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Advancements in Ophthalmic Healthcare with Deep Learning-Driven Segmentation for Multi-Stage Eye Fundus Disease Diagnosis

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Abstract

The global rise in eye diseases highlights the need for advanced diagnostic tools in ophthalmic care. This project introduces a deep learning model for classifying eye diseases, streamlining diagnosis, and improving accuracy. Using real-time images from reputable healthcare facilities like Bajwa Hospital in Punjab and Shang gong Medical Tech in China, the model is fine-tuned to clinical nuances. Segmentation of the optic disc and blood vessels is key for precise retinal structure delineation, enhancing disease identification. Various CNN models, including Mobile Net, Dense Net, Reset, and a custom CNN, were utilized for retinal image analysis. Additionally, the Vision Transformer (ViT) model was integrated to capture intricate patterns. The model is deployed as a web application using Django, HTML, SQLite, and Bootstrap, featuring a secure, user-friendly interface. Users can input images to receive prompt disease predictions, along with verified information on prevention, treatment options, and medications. This system not only automates and improves diagnostic processes but also provides reliable medical guidance.

Keywords: *Fundus Disease, Diagnosis, Delineation, Vision Transformer, Bootstrap.*

1. Introduction

The current diagnostic procedures for detecting eye diseases face a critical challenge in swiftly and accurately classifying various conditions when utilizing fundus and OCT images. Traditional methodologies exhibit limitations in granular disease assessment, especially in differentiating between subtle variations indicative of different pathologies, leading to potential misdiagnosis and delayed treatment. These shortcomings create significant healthcare risks, including irreversible vision loss and compromised patient outcomes. The lack of a sophisticated and seamlessly integrated deep learning framework impedes the timely and accurate identification of evolving eye conditions. Hence, bridging this technological gap to enhance healthcare outcomes and provide real-time intelligent solutions capable of precise disease classification and proactive treatment recommendations in response to dynamic and evolving ocular health challenges is imperative. The proposed eye disease classification model aims to revolutionize the diagnosis and management of ocular conditions through the utilization of deep learning techniques. The prevalence of ocular diseases presents a pressing challenge in healthcare, with conditions such as age-related macular degeneration, diabetic retinopathy, and glaucoma posing a significant risk to vision health [1]. The complexity of diagnosing these conditions accurately and efficiently highlights the need for advanced solutions. Leveraging deep learning technology, the proposed eye disease classification model aims to

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address this challenge by systematically analyzing diagnostic images such as retinal scans and OCT images. By employing convolutional neural networks (CNNs), the model offers precise and rapid identification of various ocular pathologies, enabling early intervention and personalized treatment strategies.

2. Proposed Solution

The proposed module utilizes fundus and OCT images to analyze a range of ocular conditions, including cataracts [2], diabetic retinopathy (across multiple stages: mild, moderate, severe, and proliferative), glaucoma, and various macular pathologies. The model swiftly adapts to varying data volumes and accommodates additional features ensuring the system's versatility in the face of evolving requirements. To maximize accessibility and usability, the model is deployed as a user-friendly web application, allowing healthcare professionals to access diagnostic results promptly and make informed clinical decisions

3. Method

3.1. Data Acquision

Thorough data collection and acquisition are essential to build our deep learning model for eye fundus and OCT disease classification. The fundus images used in this study were obtained from multiple datasets including RFMiD (Retinal Fundus Multi Disease Image Dataset), Messidor, DHRISHTI GS, REFUGE (Retinal Fundus Glaucoma Challenge), ORIGA (Online Retinal Fundus Image Dataset for Glaucoma Analysis and Research), and ACRIMA. [3] The OCT images were sourced from datasets such as the Duke OCT Retinal Dataset, OCTA 500, and ICPSR (Inter-university Consortium for Political and Social Research). In addition, images were also sourced from actual patient records from hospitals like Bajwa Hospital in Punjab and Shanggong Medical Technology in China.

3.2. Image Preprocessing

Images from patient records and research journals are optimized through resizing to 224x224 pixels, normalization, and histogram equalization with CLAHE to enhance contrast and details. [5] Colour space analysis extracts features, while edge detection and dilation highlight structures. Image sharpening enhances edges, and augmentations like flipping and zooming diversify the dataset, preventing overfitting and enhancing model robustness. These steps ensure uniformity and quality across the dataset, preparing it for analysis.

3.3. Segmentation

In fundus image segmentation, the model divides the image into distinct sections, highlighting specific anatomical features or pathologies. Trained on internal features and learned patterns, the model analyzes new images, calculating probabilities for each segmentation class (e.g., blood vessels, optic cup, wool spots, macular degeneration). It assigns each pixel or region to the class with the highest probability, delineating pathologies. This process enables accurate identification and localization of features and diseases, facilitating diagnosis and treatment.

3.4. Classification

Once the model is trained, new data is fed into the trained model's internal decision-making layers. It then compares new features with learned patterns and relationships from training and quantifies the resemblance by calculating probabilities for each possible category. These probabilities indicate how likely it is that the new data point belongs to each category based on its features. Finally, the model selects the category with the highest probability.

3.5. Evaluation and Validation

The dataset is divided into training, validation, and test sets. The model learns from the training data, fine-tunes hyper parameters on the validation set, and is evaluated on the test set. The validation set prevents overfitting, and the model's performance is monitored to balance complexity and generalization. Rigorous evaluation protocols ensure robustness and generalizability, and adjustments like regularization techniques optimize the model's ability to generalize to unseen data, ensuring reliability in real-world applications. [4]

3.6. Deployment

The proposed model for classification is trained and deployed in a website. The deep learning model is the saved as a Model.h5 file in the SQLite database. In the field of web development, frameworks such as Django facilitate the construction of complex

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applications by offering a pre-defined architectural foundation.

4. Results and Discussion

In this project, the images are classified using four different architectures namely Dense Net, Mobile Net, ResNet, and Proposed system architecture. Vision Transformer is also used to classify images. These models were evaluated using various metrics to assess their performance. Table 1 describes comparison of metrics. The evaluation results across three models provide a comprehensive perspective on their performance metrics. [6]

Table 1 Comparison of Metrics

MODEL	ACCURACY	PRECISION	RECALL	F1-SCORE	LOSS	MEAN SQUARED ERROR
RESNET	0.9665	0.9592	0.9327	0.9518	0.0409	0.0430
DENSENET	0.9446	0.9069	0.9027	0.9047	0.0529	0.0402
MOBILENET	0.9065	0.9183	0.8862	0.9019	0.0829	0.0512
PROPOSED ARCHITECTURE	0.9719	0.9594	0.9354	0.9613	0.0323	0.0302
ViT	0.9104	0.9153	0.8997	0.9065	0.0269	0.0513

4.1. Results

The provided metrics highlight the superior performance of the proposed architecture compared to Dense Net, Mobile Net, ResNet, and Vision Transformer across various evaluation criteria. With an accuracy of 97.19% and precision of 95.94%, the proposed architecture demonstrates its efficacy in correctly classifying instances and minimizing false positives. [7] Additionally, its recall score of 93.54% indicates its proficiency in capturing relevant instances, resulting in a well-balanced F1-score of 96.13%. The Vision Transformer, with an accuracy of 91.04%, shows good performance but falls short compared to the proposed architecture. Lower training loss for all systems signifies good learning during the training process. Figure [1-3] explains Proposed architecture accuracy plot, Proposed architecture loss plot, Web UI Glaucoma Diagnosis.

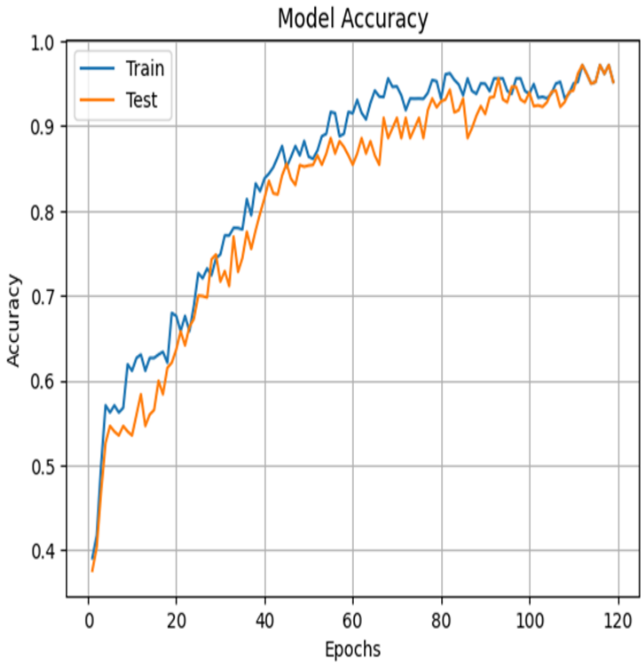

Figure 1 Proposed Architecture Accuracy Plot

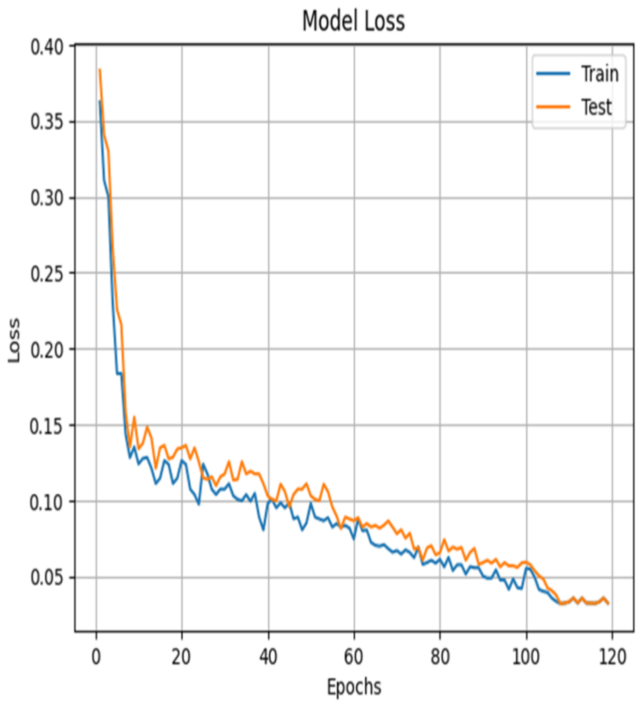

Figure 2 Proposed Architecture Loss Plot

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Figure 3 **Web UI Glaucoma Diagnosis**

4.2. Discussion

ResNet, despite its depth and residual connections, may encounter optimization challenges or limitations in capturing all relevant features, resulting in slightly lower accuracy compared to the proposed architecture. MobileNet's emphasis on efficiency and lightweight design might sacrifice some predictive accuracy due to its limited depth and capacity, hindering its ability to capture complex patterns in the data. DenseNet's lower accuracy might be due to its intricate architecture, characterized by densely connected layers, which may lead to challenges such as overfitting and increased computational overhead. In contrast, the proposed architecture excels by effectively balancing complexity and capacity, leading to superior performance across various metrics. Figure 4,5 explains Bar graph analysis and Inference rate analysis.

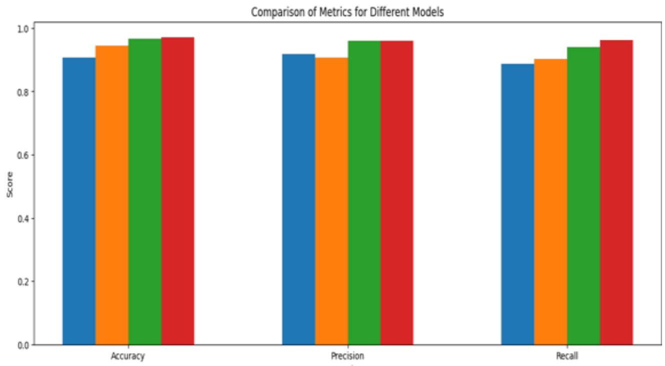

Figure 4 **Bar Graph Analysis**

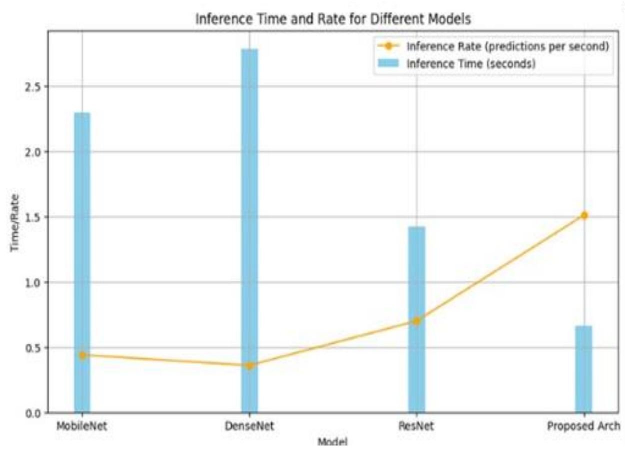

Figure 5 **Inference Rate Analysis**

Conclusion

In order to determine the best deep-learning model for eye disease prediction, several models were rigorously tested before being deployed. Following a thorough analysis, the proposed architecture was determined to be the best model, outperforming the others in terms of accuracy, performance, and generalization skills. It is essential to take into account the proposed architecture's success wasn't entirely due to the algorithm itself. Data preprocessing played a vital role in ensuring the quality and relevance of the input data The fundus and OCT datasets were meticulously cleaned, transformed, and normalized to reduce noise and inconsistencies and improve the model's prediction accuracy. During

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this process, the most significant and instructive characteristics or factors pertaining to the classification of eye diseases were chosen, and they were then transformed to more accurately depict their impact.

Future Work

In terms of future work, exploring deep learning-based models could offer a promising avenue for achieving even higher accuracy and performance. Additionally, considering more sophisticated feature engineering techniques would enable the identification of additional relevant features, potentially enhancing the model's predictive capabilities. Moreover, employing advanced optimization algorithms for hyperparameter tuning could fine-tune the model's parameters, leading to improved overall performance and better generalization We also intend to seamlessly integrate the model into cloud infrastructure, enabling a multiuser environment for global accessibility. By embedding the model in the cloud, we aim to create a collaborative platform for all the diagnosticians worldwide.

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