters obstacles, as it delivers a training score of 35.69% and a testing score of 29.59%. This signifies that the Gaussian Naive Bayes model may not be optimally tailored for handling the intricate nuances of retinal image data.

Our expedition into retinal image analysis proceeds with the implementation of a U-Net model, an innovative architecture with roots in the biomedical domain. This model achieves a commendable validation accuracy of 95.2%, showcasing its prowess in semantic segmentation, a critical component of disease diagnosis[11]. The utilization of evaluation metrics such as Jaccard and Dice coefficients, coupled with the incorporation of a checkpoint callback function, accentuates the model's aptitude for accurately delineating retinal vessels, an indispensable facet of disease detection.

Expanding the horizons of our investigation, we delve into the utilization of a DeepCNN architecture, underscoring its adaptability across a spectrum of pathological conditions. Trained on the EyeNet dataset[12], which encompasses images representing 32 types of eye diseases, the model, following 15 epochs of training and employing a learning rate of 0.01, garners a validation accuracy of 87.5%. This underscores the versatility of DeepCNN in ophthalmology, where the multifarious nature of pathological conditions necessitates a robust and adaptable approach to diagnosis.

Our voyage reaches its zenith with the implementation of the ROCT NET model, which harnesses OCT images for the diagnosis of retinal diseases. The dataset, boasting over 500 high-resolution images categorized into diverse pathological conditions, serves as a testament to the model's versatility. With a validation accuracy of 93.81%, the ROCT NET model [13]firmly establishes the pivotal role of OCT imaging in the diagnosis of retinal disorders. Its capacity to navigate the intricate retinal layers, facilitated by a myriad of convolutional layers and the integration of pre-trained models such as EfficientNetV2-B0[23] and Xception, holds significant promise for augmenting diagnostic precision.

In summation, this comprehensive exploration illuminates the transformative potential of deep learning models in the domain of retinal image analysis for disease diagnosis. Each model, with its distinctive attributes and limitations, contributes to the overarching objective of enhancing the diagnosis of eye diseases, ultimately leading to more precise and timely interventions. These findings resonate deeply within the broader medical imaging community, highlighting the pivotal role of advanced computational techniques in improving patient outcomes within the realm of ophthalmology. As we continue to push the boundaries of machine learning in healthcare, these insights pave the way for a future where the early detection of eye diseases becomes increasingly accessible and accurate.

TABLE I
SUMMARY OF PREVIOUS WORDS AND THEIR PERFORMANCES

Name of the Model	No. of Diseases	Accuracy (%)
CNN-based Approach (Diabetic Retinopathy)	1	86.0
CNN + SVM	1	71.07
CNN + Decision Trees	1	65.72
CNN + K-Nearest Neighbors (KNN)	1	74.47
CNN + Gaussian Naive Bayes (CNN-NB)	1	29.59
U-Net	N/A	95.2
DeepCNN (EyeNet Dataset)	32	87.5
ROCT NET (OCT Images)	N/A	93.81

III. METHODOLOGY

A. Dataset

Our research is anchored in the utilization of the Retinal Fundus Multi-Disease Image Dataset (RFMiD)[19], a comprehensive and openly accessible collection of retinal fundus images. This dataset was thoughtfully assembled through a collaboration between the Eye Clinic of Sushrusha Hospital and the Centre of Excellence in Signal and Image Processing at SGGS Institute of Engineering and Technology in India. It represents a substantial resource in the field of ophthalmology, meticulously curated for diagnosing various retinal diseases. The dataset's wealth of information is derived from images captured using three distinct digital cameras.

Within the RFMiD dataset, our research hones in on four primary retinal diseases: Diabetic Retinopathy (DR), Media Haze (MH), Normal (representing healthy retinas), and Optic Disc Cupping (ODC). Our selection of these specific diseases aligns with the dataset's labeling, and it provides a targeted approach to diagnosing and classifying these retinal conditions.

The dataset itself is the result of extensive data curation, involving the extraction of retinal images obtained during numerous eye examinations since 2009. Notably, 60% of the dataset, equivalent to 1920 images, is publicly available and forms the cornerstone of our research. These images are carefully captured with a focus on the optic disc or macula, ensuring their suitability for our research objectives.

To enhance the dataset's reliability and utility, expert clinicians have diligently annotated the images, classifying them into normal or abnormal categories. This categorization spans a diverse array of retinal abnormalities, making it a valuable and varied resource for our research.

As we delve into the architecture of the EyeNet model and its application to the RFMiD dataset, our unwavering focus remains on the diagnosis and classification of these key categories of retinal diseases. Our methodology revolves around extracting the valuable information embedded within this dataset and employing rigorous training and validation procedures to provide precise and dependable diagnoses for these specific retinal conditions.

B. Data augmentation and Preprocessing

A meticulously planned data preprocessing and augmentation procedure plays a pivotal role in enhancing the dataset used for model training. This procedure is indispensable for improving the model's performance and its ability to generalize effectively. It commences with the conversion of all the images in the dataset to a 'float32' data type, ensuring consistency and compatibility. The subsequent normalization step scales the pixel values within a range of 0 to 1, achieved by dividing each pixel value by 255. This critical step ensures that the data is in a standardized format, optimizing it for the training process.

To eliminate any potential bias related to the order of data, a shuffling process is introduced. All images within the dataset, as well as their corresponding labels, are randomly reorganized. This shuffling operation enhances the dataset's balance and reduces any potential bias that may have been present in the original order of data.

After the initial preprocessing, the dataset is further divided into separate training and testing subsets. The 'train_test_split' function from the scikit-learn library is employed to allocate 80% of the dataset for training purposes, while the remaining 20% is reserved for rigorous testing. This segregation ensures the model's ability to be accurately evaluated on previously unseen data, a fundamental aspect of any robust machine learning model.

One of the key aspects of our methodology is data augmentation. This is a pivotal process in our approach to diversify the training dataset by introducing subtle variations into the input images. Data augmentation becomes especially crucial when dealing with limited datasets, as it allows the model to generalize effectively to new, unseen examples. Our augmentation techniques include operations like image rotation, shearing, and horizontal flipping. These operations introduce controlled variations, simulating different angles and orientations of retinal images. These augmentations are implemented using the 'ImageDataGenerator' class from the Keras library. Importantly, these augmentations are exclusively applied to the training subset to ensure the integrity of the testing data for accurate model evaluation.

To streamline and optimize the computational overhead associated with real-time augmentation during model training, we save the augmented images and their corresponding labels to files. This allows for more efficient access to these augmented datasets during subsequent model runs. If the augmented dataset files exist, they are promptly loaded, reducing the need for real-time augmentation. However, if they do not exist, the augmentation process is executed, and the augmented images are saved for future use.

As a result of this comprehensive data augmentation and preprocessing, the dataset is considerably enlarged. The augmentation process introduces a more extensive and diverse set of training examples, empowering the model to learn from a broader range of data. This augmentation contributes significantly to the model's capacity to accurately identify and classify retinal diseases.

The described augmentation and preprocessing procedures are critical for equipping our model with the robustness, adaptability, and accuracy required to address the complexities of retinal disease diagnosis. These steps are essential to enhancing the model's reliability and predictive capabilities, furthering the field of retinal disease diagnosis.

C. System Architecture

Our research presents a systematic and well-structured system architecture devised to tackle the challenging task of diagnosing eye diseases utilizing advanced machine learning techniques. This architectural framework represents a sequence of pivotal stages aimed at ensuring the model's efficacy in recognizing and classifying various retinal diseases.

The initial stage within this architecture is Dataset Acquisition, where we source is RFMid. This dataset is meticulously curated, originating from the Eye Clinic of Sushrusha Hospital, in collaboration with the Centre of Excellence in Signal and Image Processing at SGGS Institute of Engineering and Technology in India. It is a valuable resource, encompassing retinal fundus images captured by advanced digital cameras. These high-resolution images provide a rich and diverse data source for both training and testing our model.

Following dataset acquisition, the critical phase of Dataset Augmentation and Pre-processing takes center stage. This step is pivotal for ensuring that our model is both resilient and capable of handling the intricate details presented in retinal images. As previously described, the augmentation process introduces controlled variations into the images, simulating different angles and orientations. By diversifying our dataset in this manner, we empower our model to generalize effectively, even when faced with previously unseen retinal images. Data normalization and shuffling are also implemented, standardizing the data and eliminating potential order-related biases, further elevating the dataset's quality.

The third stage of our architectural design is the Training of the EyeDeepNet model. EyeDeepNet is a sophisticated neural network that assumes a dual role in feature extraction and classification. It extracts distinctive features from the pre-processed images, capturing the unique patterns and characteristics that are indicative of various retinal diseases. This feature extraction process is instrumental in boosting the model's diagnostic accuracy. Subsequently, EyeDeepNet takes on the task of classifying the images into specific disease categories.

The classification process is accomplished through a Dense Layer, employing the softmax activation function. The softmax layer assigns a probability score to each class, denoting the likelihood of an image belonging to a particular disease category. This transformation translates the model's feature-based insights into actionable diagnostic predictions. The design of the dense layer facilitates precise retinal image classification, establishing a pivotal role in the diagnostic phase.

With the EyeDeepNet model comprehensively trained on the augmented and pre-processed dataset, it is poised for deployment in the Diagnosis of Eye Diseases. The trained model's ability to recognize and classify retinal diseases comes into play, making it a valuable tool for ophthalmologists and healthcare professionals. By inputting retinal images into the trained model, we gain swift and accurate disease predictions, ultimately aiding in timely and effective interventions for patients.

This system architecture represents a robust framework for addressing the complexities associated with eye disease diagnosis, merging state-of-the-art data acquisition, augmentation, feature extraction, and classification techniques. As depicted in Figure 1, the accompanying flowchart illustrates these stages, providing a visual representation of the model's workflow and ensuring a clear and organized approach to retinal disease diagnosis

IV. State of Art

A study has developed an advanced deep learning framework that leverages color fundus images for early detection and diagnosis of various eye diseases[20]. These retinal images are crucial for uncovering microvascular changes associated with eye conditions. The framework, designed to be non-invasive, eliminates the need for invasive procedures or tests. It relies on a diverse dataset called RFMiD, specially curated for diagnosing multiple eye diseases. To enhance its robustness, the system incorporates various image augmentation techniques, optimizing its performance while maintaining low computational demands.

At the core of this framework lies the EyeDeep-Net[14], a neural network that employs convolutional neural networks to extract pertinent features from the input color fundus images. These extracted features are then utilized to make accurate diagnostic predictions. Rigorous evaluation using statistical parameters confirms that the EyeDeep-Net outperforms several state-of-the-art models commonly used in the field. In comparison with recent approaches, this method excels in classifying different eye diseases and identifying specific conditions through digital fundus images. Ultimately, this research presents a promising and effective non-invasive solution for the early diagnosis and management of a variety of eye diseases.

Retinal disease detection using Convolutional Neural Networks (CNNs) has seen significant developments, breakthroughs, and ongoing trends in recent years.The development of CNN models for retinal disease detection has not only been about achieving high accuracy but also ensuring transparency and trustworthiness in the decision-making process. Explainable AI (XAI)[15] is a critical component of this endeavor. XAI aims to create models that not only provide accurate predictions but also offer explanations for why a particular diagnosis or classification was made.

In the context of retinal disease detection, XAI is essential for several reasons.Healthcare professionals and clinicians need to trust the AI-based diagnostic tools to make informed decisions about patient care. By providing explanations, these models can justify their recommendations, making it easier for medical practitioners to understand and interpret the results.

XAI techniques include feature attribution methods, saliency maps, and model-agnostic approaches, all of which aim to highlight the regions of an image that influenced the model's decision. By incorporating XAI into CNN models for retinal disease detection, the field is taking a significant step towards ensuring the responsible and ethical use of AI in healthcare.

One of the major breakthroughs in retinal disease detection using CNNs is the automatic grading and assessment of disease severity. The capability is fundamental for determining the appropriate treatment plan and managing patients effectively.

Grading and severity assessment involve categorizing retinal diseases into different stages or levels based on their severity and progression. For example, diabetic retinopathy[16][24] may be graded from mild to severe, with each grade requiring a different level of intervention. CNN models have made significant progress in automating this process.

The models can accurately analyze retinal images and provide precise grading and severity assessments. This not only saves valuable time for healthcare professionals but also reduces the risk of human error in disease assessment. The automated grading also ensures consistency in diagnosis, which is particularly important in large-scale screening programs and telemedicine.

The integration of AI-driven diagnostic models with Electronic Health Records (EHR)[17] is a significant ongoing trend in retinal disease detection. This integration facilitates the seamless transfer of patient data and diagnostic information, enhancing patient management and decision support. EHRs provide a comprehensive patient history, and when combined with retinal disease detection models, they empower healthcare professionals to make more informed decisions. This collaboration reduces information gaps and ensures comprehensive patient care, improving the efficiency and accuracy of retinal disease diagnosis and management.

The ongoing trend in retinal disease detection involves adapting AI-based models for telemedicine[18][22] and remote patient monitoring. The increased prominence of telemedicine, spurred by the challenges of the COVID-19 pandemic[25], has led to a heightened demand for remote diagnostic solutions. AI-driven retinal disease detection models are now enabling remote consultations and patient monitoring, irrespective of the patient's physical location. This trend aims to enhance healthcare accessibility, especially for those in remote areas, and allows for real-time tracking of disease progression and treatment efficacy, ensuring timely interventions. As technology advances, the integration of retinal disease detection with telemedicine is expected to persist, providing convenient and accessible care while maintaining diagnostic accuracy and quality.

V. Result Analysis

The results from our experiments with the EyeDeep-Net model on the Rmfid dataset, employing two distinct optimization algorithms, SGD and Adam, each with a fixed learning rate of 0.001 and 40 training epochs, provide valuable insights into the model's performance. In the case of the SGD optimizer, we achieved a Validation Accuracy of 80.0%, highlighting the model's competence in the training phase. SGD stands as a commonly employed optimization algorithm, working through iterative steps to minimize the loss function by adjusting the model's parameters in the direction opposite

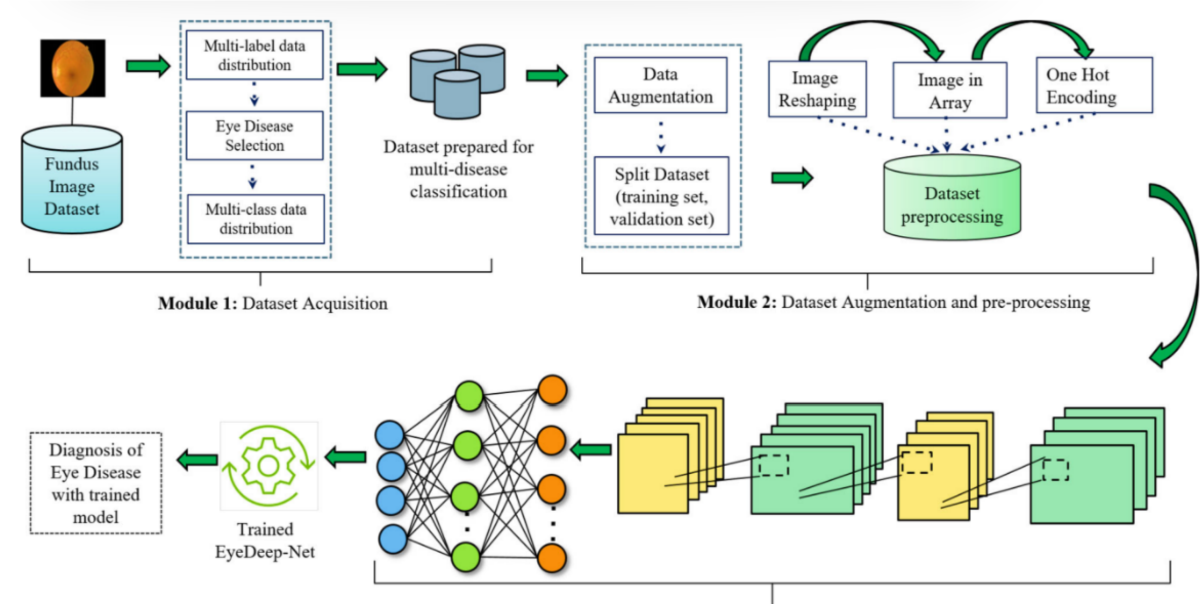

Fig. 1. System architecture

to the gradient. The Equation (1) is used for parameter updation.

$$\theta_{t+1} = \theta_t - \eta \nabla J(\theta_t) \tag{1}$$

Here, θ_t represents the model parameters at iteration t, η stands for the learning rate, and $\nabla J(\theta_t)$ denotes the gradient of the loss function with respect to the parameters.

On the other hand, Adam, an abbreviation for Adaptive Moment Estimation, stands as an optimization algorithm that amalgamates the merits of both momentum and RMSprop, facilitating adaptive learning rate adjustments. The model's parameters are updated according to the following set of equations: Equations from (2) to (8)

$$\theta_{t+1} = \theta_t - \frac{(\hat{v}_t + \epsilon) \odot \hat{m}_t}{1 - \beta_1^t} \tag{2}$$

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) \nabla J(\theta_t) \tag{3}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2)(\nabla J(\theta_t))^2 \tag{4}$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \tag{5}$$

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t} \tag{6}$$

$$1 = \hat{m}_t - \beta_1^t m_t \tag{7}$$

$$1 = \hat{v}_t - \beta_2^t v_t \tag{8}$$

Within these equations, $\hat{m}_t$ and $\hat{v}_t$ serve as representations of the first and second moment estimates, β_1 and β_2 correspond to the exponentially decaying factors, η reflects the learning rate, and ϵ acts as a minute constant, strategically inserted to avert division by zero. This adaptive learning rate mechanism is geared towards promoting swifter convergence and ultimately enhancing the overall performance of the model.

TABLE II
COMPARISON OF ACCURACY USING DIFFERENT OPTIMIZERS.

Optimizer Used	EyeDeep-Net Accuracy
SGD	79.64%
ADAM	83.33%

Moreover, our findings showcased a Testing Accuracy of 79.29%, alongside Precision, Recall, and F-Score metrics approximately at 79.64%, 78.00%, and 78.06%, respectively. These findings attest to the model's ability to generalize effectively, even when faced with data it has not encountered before. Subsequently, we undertook a comparative analysis with the results obtained from training the identical EyeDeep-Net model using the Adam optimizer, revealing marked improvements in its performance. As indicated in Table II, the contrast in Validation and Testing Accuracy between these distinct optimizers underscores the notable enhancements associated with Adam's implementation.The Figure2 provided shows the output of the model with sample images, indicating the output classes, namely Diabetic Retinopathy (DR), Media Haze (MH), Normal (representing healthy retinas), and Optic Disc Cupping (ODC).

The performance of the proposed EyeDeep-Net architecture is additionally evaluated against four established deep learning models: VGG16, AlexNet,VGG19 and ResNet in the below figure3.These models are widely recognized for their robust classification capabilities and have been employed in various

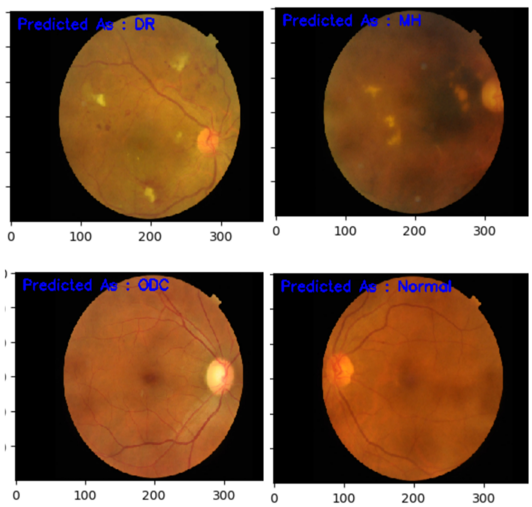

Fig. 2. Sample Outputs

studies, demonstrating significant performance in diverse applications.

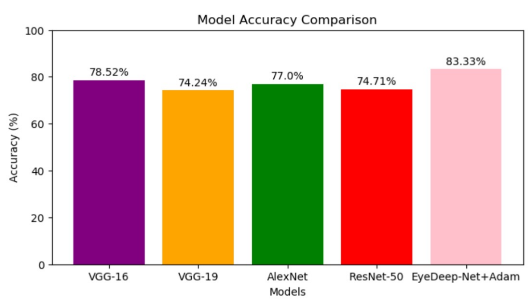

Fig. 3. Model Comparison Chart

VI. Conclusion

In conclusion, this comprehensive exploration of deep learning applications in retinal image analysis for disease diagnosis highlights their significant impact on the field of ophthalmology. The incorporation of Convolutional Neural Networks (CNNs) has led to a paradigm shift in the detection of eye diseases, particularly in cases like diabetic retinopathy, through the analysis of retinal images. This study underscores the promise of CNNs as potent tools for enhancing the precision and speed of disease identification.

The research offers a thorough assessment of the EyeNet architecture by utilizing the RFMID dataset, employing two different optimization techniques, namely SGD and Adam. The research seeks to gauge the model's effectiveness in detecting retinal diseases, providing valuable perspectives on the proposed approach's performance.

The research provides evidence of the effectiveness of the EyeNet architecture in diagnosing retinal diseases, with the Adam optimizer showcasing slightly superior performance in terms of accuracy and overall diagnostic quality. These results encourage further exploration and refinement of deep learning techniques for retinal disease diagnosis, ultimately contributing to improved healthcare outcomes.

In the realm of retinal disease detection, the future holds promising advancements. By fine-tuning model architecture through altering padding, optimizing choice of algorithms and optimizers, and reconfiguring layers, we can significantly impact both the accuracy and efficiency of detection. These adjustments, coupled with the potential of upgrading models with cutting-edge algorithms, offer a pathway to more effective diagnosis and early intervention, ultimately improving patient outcomes and healthcare efficiency in the field of retinal diseases.

In summary, these findings hold immense promise for the broader medical imaging community, illuminating the transformative potential of advanced computational techniques in ophthalmology. As the frontiers of CNNs in healthcare continue to expand, these insights pave the way for a future where the early detection of eye diseases becomes more accessible and accurate, ultimately benefiting patients and advancing the field of ophthalmology.

VII. Acknowledgment

The study is made as part of the academic project in the Department of Information Technology at Chaitanya Bharathi Institute of Technology, Hyderabad. Key supporters in mobilizing resources,and technologies and compiling the objectives of the research are Supervisor Prof D.Jayaram, Co-Supervisors Prof Ramakrishna Kolikipogu, Dr. T. Prathima, Dr. Ramu Kuchipudi, Head, Dr Rajanikanth A, Principal Dr. C.V. Narasimhulu. Thanks to the Management of CBIT for providing us the amenities and extended technical support in completing the research on time.

References

[1] AMDNet: Age-related Macular Degeneration diagnosis through retinal Fundus Images using Lightweight Convolutional Neural Network Kiran Venneti; Hrishikesh Kashyap; R Murugan; N Jagan Mohan; Tripti Goel Published in: 2022 IEEE Silchar Subsection Conference (SILCON) Date of Conference: 04-06 November 2022 Date Added to IEEE Xplore: 31 January 2023 ISBN Information: Electronic ISBN:978-1-6654-7100-8 Print on Demand(PoD) ISBN:978-1-6654-7101-5 INSPEC Accession Number: 22572016 DOI: 10.1109/SILCON55242.2022.10028813 Publisher: IEEE

[2] Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) Network Alex Sherstinsky.https://doi.org/10.48550/arXiv.1808.03314

[3] An Introduction to Convolutional Neural Networks Keiron O'Shea, Ryan Nash https://doi.org/10.48550/arXiv.1511.08458

[4] ImageNet Classification with Deep Convolutional Neural Networks January 2012Advances in Neural Information Processing Systems 25(2) DOI:10.1145/3065386

[5] Deep Residual Learning for Image Recognition Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun https://doi.org/10.48550/arXiv.1512.03385

[6] Very Deep Convolutional Networks for Large-Scale Image Recognition Karen Simonyan, Andrew Zisserman https://doi.org/10.48550/arXiv.1409.1556

[7] Diabetic Retinopathy Classification Using CNN and Hybrid Deep Convolutional Neural Networks by Yasashvini R.,Vergin Raja Sarobin M. *,Rukmani Panjanathan,Graceline Jasmine S. andJani Anbarasi L.ORCID https://doi.org/10.3390/sym14091932

[8] An Explainable Fully Dense Fusion Neural Network with Deep Support Vector Machine for Retinal Disease Determination Research Article volume 16, Article number: 28 (2023)

[9] DL-CNN-based approach with image processing techniques for diagnosis of retinal diseases August 2022Multimedia Systems 28(9) DOI:10.1007/s00530-021-00769-7

[10] S. S. Nath, B. K. Anoop and P. Sankar, "Classification of Outer Retinal Layers Based on KNN-Classifier," 2018 International Conference on Emerging Trends and Innovations In Engineering And Technological Research (ICETIETR), Ernakulam, India, 2018, pp. 1-4, doi: 10.1109/ICETIETR.2018.8529098.

[11] An improved U-net based retinal vessel image segmentation method Author links open overlay panelKan Ren, Longdan Chang, Minjie Wan, Guohua Gu, Qian Chen https://doi.org/10.1016/j.heliyon.2022.e11187

[12] A. Nawaz, T. Ali, G. Mustafa, M. Babar and B. Qureshi, "Multi-Class Retinal Diseases Detection Using Deep CNN With Minimal Memory Consumption," in IEEE Access, vol. 11, pp. 56170-56180, 2023, doi: 10.1109/ACCESS.2023.3281859.

[13] ROCT-Net: A new ensemble deep convolutional model with improved spatial resolution learning for detecting common diseases from retinal OCT images Mohammad Rahimzadeh, Mahmoud Reza Mohammadi https://doi.org/10.48550/arXiv.2203.01883

[14] EyeDeep-Net: a multi-class diagnosis of retinal diseases using deep neural network Neha Sengar, Rakesh Chandra Joshi, Malay Kishore Dutta Radim Burget Published: 21 January 2023 volume 35, pages10551–10571 (2023)

[15] Liquid-biopsy proteomics combined with AI identifies cellular drivers of eye aging and disease in vivo panelJulian Wolf, Ditte K. Rasmussen , Young Joo Sun, Jennifer T. Vu , Elena Wang, Camilo Espinosa, Fabio Bigini, Robert T. Chang , Artis A. Montague , Peter H. Tang , Prithvi Mruthyunjaya , Nima Aghaeepour , Antoine Dufour , Alexander G. Bassuk, Vinit B. Mahajan

[16] Automated identification and grading system of diabetic retinopathy using deep neural networks panelWei Zhang, Jie Zhong, Shijun Yang, Zhentao Gao, Junjie Hu, Yuanyuan Chen, Zhang Yi https://doi.org/10.1016/j.knosys.2019.03.016

[17] GRIK5 Genetically Regulated Expression Associated with Eye and Vascular Phenomes: Discovery through Iteration among Biobanks, Electronic Health Records, and Zebrafish panelGokhan Unlu, Eric R. Gamazon, Xinzi Qi, Daniel S. Levic , Lisa Bastarache , Joshua C. Denny, Dan M. Roden, Ilya Mayzus , Max Breyer, Xue Zhong, Anuar I. Konkashbaev, Andrey Rzhetsky, Ela W. Knapik, Nancy J. Cox

[18] AI telemedicine screening in ophthalmology: health economic considerations panelZhen Ling Teo a, Daniel Shu Wei Ting Singapore National Eye Center, Singapore Eye Research Institute, Singapore Duke-NUS Medical School, National University of Singapore, Singapore

[19] Pachade S, Porwal P, Thulkar D, Kokare M, Deshmukh G, Sahasrabuddhe V, Giancardo L, Quellec G, Me riaudeau F (2021) Retinal fundus multi-disease image dataset (RFMiD): a dataset for multi-disease detection research. Data 6:14.https://doi.org/10. 3390/data6020014

[20] A Comprehensive Review of Deep Learning Strategies in Retinal Disease Diagnosis Using Fundus Images Published in: IEEE Access (Volume: 10) Page(s): 57796 - 57823 Date of Publication: 27 May 2022 Electronic ISSN: 2169-3536 DOI: 10.1109/ACCESS.2022.3178372 Publisher: IEEE

[21] Deep Ensemble Learning for Retinal Image Classification Edward Ho; Edward Wang; Saerom Youn; Asaanth Sivajohan; Kevin Lane; Jin Chun; Cindy M. L. Hutnik https://doi.org/10.1167/tvst.11.10.39

[22] Digital innovations for retinal care in diabetic retinopathy,Stela Vujosevic, Celeste Limoli, Livio Luzi Paolo Nucci Published: 12 August 2022 Volume 59, pages 1521–1530, (2022)

[23] Few-shot out-of-distribution detection for automated screening in retinal OCT images using deep learning Teresa Araújo, Guilherme Aresta, Ursula Schmidt-Erfurth Hrvoje Bogunović Published: 27 September 2023 Article number: 16231 (2023)

[24] Deep convolutional neural networks for diabetic retinopathy detection by image classification Shaohua Wan , Yan Liang , Yin Zhang

[25] Retinal microvascular abnormalities in patients after COVID-19 depending on disease severity Miguel Ángel Zapata1, http://orcid.org/0000-0002-3641-3806 Sandra Banderas García1, Adrián Sánchez, Anna Falcó, Susana Otero-Romero, Gabriel Arcos, http://orcid.org/0000-0002-8677-6859Daniel Velazquez-Villoria, Jose García-Arumí