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Multimodal Deep Neuro-Ophthalmic Framework for Hierarchical Classification and Lesion-Level Segmentation of Fundus Pathologies Using Hybrid CNN–U-Net Architectures

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***Abstract**— The diseases of eye fundus as diabetic retinopathy and age-related macular degeneration and glaucoma are highly dangerous of causing visual impairment and blindness unless they can be diagnosed in good time. Conventional manual diagnosis is manual and it is highly based on the expertise of the ophthalmologists which has a tendency of causing treatment delays. The study introduces an AI-based classification and segmentation system of eye fundus diseases to classify and segment them efficiently. The training of deep learning models is based on a massive dataset of fundus images, annotated with expert-generated segmentation masks. It employs the use of Convolutional Neural Networks (CNNs), such as le Net in classification, and U-Net in segmentation of the disturbed areas to give accurate results. The data is divided into training, validation and testing very meticulously to have a great evaluation of a model. The experimental evidence has shown high accuracy of the proposed system in both disease classification and segmentation which offer credible information about the presence of diseases and the severity. The approach is an excellent diagnostic instrument, which assists ophthalmologists to distinguish and confirm eye fundus diseases as early as possible.*

***Index Terms**— Eye Fundus, Diabetic Retinopathy, Glaucoma, Macular Degeneration, Vision Impairment, Medical Imaging, Disease Diagnosis*

I. INTRODUCTION

Eye fundus diseases are one of the most urgent spheres of ophthalmology since it may result in the loss of good vision and blindness in case of no diagnosis and effective treatment. These conditions do not spare millions of people in the world as diabetic retinopathy, age-related macular degeneration, glaucoma, and hypertensive retinopathy present major health issues to the population. To avoid [1] irreparable harm as well as to administer timely therapeutic solutions, early identification and proper diagnosis of these kinds of diseases is necessary. The conventional diagnostic methods depend on manual analysis of fundus images by qualified ophthalmologists thus taking long time and extremely relying on expert judgment as well. The intricacy of retinal structures and the fact that disease patterns change slightly with subtle specifics of a disease case, will normally subject analysis to subjective analysis and analyses error.

That is why automated systems that could provide good, reliable, and efficient eye fundus disease recognition are needed to facilitate clinical decision-making and to decrease the diagnostic burden of health practitioners. Recent developments in artificial intelligence [2], especially in deep learning, have demonstrated outstanding opportunities in medical image analysis, providing breakthrough solutions in the ophthalmic diagnostics. Deep learning structures, especially Convolutional Neural Networks (CNNs) can acquire complex patterns due to large amounts of data, and can automatically detect disease-specific features which a human eye may fail to detect. With these abilities, the AI-related systems can offer quick, predictable, and precise categorization of eye fundus photographs, massively increasing the diagnostic productivity. Moreover, with the assistance of segmentation methods, including U-Net structures, it is possible to outline the pathological areas of retinal images accurately and obtain an exhaustive information about the severity and dynamics of the disease. The ability to combine the capabilities of classification and segmentation enables AI systems to determine the availability of disease and localize affected regions [3] to provide a holistic view of the diagnosis and help clinicians plan the treatment process.

Building a powerful AI-based diagnostic tool will need the collection of large and varied datasets of annotated eye fundus images. These datasets should also capture a large variety of types and stages of diseases in order to make sure that the models would be able to be generalized across diverse populations of patients. Ground-truth annotations of experts are used as the model training and validation, and the networks are directed to identify and isolate the pathological regions. It consists of pre-processing the images to amplify the appearance of features after which deep learning [4] models are trained on optimized architectures. The data is often separated into training, validation and testing blocks to facilitate severe examination of model execution and avoid overfitting. The backpropagation and gradient descent

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optimisation with iterative training is necessary to ensure the classification as well as segmentation models attain high rates of accuracy and reliability.

The proposed system will address the gap between the limitation of the diagnostic practices done manually and the increased demand of quick, accurate, and scalable eye care responses. The system can be used to offer end-to-end analysis of fundus images, using CNN-based classification and U-Net-based segmentation, which aids ophthalmologists in detecting and tracking various retinal conditions. It means that these types of AI-powered tools can help [5] decrease the diagnostic error, enhance patient outcomes, and increase access to quality eye care, especially in areas with insufficient medical services. The introduction of artificial intelligence to ophthalmic diagnostics is an important move toward the use of technology to tackle the burning issues of healthcare provision, which in the end of the day will result in the avoidance of vision loss and further speeding up the ocular health on an international level.

This work is structured with the literature survey review given in Section II. Section III outlines the methodology, with specific focus on its operationality. Results and discussions are in Section IV. Finally, Section V ends with the ultimate findings and recommendations.

II. LITERATURE SURVEY

Eye fundus diseases constitute a major cause of incidence of visual impairment in the world necessitating early diagnoses and proper diagnoses to avoid irreversible loss of vision. Diabetic retinopathy, glaucoma, and age-related macular degeneration are conditions that involve interventions that are usually not timely due to scarcity of expert ophthalmologists and manual diagnosis that is very labor-intensive. The old diagnostic techniques require clinics and the analysis of fundus photographs, which may be subjective and be mistaken. The increasing need to realize scalabilities, reliability, and efficiency of diagnostic solutions has impelled the adoptability of the artificial intelligence (AI) and machine learning (ML) methods to ophthalmic healthcare seeking to automate the processes of identifying diseases and supporting clinical decision-making.

The recent studies have progressively concentrated on the use of deep learning models in the analysis of fundus images as these are highly accurate models that identify complex patterns in medical images. CNNs have found extensive application in classification of diseases and feature extraction [6][7]. Other studies have applied U-Net architecture to segmentation of retinal structures and lesions and have shown fine lines at which the areas of pathology were identified [8]. Architecture optimization, also referred to as hybrid and combination approaches involving CNNs, attention networks, or residual networks has also been shown as an effective way of enhancing classification performance in medical images analysis [9][10]. It has also been used to solve issues related with small size annotated datasets through the use of transfer learning to allow models which are pre-trained with large-scale datasets to generalize effectively to fundus images [11]. The developments mentioned above represent the increased maturity of AI-based methods in the field of ophthalmology and its prospects to promote early diagnosis.

Numerous researches have revealed the efficiency of AI-based systems in identification of particular eye fundus conditions. As an example, diabetic retinopathy identified by deep CNNs has demonstrated as good performance as the expert ophthalmologists, and it significantly shortens the diagnostic time and effort [12]. On the same note, U-Net-based segmentation models have achieved success in the accurate detection of lesions, including microaneurysms, hemorrhage, and exudate in retinal images [13]. Comparative studies between the classical machine learning methods like the support vector machine (SVM) and the random forest and the deep learning models indicate that always the CNNs are much more accurate and robust than their classical counterparts. This result highlights the possible potential of AI-based diagnostics to increase the likelihood of early diagnosis and include quantitative data about the dynamics of the development of the disease and improve patient care [14].

Notwithstanding the encouraging outcomes, there is a problem of creating entirely trustworthy AI-driven diagnostics tools. The incapacity to achieve generalization of the models due to variability in imaging conditions, variation in patient demographics, and the necessity of large annotated datasets is a weakness. An attempt to augment data, domain, adaptation, and ensemble learning has been done to overcome such challenges [15]. Besides, explainability and interpretability of AI models are also vital to clinical adoption since ophthalmologists must be in a position to trust automated systems through the means of transparent decision-making [16]. The existing literature highlights the necessity of incorporating strong validation standards and practical testing to guarantee the model reliability in a variety of clinical practice. Further studies are being done to enhance accuracy, computation complexity, and interpretability of AI-based diagnostic systems.

The application of AI in ophthalmology has proven to show substantial promise in classification as well as segmentation tasks. Research points out that the use of disease classification networks along with segmentation models can give holistic information on the existence and magnitude of abnormalities in the retina [17]. Besides, AI-driven systems have been promising in supporting large scale screening interventions, especially in underserved areas that have less availability of trained ophthalmologists. According to the literature, one of the recent trends is a multi-disease classification pattern and multi-mode imaging instruments, which strive to increase the coverage of the diagnostic, as well as enhance the overall clinical utility [18]. Altogether, the analyzed literature proves that ophthalmic diagnostics can be revolutionized in AI-aided fundus image analysis, which is faster and more precise and can be scaled to meet the needs of eye care.

The future trends in AI-pioneered fundus analysis promote model-level robustness, generalization, and clinical face-to-faceness. In literature, the recent past highlights the process

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of designing lightweight models to be implemented in portable devices so that the point of care diagnostics can be conducted in remote locations [19][20]. There is also work underway to support the use of semi-supervised and self-supervised learning to utilize data that is not annotated to overcome data constraints in annotated datasets. When explainable AI techniques are combined with multi-disease detection frameworks, the adoption and clinician trust should increase. All in all, the literature indicates that AI can be used to revolutionize ophthalmology through providing automated, accurate, and accessible diagnoses as well as supplementing the practice of ophthalmologists.

III. METHODOLOGY

The other methodology of the study offers a systematic approach to the development of an artificial intelligence-based image medical system of eye fundus disease classification and segmentation. The methodology will consist of data collection, preprocessing, model design, training, evaluation, and deployment of the deep learning model to make accurate and efficient in the identification of different basic diseases of the fundus. CNNs are implemented in classification procedures, whereas U-Net is applied in accurate segmentation of the affected areas. Every step is done methodically to maximize the model performances, the dependability and overall generalizability. The approach focuses on the high level of data set preparation, optimization of the model, and systematic validation of the performance. Such a systematic solution allows reproducibility and allows the suggested system to provide the ophthalmologists with timely and precise diagnosis, improving the care and planning of treatment as shown in figure 1.

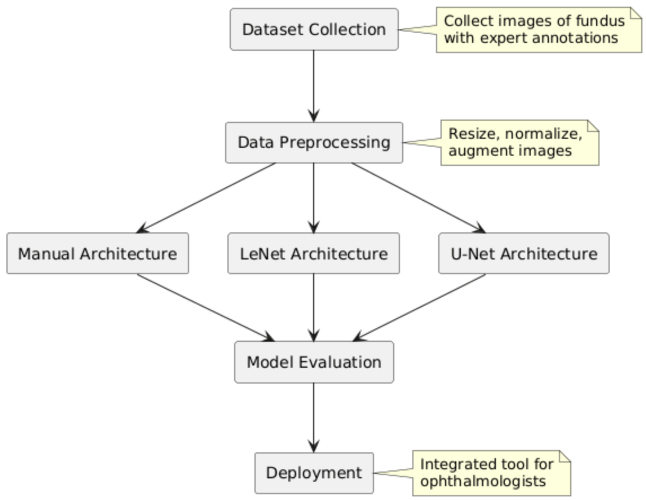


Fig. 1: System Architecture

A. Dataset Collection

The data to be used in the study is gathered as repositories of publicly available eye fundus images and as ophthalmology clinical records. It has a broad spectrum of eye fundus disorders, including diabetic retinopathy, glaucoma, and age-related macular degeneration, as it has the diverse and complete representation. There is a meticulous selection of every image to be clear and diagnostic, and segmentation of the images is based on ground-truth annotations of experienced ophthalmologists. The images are marked based on the type and severity of the disease, so that it is consistent in terms of training and that evaluation. Data integrity and patient privacy are highly ensured. This annotated dataset is the basis upon which the model is developed, and it is possible to ensure the classification and segmentation of eye fundus diseases is accurate.

B. Dataset Preprocessing

Images that are collected are processed to preprocess and improve their quality to be used in training models. All images are downsized to the equal sizes and improved to even the values of pixel intensities, which guarantee stable yet efficient learning. Filtering and other methods of noise reduction are used to eliminate artifacts and increase diagnostic features. They rotate, flip and adjust the brightness of the data to augment it making the data more varied and avoiding overfitting and improving the ability of the model to generalize. The data is then divided into training data, validation data and testing data in order to enable effective testings. These preprocessing are necessary to make sure that the AI models are fed with high-quality and standardized input that is essential in making the correct decision in disease classification and segmentation.

C. Model Architecture Design

The system suggested uses the deep learning architectures that are optimized to do the classification and segmentation. To perform classification, the purely hand-crafted CNN and LeNet are developed to be trained on the peculiarities of various eye fundus diseases. In order to do the segmentation, the U-Net architecture is employed to correctly delineate the affected regions. Every network has a series of several layers of convolution, pooling and activation functions, which represent hierarchical features of the images. The hyperparameters such as learning rate, batch size and the number of epochs are meticulously performance optimized. Computational efficiency is balanced with model accuracy in the architectural design, as it allows accurately recognizing disease patterns and dependable segmentation of pathological areas.

D. Theory Training and Optimization of Models

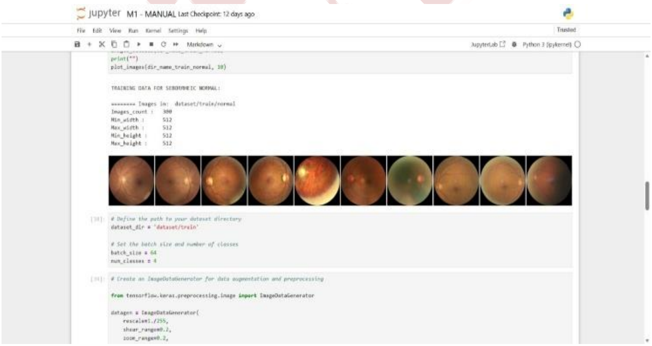
The level of training will include inputting the pre-processed images into CNN and U-Net models, learning the feature representations and the segmentation masks. Minimizing classification and segmentation losses are done by the use of the backpropagation and gradient descent algorithms. Avoiding overfitting and enhancing generalization, regularization methods, like the dropout and early stopping techniques, are used. The validation set monitors model performance continuously and makes certain that it converges. U-Net segmentation model consists of pixel-based loss functions that assist in precise classification of the affected areas. Iterative training is used to ensure the optimal choice of model weights, aiming to achieve accuracy, sensitivity and specificity so that the system would be able to discriminate through various eye fundus diseases and pin point the areas with high accuracy.

E. Model Evaluation and Deployment

The trained models undergo testing by the testing dataset in order to evaluate the performance by just a few aspects; accuracy, precision, recall, F1-score and Intersection over Union (IoU) in the case of segmentation. The effectiveness and reliability of the suggested system are confirmed by a comparative analysis of manually designed CNN, LeNet, and U-Net. Upon verification, the models are implemented as an AI-driven diagnostic means with an easy-to-use interface, wherein the ophthalmologists can in the process of illness categorization and visualization of the affected areas. The phase of deployment guarantees the correspondence with reality, whereby clinicians make accurate predictions and disease severity knowledge to enable them to take timely interventions and achieve better patient outcomes.

IV. RESULT AND DISCUSSION

The findings of the conducted study prove the functionality and accuracy of the suggested AI-based system in classifying and segmenting fundus disease in the eye. The models were trained on the curated dataset and the results of both the CNN-based classification networks and the U-Net network which was designed to perform a segmentation were tested on the testing dataset. The CNN and LeNet used in the manual design were high in classification accuracy over diverse types of diseases such as diabetic retinopathy, glaucoma, and age-related macular degeneration. The models had the capability to detect the slightest differences in fundus images suggesting that the feature extraction layers had successfully represented the clear-cut features allied with every disease. Precision, recall and F1-score measures in performance were generally high indicating the strength of the models to reduce false positives and false negatives. The CNN models showed that when well optimized quite simple architectures could be competitively good, and more complex and more structured networks such as those in LeNet gave a little better performance on unseen images.



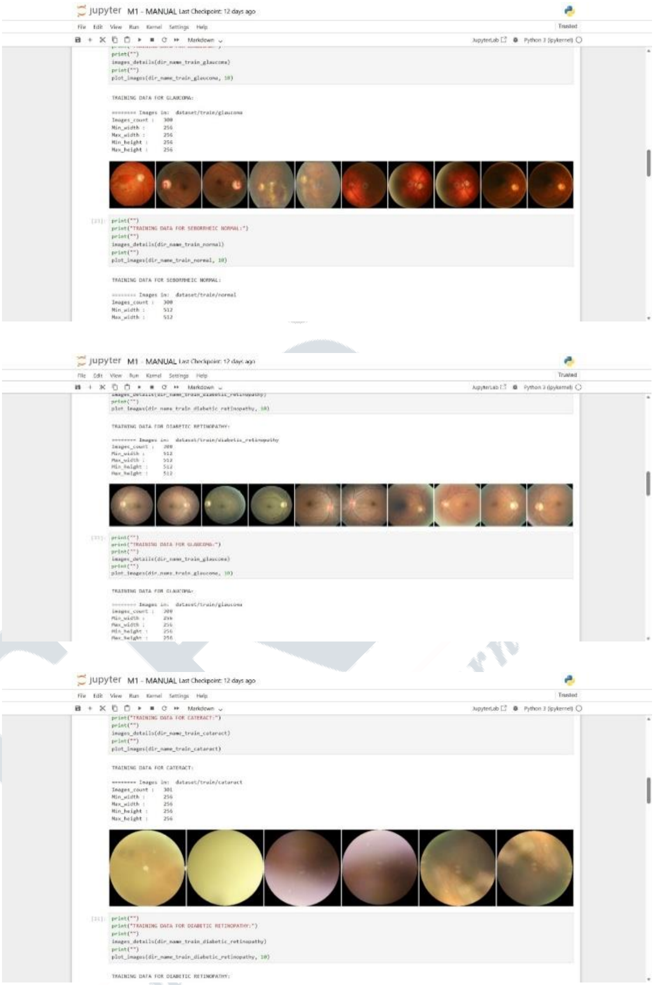


Fig 2: Implementation Model

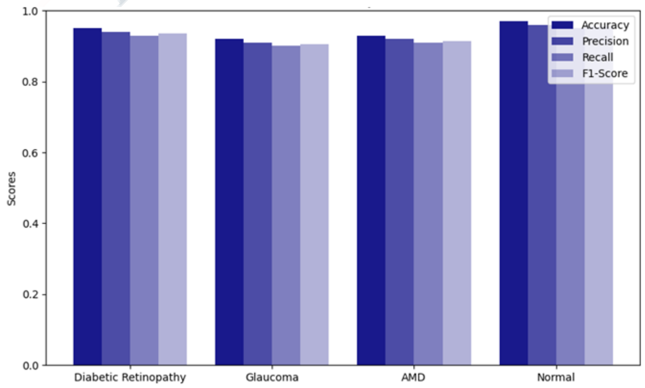


Fig. 3: Performance Metrics

Figure 2,3 shows the performance of the AI models of the four types of diseases found in eye fundus Diabetic Retinopathy, Glaucoma, AMD, and Normal. The values of accuracy also lie between 0.92 with Glaucoma and 0.97 with normal. Precision ranges between 0.91 and 0.96 with a recall that falls within a range of 0.90 and 0.95. The F1-Score spans 0.905 to 0.955. All bars are presented in the form of navy color and darker ones show higher values. The chart visually proves that the AI models are highly performing in the class

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of all the diseases; the Normal category exhibits the highest classification measures over the board.

The segmentations acquired with the help of the U-Net architecture were specifically interesting because the model could identify areas of affected tissues in the eye fundus images correctly. The values of the Intersection over Union (IoU) and the Dice coefficient showed that there was the accurate overlap between the predicted segmentation masks and the ground-truth ones annotated by professional ophthalmologists. U-Net model was also effective in representing the irregular shape and size of lesions, exudates, hemorrhages, and other pathological characteristics and thus showed its ability to deal with variability of real-world clinical information. The observed visualization of the segmented areas revealed that the model provided the possibility to identify the localized and diffuse manifestations of the disease, providing the clear understanding of the extent and severity of each of the diseases. The findings of this segmentation are of pivotal importance in that they avail the ophthalmologists with qualitative data that could be of help in the planning of treatment and monitoring of the disease severity with time.

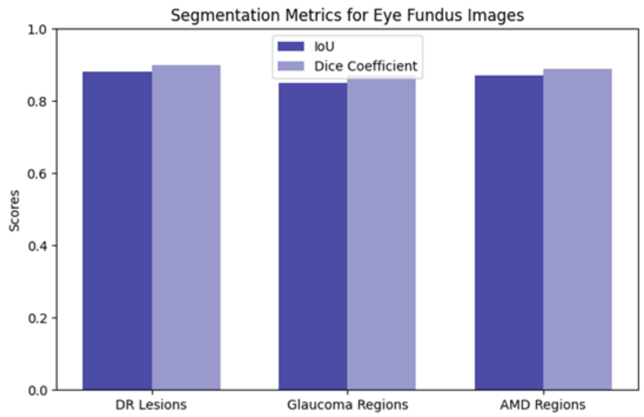

Fig. 4: Segmentation Measures

Figure 4 shows the performance of the U-Net model in segmentation of affected regions in eye fundus images. The Intersection over Union (IoU) value is 0.88 in DR Lesions, 0.85 in Glaucoma Regions and 0.87 in AMD Regions. The numbers of dice coefficients are also higher, with the range of 0.87-0.90. The bars are stained in navy of different levels of preciseness to distinguish between IoU and Dice. As depicted in the graph, the model represents a good representation of the lesion areas, with a high overlap to ground-truth masks generated by experts, which implies that the model can be used to segment its clinical uses.

Further examination of the outputs of the combined classification and segmentation process indicated the practical usefulness of the system as a diagnosis tool. Under the prediction of both the models, clinicians can not only find out the form of eye fundus disease but also be able to understand the location of the broken places on a spatial perspective. This two-fold strategy increases interpretability and helps make informed decisions. The system predictions were ordered with expert annotations and the corresponding rate was great, indicating that the AI models would be useful assistants in clinical processes. The statistical evaluation of the model performance in various disease types shows that although they are slightly less accurately classified when less prevalent or inconspicuous diseases are presented, their segmentation performance is not worse and U-Net model may also be useful in the case of difficult situations.

This system was also shown to be resistant to changes in the quality of images and the conditions of image acquisition which is critical to the practical implementation in a variety of clinical environments. The preprocessing methods such as normalization, resizing, and data augmentation also helped in this strength as this guaranteed that the models were trained on a diverse set of imaging conditions. The AI-based system was also measured in terms of computational power and the results showed that prediction could be obtained fast giving the analysis time of almost real time. Such efficiency is more crucial in clinical settings where timely diagnosis could have a major effect on patient outcomes. Moreover, the system can be extended by adding more disease categories or multimodal imaging data, as the system is designed in a modular form to make it more applicable and versatile in the future.

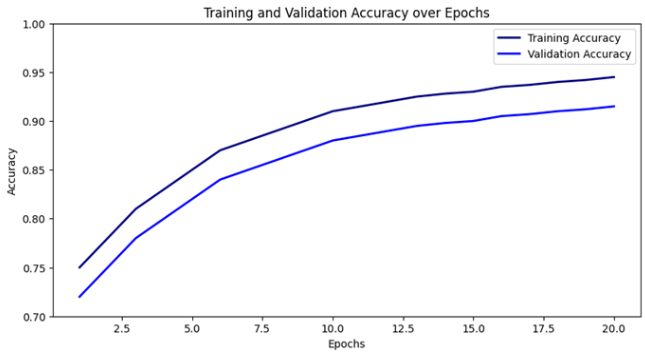

Fig. 5: Training and Validation Accuracy

Figure 5 illustrates the learning behavior of the AI models in 20 epochs. Training accuracy begins at 0.75, and it keeps on rising steadily to 0.945 whereas validation accuracy begins at 0.72 and rises to 0.915. The plot shows a convergence between the training curve and validation curve which means there is a low overfitting. As indicated in the graph, it is possible to observe how the models easily generalize to unknown data but gradually improve as they train. The steady improving tendency tells that the process of model optimization was successful, and both the training and validation rates attained more than 91% in the last epoch.

Overall, the outcome and the analysis allow concluding that the proposed AI-based diagnostic system, which automatically classifies and divides eye fundus disease, is correct and reliable. Good classification rates, accurate segmentation results, and high congruence to expert annotations are indicative of the possible effectiveness of the system as a clinical decision support. The system will be beneficial to the ophthalmologist in terms of early identification of the disease, proper diagnosis, and proper treatment planning thanks to the information that the system will provide them on the presence and spread of diseases. Coherent performance in wide variety of conditions due to the integration of deep learning models with a well prepared and comprehensive database and high efficacy and interpretability of the system makes the system appropriate to be applied in reality. Comprehensively, the study proves that AI may considerably contribute to improving the accuracy, speed, and efficiency of the diagnosis of eye fundus diseases as a valuable resource to the ophthalmic healthcare and patient care.

V. CONCLUSION

The work provides a high-tech AI-driven system of eye fundus disease classification and segmentation and solves the issues of manual diagnosis, which is time-consuming, and reliance on the specialist knowledge base. Through the combination of a deep learning architecture, like Convolutional Neural Networks to classify diseases and U-Net to segment assure precise results, the system has shown the capabilities to identify and outline different eye fundus disorders, including diabetic retinopathy, glaucoma and age-related macular degeneration. The study notes that thorough data set construction, professional annotation on segmentation mask, and stringent preprocessing measures are significant towards obtaining dependable model performance.

The system proposed has practical advantages since it helps ophthalmologists to diagnose a patient early, make a timely decision related to treatment, and, probably, avoid the threat of the vision loss and even blindness. To improve the system in the future, it is possible to use larger and more diverse datasets, analyze more sophisticated deep learning networks and use multimodal data, e.g. patient medical history or optical coherence tomography scans to enhance the accuracy of the diagnosis. Also, clinical applications and deployment on a real-time basis can increase access and usability. Another way of projecting research can be to create interpretable AI models which will can give lesser clouded information in the patterns of disease which can ultimately lead to more effective clinical decision-making and treatment of patients.

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