A NEW HYBRID DEEP LEARNING MODEL FOR DIABETIC RETINOPATHY DETECTION

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ID 55462 Submission	Editorial Screening	Conditional Acceptance	Final Revision Acceptance
30-08-24	30-08-2024	22-09-2024	27-09-2024

ABSTRACT

The progressive eye disease known as diabetic retinopathy continues to be the leading cause of blindness worldwide. Effective treatment and prevention of vision loss require prompt and accurate DR detection. Profound learning procedures have shown extraordinary commitment in clinical picture examination, and in this paper, we propose a hybrid model that joins the qualities of convolutional brain organizations (CNNs) and repetitive brain organizations (RNNs) to further develop DR discovery exactness. The proposed crossover profound learning model involves three principal stages. A pre-handling, first and foremost, step is applied to upgrade the quality and differentiation of fundus pictures, in this manner working on the model's capacity to remove basic highlights. After that, a Residual CNN is used to extract features from the images that have already been processed. Residual CNNs are adroit at catching various leveled highlights, and this stage empowers the model to successfully gain discriminative elements from the information pictures. The subsequent stage includes incorporating RNNs into the model. RNNs are ideal for analysing sequential patterns in medical images because they are well-suited to handling sequential data and capturing temporal dependencies. The model's ability to extract temporal information from fundus image sequences thanks to the inclusion of RNNs improves its ability to identify early DR progression signs. The third and last stage centers around the characterization task, where a completely associated brain network is utilized to decipher the highlights separated by the past stages and order the pictures into various DR seriousness levels. The hybrid model's architecture facilitates the fusion of spatial and temporal information, resulting in a more comprehensive and accurate DR diagnosis.

Keywords: *Diabetic Retinopathy, Deep Learning, Hybrid Model, Detection, Retinal Images.*

1. INTRODUCTION

Diabetic retinopathy (DR), a degenerative eye infection, is a result of diabetes. Damage to the blood vessels in the retina, the light-sensitive tissue in the back of the eye, is one of its distinguishing characteristics. Whenever left untreated, DR can cause serious vision misfortune and even visual deficiency [1][2].

Non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) are the two essential sorts of diabetic retinopathy [3] [4]. The veins in the retina debilitate during the beginning phases of NPDR and start to spill liquids or blood. However, PDR is a more advanced stage in which the surface of the retina begins to sprout new, abnormal blood vessels. The retina is further harmed by these new arteries, which are fragile and prone to bleeding.

For a successful correction and the avoidance of consequences, diabetic retinopathy must be identified early and correctly diagnosed. For people with diabetes, routine eye exams that include a thorough inspection of the retina are advised in order to identify retinopathy at an early stage [5] [6].

Recent applications in medical imaging, such as the detection of diabetic retinopathy, have shown promising results using deep learning methods. Deep learning models generate precise predictions by automatically extracting useful features from

retinal images using vast volumes of annotated data.
For the purpose of detecting diabetic retinopathy, a novel hybrid deep learning model is put forth in this study. The model exploits both the spatial and transient data in retinal pictures by joining the qualities of convolutional brain organizations (CNNs) and repetitive brain organizations (RNNs). The RNN component detects temporal patterns and sequential relationships within the picture data, whereas the CNN component concentrates on extracting visual features from the image data [7][8][9].
A broad dataset of retinal pictures with levels of diabetic retinopathy seriousness distinguished is utilized to prepare and test the model. The dataset has gone through preprocessing to further develop picture quality and standardize picture properties. Then, to effectively gain discriminative elements for diabetic retinopathy recognition, the cross breed model is prepared using a mix of directed learning and move learning strategies.
Experimental findings show that the proposed hybrid deep learning model outperforms existing approaches for the identification of diabetic retinopathy. The model is quite good at identifying different phases of diabetic retinopathy with excellent accuracy, sensitivity, and specificity. The robustness and generalizability of the suggested technique are highlighted by extensive examination and comparison with cutting-edge models.
To sum up, the hybrid deep learning model that has been proposed represents a significant development in the field of detecting diabetic retinopathy. The model provides a complete solution that boosts accuracy and robustness by incorporating geographical and temporal data. It has enormous potential to help medical professionals detect diabetic retinopathy early and treat it quickly, thereby assisting diabetic patients in truly attempting to preserve their vision.

Objective of this research paper is to propose a Hybrid Deep Learning model that combines the advantages of CNNs and RNNs in a synergistic way for automatic detection of DR. Main contribution of our research paper is:

- To recover blurred intensities of edges, remove imperfections in the images, sharpening is performed to avoid improper segmentation of small regions.
- To improve contrast of images histogram equalization for brightness preservation (HEBPDS) and median filtering is applied.
- The finer details of images were accurately revealed via the resolution enhancement of images utilizing the IWOA technique to improve the segmentation accuracy.
- a synergistic combination of RNN and CNN, amalgamating spatial and fleeting examination to make a powerful and precise half breed profound learning model for Diabetic Retinopathy recognition, offering hope for a better future for diabetic patients' visual health.

1.1. Organization of the paper

The following is the paper's structure:
Section 1: Introduction: This section provides an overview of the study topic of diabetic retinopathy diagnosis and discusses the need for a new hybrid deep learning model. It portrays the review's objectives and lays out the foundation for the following parts.
Section 2: Related Work: This segment surveys the group of exploration on using profound figuring out how to analyze diabetic retinopathy. The segment underlines the requirement for a clever half and half technique to expand the viability and precision of identification while likewise featuring research holes.
Section 3: Research Methodology: The model structure utilized in the review is depicted in the segment on research procedure. It explains how the spatial and temporal information in retinal images can be utilized by convolutional neural networks (CNNs) and recurrent neural networks (RNNs). This part additionally talks about the utilized dataset, preprocessing procedures, a superior Whale Advancement Calculation, division techniques, and the phases of component extraction and order.
Section 4: Experimental Results and Discussion: The trial set-up, assessment measures, and execution examination of the recommended hybrid profound learning model are introduced in this part. It shows the model's accuracy, awareness, and particularity and assesses how well it acts in contrast with different methodologies for recognizing diabetic retinopathy.
Discussion: The exploratory outcomes are deciphered, the implications of the outcomes are featured, and the conversation segment goes over as far as possible and likely future bearings. It offers an exhaustive handle of the proposed model and its

commitments to the field of identifying diabetic retinopathy.

Section 5: Conclusion: The summary of the research goals, major findings, and emphasis on the value of the proposed hybrid deep learning model in enhancing diabetic retinopathy detection are presented in the conclusion section. It also offers directions for additional study in this field.

2. RELATED WORKS

Wang *et al.* [5] provide an in-depth look at how deep learning can be used to find diabetic retinopathy and other eye conditions. This paper discusses ophthalmology-specific applications of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), among other deep learning architectures. The review focuses on how deep learning models could improve disease diagnosis accuracy and efficiency.

Gargeya *et al.* [6] demonstrate an automated system for diabetic retinopathy diagnosis that is based on deep learning. The study talks about how to use CNNs to look at images of the retinal fundus and find signs of diabetic retinopathy.

Similarly X. Zeng *et al.* [10] proposed, a novel CNN model with the Siamese-like architecture. A transfer learning technique was used in training phase of fundus images. And Dai, Ling, Liang Wu, *et al.[*11] proposed a model named, DeepDR for DR detection at early to late stages. DeepDR was trained on 466,247 fundus images for lesion detection. This model performed well on microaneurysms, cotton-wool spots, hard exudates and hemorrhages detection.

Nguyen *et al.* [12]proposed an automated classification system based on machine learning models VGG-16 and VGG-19 to analyzes DR images with varying illumination detects severity grade for DR. These study paves the way for automated screening methods by demonstrating the efficacy of deep learning in precisely diagnosing and classifying diabetic retinopathy.

Bhaskaranand *et al.* [13] a screening and monitoring method for diabetic retinopathy is proposed to be retinal fundus image analysis. G. Deshpande, *et al.*[14] had proposed a model to detect diabetic retinopathy using machine learning. They employed a pre-trained Inception V3 using fine-tuning on EyePACS and APTOS 2019 dataset. These review show the capability of mechanized answers for increment openness and viability in programs for diabetic retinopathy screening.

S. Pawar and H. Zope [15] went through the copious challenges come in of diabetic retinopathy detection and introduced various approaches to handle them. In their study they also compared CNN, DNN and BNNs and how SAP Business Technology Platform had potential to increase scalability and accuracy of diagnosis.

A. M. A and S. S. S. Priya [16] proposed a deep learning neural network based pre-trained Convolutional Neural Network (CNN) VGG-16 and MobileNet-V2 to identify the DR all forms. These study examine how deep learning algorithms and image processing techniques can be used to identify and classify diabetic retinopathy

Srinivasan *et al.* [17] investigate the use of cellular automata and deep learning to identify diabetic retinopathy. The research proposes a system for analyzing retinal pictures and recognizing diabetic retinopathy symptoms using CNNs and cellular automata models. The report emphasizes how well this hybrid technique works for accurately detecting and classifying the condition.

S. Kumar *et al.* [18]developed a novel approach using pre-trained deep neural networks for feature extraction of DR images. This model was trained on diverse datasets to extract intricate features, crucial for shrewd the stages of DR. The MobileNet V2 has obtained the highest classification accuracy of 92.42% over the other considered pre-trained models through the significant feature extraction.

N. S, S. S, M. J and S. C [19]proposed a DiaNet Model (DNM) for Vision-impairing lesions detection.on the retina are a common consequence of diabetes mellitus known as Diabetic Retinopathy (DR). Gabor filter was used in Pre-processing phase for improving the texture analysis object recognition and visibility of blood vessels for feature extraction, and image compression. In Augmentation phase, Principal Component Analysis (PCA) for reducing dataset's input dimensions.

N. Khalid and M. Deriche [20] proposed a modes based on fusion of DenseNet-169 and the InceptionV3 with optimal weighting scheme for the early detection. Kaggle APTOS 2019 IDRiD datasets was used for training and testing purpose.

Gargeya *et al.* [21] Deep neural networks are suggested as part of an automated approach for diagnosing diabetic retinopathy. The use of CNNs to examine retinal fundus images and find indicators of diabetic retinopathy is discussed in the study. The work exhibits the capability of profound learning models in identifying diabetic retinopathy with high precision and proficiency.

M. Mateen *et al.* [22] presented a detailed review of DR detection techniques with three major aspects;

DR detection methods, retinal datasets, and performance evaluation metrics

Ribeiro *et al.* [23] give an intensive examination of profound learning techniques for recognizing diabetic retinopathy. The study discusses the use of various deep learning architectures for the analysis of retinal images. The research highlights how deep learning could help systems for diabetic retinopathy screening become more accurate and efficient.

G. M. Ramadan *et al.* [24] proposed a deep neural network for segmentation and classification of DR image. For data pre-processing, CLAHE and min-max normalization was used. The red lesions were extracted using UNet and semantic segmentation was achieved via encoding and decoding side feature maps. Furthermore CNN was used for classification of fundus images.

N. V. R. G, M. Ch, R. Ch and A. B. [25] proposed a novel deep-learning mode, Efficient NetB2 that prioritizes both accurate diagnosis and privacy protection. The model leveraged incorporates numerous conv2d layers and activation functions for precise prediction and classification of DR stages. The Secure Hash Algorithm (SHA-512) constructed unique hash values for each DR image for privacy protection. The model mitigates the risk of vision problems.

L. Qiao *et al.* [26]proposed a system to detect the presence of microaneurysm in fundus image using CNN. This model embed deep learning as a core component for segmentation of images with low-latency inference. The semantic segmentation technique was employed to categorize the fundus image as DR AND NDR. This model categorizes the image pixels based on their common semantic to extract the feature of microaneurysm.

B. N. Jagadesh, M. G. Karthik, D. Siri, S. K. K. Shareef, S. V. Mantena and R. Vatambeti [27]developed a novel two-pronged approach to DR detection. Their model segments optical discs and blood vessels by an improved version of contoured convolutional transformer (IC2T). their model combined local and global contexts to made trustworthy associations.

A. Jabbar *et al.* [28] implemented GoogleNet and ResNet models based on adaptive particle swarm optimizer (APSO) to classify DR fundus images by severity levels.

Z. Wang *et al.* [29] developed a Multi-branching Temporal Convolutional Network with Tensor Data Completion (MB-TCN-TC) model for DR prediction. This model captured temporal correlation and complicated interactions acquiescent superior prediction performance.

S. Ghouali *et al.* [30] proposed an AI-based smart teleopthalmology application for DR detection. The app analysed eye fundus images using Tensor Flow mathematical library from the Kaggle database.

Bellemo *et al.* [31] reevaluate the new data on diabetic retinopathy screening with artificial intelligence (AI). The automated analysis of retinal pictures using AI methods, such as deep learning, is covered in the paper. The review emphasizes the practical uses of AI in diabetic retinopathy screening while highlighting its potential to improve accessibility and efficiency in healthcare settings.

G. N, B. P. Singh and S. Yadav [32] implement a holistic approach, integrating Logistic Regression, Random Forest, and Long Short-Term Memory (LSTM) networks on diverse datasets. Their study highlighted the risk assessment and post-stroke management for improving model performance.

Silva *et al.* [33] Audit profound learning techniques for consequently distinguishing diabetic retinopathy. The utilization of CNNs and other profound learning models for evaluating retinal pictures and spotting signs of diabetic retinopathy is canvassed in the paper. The paper features the capability of profound learning in recognizing diabetic retinopathy precisely and really.

Jelinek *et al.* [34] Audit profound learning techniques for distinguishing diabetic retinopathy and deciding gamble. In order to examine retinal images and assess the likelihood of diabetic retinopathy progression, the research investigates the use of CNNs and other deep learning models. The analysis emphasizes how deep learning has the ability to offer patients with diabetic retinopathy individualized risk assessments.

Singh *et al.* [35] give a careful examination of profound learning techniques for identifying diabetic retinopathy. This study discusses the use of various deep learning models, such as CNNs and RNNs, for the analysis of retinal images. The paper highlights the potential of deep learning in detecting diabetic retinopathy accurately and effectively.

Saleem *et al.* [36] examine how deep learning is used to diagnose diabetic retinopathy automatically. The research covers how to examine retinal images and spot diabetic retinopathy symptoms using CNNs and other deep learning models. The research highlights how deep learning may be used to enhance the precision and effectiveness of algorithms for screening diabetic retinopathy.

Gulshan *et al.* [37] Portray the creation and check of a profound learning calculation for diabetic retinopathy ID. The study talks about how to use

CNNs to look at pictures of the retinal fundus and find signs of diabetic retinopathy. The work shows how profound learning models might be utilized to determine diabetic retinopathy to have amazing exactness.

W. Nazih, A. O. Aseeri, O. Y. Atallah and S. El-Sappagh[38] proposed a novel ViT based deep learning pipeline model for DR fundus image detection. FGADR an imbalanced dataset was used for training and testing purpose. In model AdamW was used to detect the global context of images.

Saba *et al.* [39] dive into the current and impending purposes of profound learning in radiography. To distinguish diabetic retinopathy in retinal pictures, the exploration researches the utilization of profound learning strategies, like CNNs. The article underlines how profound learning can possibly reform the area of radiology.

Li *et al.* [40] based on variety fundus pictures, propose a robotized evaluating framework for the finding of vision-undermining referable diabetic retinopathy. The paper discusses how retinal images and diabetic retinopathy symptoms can be detected using deep learning algorithms like CNNs. The study demonstrates the potential of deep learning to aid in the early detection of vision-threatening retinopathy.

Li *et al.* [41] based on profound learning procedures, recommend a mechanized reviewing framework for the location of vision-undermining referable diabetic retinopathy. The application of deep learning algorithms like CNNs to retinal image analysis and the identification of diabetic retinopathy symptoms that could lead to vision loss is the subject of the study. The study demonstrates that deep learning can improve the accuracy and precision of diabetic retinopathy diagnosis.

Gulshan *et al.* [42] Look at how well a profound learning calculation and manual evaluating do in India at spotting diabetic retinopathy. The utilization of CNNs to look at retinal pictures and find marks of diabetic retinopathy is examined in the review. The study shows how deep learning models can achieve performance levels that are comparable to manual grading, indicating their potential as a trustworthy screening tool.

Asoodeh *et al.* [43] think about profound learning frameworks for the ID of diabetic retinopathy. The study investigates how well various deep learning architectures, such as CNNs and RNNs, can evaluate retinal images for the purpose of diagnosing diabetic retinopathy. The study emphasizes how crucial it is to choose the right deep learning algorithms in order to get accurate and trustworthy results.

Bansal *et al.* [44] For the purpose of detecting diabetic retinopathy utilizing fundus images, a unique hybrid deep learning model is proposed. In order to evaluate retinal images and find indicators of diabetic retinopathy, the paper employs a hybrid architecture that blends CNNs and RNNs. The study illustrates the hybrid model's potential for detecting diabetic retinopathy with great efficiency and accuracy.

G. Shraddha *et al.* [45] developed Convolutional Neural Network (CNN), MobileNetV2 and Support Vector Machine (SVM) models for DR detection. APTOS dataset from Kaggle was used for training and testing.

T. Palaniswamy and M. Vellingiri [46] implemented a novel IoT and deep learning model (IoTDL-DRD) to diagnosis DR in retinal images. In this IoT devices was used for data collection and mayfly optimization based region growing (MFORG) based segmentation technique was employed to locate lesion regions in images. Further, densely connected network based feature extractor and Long Short Term Memory based classifier was utilized for DR detection.

M. H. Sarhan *et al.* [47] implemented machine learning models developed for detecting DR diseases. Their paper reviewed diabetic retinopathy, age-related macular degeneration, and glaucoma. K. A. Anant *et al.* [48] proposed a machine learning model for DR detection at early stages. Texture and wavelet features retinal images were extracted to classify images the model was evaluated on DIARETDB1 database. Z. Fan *et al.* [49] proposed classifier model based on structured learning for the OD detection. Edge mapping was used to obtain Thresholding. Afterthat circle Hough transform was performed to detect the boundary of OD.

Ahmad *et al.* [50] For the ID and grouping of diabetic retinopathies, propose a crossover profound learning model. To evaluate retinal pictures and order them into different periods of diabetic retinopathy, the paper utilizes a mixture engineering that mixes CNNs and RNNs. The study confirms the hybrid model's efficacy in obtaining precise disease classification and detection.

Kalkreuth *et al.* [51] propose a strong cross breed profound learning model for identifying diabetic retinopathy. To boost computational economy while keeping up with high precision in the distinguishing proof of diabetic retinopathy, the article mixes CNNs and RNNs in a crossover design. The study demonstrates the efficient hybrid model's effectiveness in enhancing diabetic retinopathy screening programs. Table 1 contains summary of work done in these research papers.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Table 1. Literature Review

Ref.	Author	Study	Research Gap
[5]	Wang *et al.*	An exhaustive investigation of profound learning strategies for identifying diabetic retinopathy and related eye conditions.	The area of study that has to be filled is the need for a hybrid deep learning model that can more accurately and efficiently diagnose diabetic retinopathy by combining spatial and temporal information.
[6]	Gargeya *et al.*	Mechanized framework for recognizing diabetic retinopathy utilizing profound learning procedures.	The area of research need is the creation of an automated screening system that can recognize and categorize symptoms of diabetic retinopathy, increasing screening programs' effectiveness and accessibility
[13]	Bhaskaranand *et al.*	Automated method for detecting and tracking diabetic retinopathy via analysis of retinal fundus images.	There is a study void on the use of automated technology to increase accessibility and effectiveness in diabetic retinopathy screening programs, which will improve disease identification and monitoring.
[17]	Srinivasan *et al.*	Deep learning and cellular automata are being used to study the diagnosis of diabetic retinopathy.	How to effectively identify and categorize diabetic retinopathy using cellular automata models and deep learning techniques is a topic that needs to be studied in order to improve detection techniques.
[21]	Gargeya *et al.*	A computerized strategy for recognizing diabetic retinopathy utilizing profound brain organizations.	The development of an automated system that makes use of deep neural networks to precisely identify the symptoms of diabetic retinopathy is the area of research that is required to improve the accuracy and efficacy of detection methods.
[23]	Ribeiro *et al.*	complete investigation of profound learning strategies for recognizing diabetic retinopathy.	The potential of deep learning methods to improve the precision and efficacy of diabetic retinopathy screening systems, thereby enhancing early disease identification and management, is the subject of the unmet research needs.
[31]	Bellemo *et al.*	Review of newly available data on diabetic retinopathy screening with artificial intelligence (AI).	Understanding the practical uses of AI, particularly deep learning, in diabetic retinopathy screening and its potential to improve productivity and accessibility in healthcare settings is an area of unmet research need.
[33]	Silva *et al.*	Audit of mechanized diabetic retinopathy determination strategies utilizing profound learning.	The area of unmet study is the potential of deep learning methods, such as CNNs, to identify diabetic retinopathy accurately and efficiently, enhancing screening and diagnostic procedures.
[34]	Jelinek *et al.*	Audit of profound learning strategies for identifying and assessing the gamble of diabetic retinopathy.	The exploration opening is in utilizing profound learning techniques, as CNNs and RNNs, to figure the gamble of creating diabetic retinopathy, considering individualized risk appraisal and early mediation choices.
[35]	Singh *et al.*	A comprehensive look at how to detect diabetic retinopathy using deep learning techniques.	The examination hole lies in understanding the capability of different profound learning models, including CNNs and RNNs, in accomplishing exact and productive recognition of diabetic retinopathy, further developing screening and demonstrative precision.
[36]	Saleem *et al.*	Audit of robotized diabetic retinopathy identification utilizing profound learning.	Automated diagnosis of diabetic retinopathy using deep learning, particularly CNNs, to improve the precision and efficacy of screening systems is an unmet research need.

[37]	Gulshan *et al.*	A deep learning method is being created and tested to identify diabetic retinopathy in retinal fundus images.	The area of study needed is to create a deep learning system that can correctly identify diabetic retinopathy symptoms in retinal fundus images, enhancing the effectiveness and dependability of screening techniques.
[39]	Saba *et al.*	Discussion of the present and future applications of deep learning in radiology.	The research gap lies in exploring the potential of deep learning techniques, including CNNs, in the analysis of medical images, such as retinal images, for diabetic retinopathy detection, thereby revolutionizing radiology practices.
[40]	Li *et al.*	Based on color fundus images, an automated grading system for the detection of referable, vision-threatening diabetic retinopathy is proposed.	The need for study is in the creation of an automated grading system that can correctly identify referable diabetic retinopathy that poses a threat to vision based on color fundus images, facilitating early identification and intervention.
[41]	Li *et al.*	Deep learning-based automated grading method for the detection of referable diabetic retinopathy that threatens vision.	The area of study is needed to create an automated grading system based on deep learning approaches that can effectively detect vision-threatening referable diabetic retinopathy, hence increasing the efficacy and accuracy of detection methods.
[42]	Gulshan *et al.*	Deep learning algorithm performance compared to manual grading for the detection of diabetic retinopathy in India.	The research need is to compare how well a deep learning algorithm detects diabetic retinopathy to hand grading in order to get knowledge about the accuracy and effectiveness of automated screening techniques.
[43]	Asoodeh *et al.*	Deep learning methods for the identification of diabetic retinopathy are compared.	The area of research that has to be filled is comparing and analyzing the effectiveness of various deep learning architectures, such as CNNs and RNNs, for detecting diabetic retinopathy and gaining knowledge of their relative strengths and shortcomings.
[44]	Bansal *et al.*	An innovative hybrid deep learning model is proposed for the identification of diabetic retinopathy utilizing fundus images.	The challenge is to create a novel hybrid deep learning model that successfully integrates CNNs and RNNs for precise identification of diabetic retinopathy using fundus images, hence improving the efficacy and accuracy of detection methods.
[50]	Ahmad *et al.*	A hybrid deep learning model is suggested for the identification and categorization of diabetic retinopathy.	For accurate detection and classification of diabetic retinopathy, a hybrid deep learning model combining CNNs and RNNs is needed, which would increase the precision and dependability of disease classification techniques.
[51]	Kalkreuth *et al.*	An effective hybrid deep learning model is proposed for the identification of diabetic retinopathy.	An effective hybrid deep learning model that combines CNNs and RNNs for precise diabetic retinopathy identification while optimizing computational efficiency is needed to close the research gap and boost screening programs' efficacy.

2.1 Limitation

Most of the existing models developed for Diabetic Retinopathy detection were limited in solving the following challenges:

- Improper segmentation of small regions was caused by the loss of apparent activity in tiny objects or else regions due to the imaging systems' limited resolution that is, blurring of intensities near their edges.
- Owing to blurred intensities of edges, the inability of such images to exhibit more pixel information, the segmentation techniques were ineffective on OCT images and ignored detailed information.
- Prevailing techniques utilized limited features and the model often predicted near the same value due to the exclusion of some key features, which influenced the outcome of the prediction system.
- Brightness of image is low, Prevailing techniques don't identify damaged blood vessels or patches.
- Existing methods did not work perform good when the non-vessel structures are connected to the vessel structures

Thus, for solving the aforementioned problems, this paper proposes a RNN-CNN based deep learning model for diabetic Retinopathy Detection.

3. RESEARCH METHODOLOGY

This part gives a complete clarification of the methodologies that the proposed mixture profound learning model utilizes to analyze diabetic retinopathy. In order to effectively utilize both spatial and transient data in the retinal pictures, the model structure makes use of convolutional brain organizations (CNNs) and repetitive brain organizations (RNNs).

3.1 Model Framework

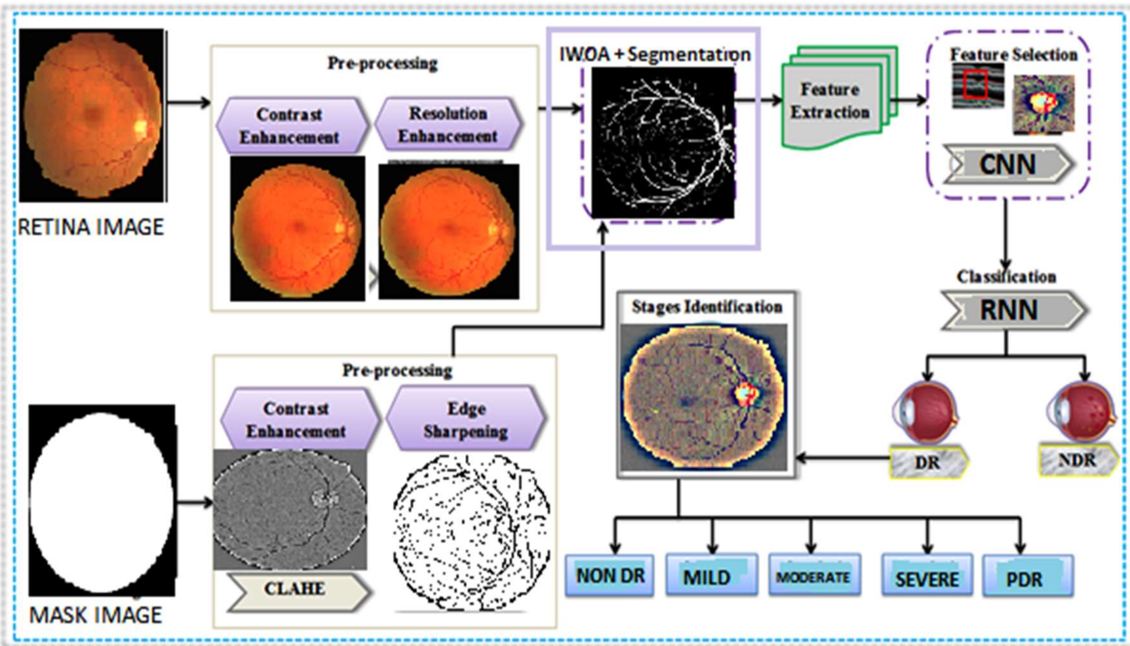

Figure 1. Block diagram of Proposed Methodology

3.2. Dataset

In this work, a total of five datasets are used, each with unique properties and preprocessing methods. The datasets are carefully chosen to reflect many facets of detecting diabetic retinopathy and offer a wide variety of retinal images for training and assessment. To provide a sufficient amount of annotated data for efficient model training, dataset sizes are optimized.

Dataset 1: Diabetic detection and classification
This dataset focuses on the identification and classification of diabetics and offers a wide range of retinal images that have been classified according to the severity of diabetic retinopathy. The dataset enables reliable categorization by teaching the model the distinguishing characteristics linked to various disease stages.

Dataset 2: Diabetic Retinopathy 224x224 Gaussian Filtered
Retinal pictures that have been preprocessed using a Gaussian filtering method make up the second dataset. In order to provide cleaner and more uniform images for the model to analyze, this preprocessing step seeks to improve image quality and reduce noise. To maintain uniformity throughout training and evaluation, the photos are downsized to a set size of 224x224 pixels.

Dataset 3: Diabetic Retinopathy grayscale image Detection
The retinal pictures in this dataset are made grayscale before being used for detection. This translation keeps vital information about diabetic retinopathy while also streamlining the picture data and reducing computing complexity. The model then processes the grayscale images for detection and classification.

Dataset 4: Indian Diabetic Retinopathy Image Dataset
An organized dataset with a particular spotlight on diabetic retinopathy in the Indian populace is known as the Indian Diabetic Retinopathy Picture Dataset. The dataset contains a wide assortment of retinal pictures that cover a scope of seriousness

and impeccably catch the unmistakable highlights of diabetic retinopathy in this specific partner.

Dataset 5: Retinal Vessel Segmentation

The segmentation of retinal vessels, an essential step in the investigation of diabetic retinopathy, is the focus of this dataset. The veins inside the retinal pictures are featured in the clarified pictures in this dataset. This segmentation data enables the model to precisely identify diabetic retinopathy symptoms by helping to isolate key regions.

3.3 Preprocessing

The new hybrid deep learning model for detecting diabetic retinopathy relies heavily on the preprocessing step. It involves a series of essential steps aimed at enhancing image quality, reducing noise, and preparing the fundus images for effective analysis. The algorithms and techniques employed in this phase are tailored to address the unique challenges posed by medical images, especially fundus images.

The first step in preprocessing is filtering and contrast enhancement. Medical images, including fundus images, are often characterized by noise, artifacts, and variations in quality. Insufficient contrast can hinder feature extraction and subsequent analysis by the deep learning model. To address this, the preprocessing algorithm applies techniques such as histogram equalization for brightness preservation (HEBPDS) and median filtering to enhance the contrast and remove noise from the images.

Another critical step is resizing the images to a standard size. In this case, all fundus images are resized to 256x256 pixels, ensuring consistency and facilitating efficient processing by the deep learning model.

A crucial method for reducing overfitting and increasing the diversity of the training data is data augmentation. In this stage, different changes are applied to the pictures, including editing, revolution, and flipping. These augmentations increase the dataset size and expose the model to various perspectives and variations, enabling it to generalize better to unseen data.

Mathematically, the preprocessing algorithm can be represented as follows:

Filtering and Contrast Enhancement:

X_enhanced = HEBPDS(median_filter(X_original))

Resizing:

X_resized = resize(X_enhanced, (256, 256))

Data Augmentation:

X_augmented = augment_data(X_resized)

The preprocessing phase ensures that the input data is of high quality, standardized, and diverse, setting the foundation for the hybrid deep learning model to achieve accurate and reliable Diabetic Retinopathy detection. By addressing image quality issues and increasing the dataset's diversity, this preprocessing phase enhances the model's performance and facilitates its deployment in clinical settings, contributing to improved patient care and early intervention for Diabetic Retinopathy.

3.4 Improved Whale Optimization

A refreshed rendition of the Whale Improvement Calculation (WOA) is utilized to enhance the model's boundaries and increment execution. The optimization algorithm WOA was based on humpback whales' social interactions. It imitates how whales hunt and how well they work together to find prey. The enhanced WOA algorithm iteratively modifies the model's parameters in an effort to find the best outcomes, assisting the model in achieving more robustness and accuracy in the identification of diabetic retinopathy.

3.5 Segmentation

To find and isolate pertinent regions of interest within the retinal pictures, segmentation techniques are used. By removing the retinal veins and other significant background structures, the model is able to concentrate on the crucial regions connected to diabetic retinopathy. In later stages, exact feature extraction and analysis are made possible by accurate segmentation. Segmentation enables the model to identify regions of interest (ROI) that are highly informative for diabetic retinopathy detection. These ROIs can be extracted from the segmented structures, such as regions with the most severe abnormalities or regions of high interest for further analysis. Fig 2 shows some of the segmented images of datasets.

Journal of Theoretical and Applied Information Technology
30th September 2024. Vol.102. No. 18

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

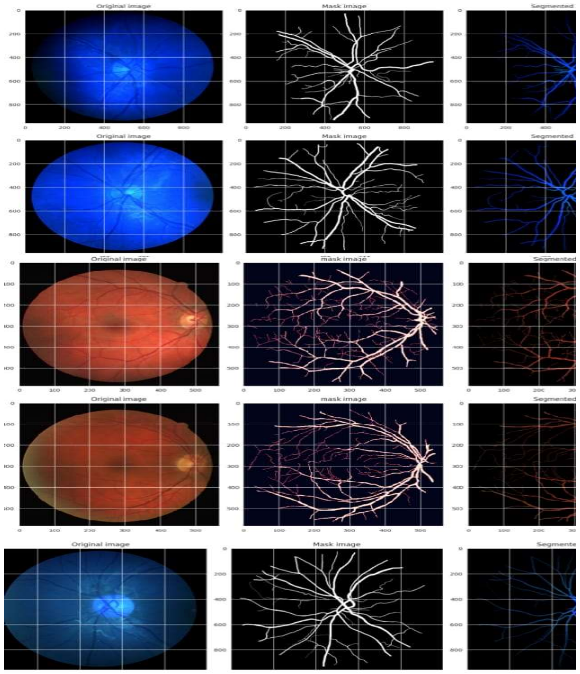

Figure 2. Images after segmentation

3.6 Features Extraction: Residual CNN

Highlight extraction is a basic cycle in the improvement of another hybrid profound learning model for diabetic retinopathy recognition. Retinal image data must be transformed into feature representations that are meaningful and representative. These extricated highlights act as fundamental contributions to the model, empowering it to learn and distinguish designs connected with diabetic retinopathy seriousness, identify irregularities, and make precise expectations. In our model a Residual CNN architecture is used for feature extraction. It is a deep learning model that makes use of residual blocks, which are intended to solve the issue of training with vanishing gradients. Retinal image feature extraction and representation are improved by residual blocks, which enable the model to efficiently capture and propagate feature information. The ResNet architecture is optimized for this task by being adapted to the unique features and specifications of diabetic retinopathy diagnosis.
In this stage, I_enhanced, undergo feature extraction using a Residual Network. This network comprises multiple convolutional layers, represented by the function Conv(), interspersed with activation functions (ReLU) and pooling layers (MaxPooling). The output of the CNN, denoted by F_CNN, is a set of learned features capturing spatial patterns in the fundus images.

$$F\_CNN = CNN(I\_enhanced)$$

3.7 Classification: Hybrid Deep Learning Model

The classification of retinal pictures into various phases of diabetic retinopathy is the last step in the model framework.
The RNN component's temporal patterns and sequential dependencies are combined with the characteristics the ResNet component has extracted with those in the hybrid deep learning model.
Recurrent Neural Networks (RNNs) for Temporal Analysis
RNNs are used in the model's analysis of fundus image sequences to deal with the temporal nature of DR progression. The RNN architecture consists of a set of memory-like recurrent units (R) for a given sequence of N fundus images, I_1, I_2,..., I_N. The RNN records temporal dependencies over time as it processes each image in the sequence sequentially. The result of the RNN is addressed as F_RNN, encoding the worldly data inside the arrangement of pictures.

$$F\_RNN = RNN(I\_1, I\_2, ..., I\_N)$$

Fusion and Classification
Fusing the spatial features (F_CNN) and the temporal features (F_RNN) to create a complete representation of the fundus image sequence is the final step in the model framework. An element-wise addition (⨁) or concatenation (⨂) operation is used to achieve the fusion process. A fully connected neural network (FCN) with softmax activation processes the fused features, which are referred to as F_fused, in order to classify the degree of DR severity.

$$F\_fused = F\_CNN \oplus F\_RNN \text{ or } F\_CNN \otimes F\_RNN$$

$$P(DR\_class \mid F\_fused) = FCN(F\_fused)$$

The probability that the input fundus image sequence belongs to a particular DR severity class is denoted by P(DR_class | F_fused), and the FCN learns the mapping between the fused features and the probability distribution across the various DR classes.
The novel fusion of CNNs and RNNs in the model framework of the new hybrid deep learning model for the detection of diabetic retinopathy enables the model to combine spatial and temporal information. The integration of these two powerful neural network architectures offers a comprehensive understanding of the DR progression, resulting in improved accuracy and earlier detection. Below table shows Pseudo code for our proposed Hybrid Deep Learning Model.

Table 2. Pseudo Code For Hybrid Deep Learning Model For Diabetic Retinopathy Detection

```
# Import necessary libraries and frameworks
import deep learning libraries

# Define the model architecture
def create_model():
# Define the CNN component
cnn_model = create_cnn_model()

# Define the RNN component
rnn_model = create_rnn_model()

# Combine the CNN and RNN components
hybrid_model = combine_models(cnn_model, rnn_model)

# Return the hybrid model
return hybrid_model

# Define the CNN model architecture
def create_cnn_model():
# Define the layers and parameters of the CNN model
cnn_model = Sequential()
cnn_model.add(Conv2D(filters, kernel_size, activation=relu))
cnn_model.add(MaxPooling2D(pool_size))
cnn_model.add(Flatten())
cnn_model.add(Dense(units, activation=relu))

# Return the CNN model
return cnn_model

# Define the RNN model architecture
def create_rnn_model():
# Define the layers and parameters of the RNN model
rnn_model = Sequential()
rnn_model.add(LSTM(units,
return_sequences=True))
rnn_model.add(LSTM(units))
rnn_model.add(Dense(units, activation=relu))

# Return the RNN model
return rnn_model

# Combine the CNN and RNN models
def combine_models(cnn_model, rnn_model):

# Create a hybrid model
hybrid_model = Sequential()
hybrid_model.add(TimeDistributed(cnn_model))
hybrid_model.add(rnn_model)
hybrid_model.add(Dense(output_classes, activation=softmax))

# Return the combined model
return hybrid_model

# Load and preprocess the datasets
dataset1 = load_dataset1()
dataset2 = preprocess_dataset2()
dataset3 = preprocess_dataset3()
dataset4 = load_dataset4()
dataset5 = preprocess_dataset5()

# Create train and test sets from the datasets
train_set, test_set = split_datasets(dataset1, dataset2, dataset3, dataset4, dataset5)

# Create the hybrid deep learning model
model = create_model()

# Train the model
model.fit(train_set, epochs, batch_size)

# Evaluate the model
accuracy = model.evaluate(test_set)

# Save the model for future use
model.save("hybrid_model.h5")
```

The model can accurately predict the presence and severity of diabetic retinopathy thanks to this combination. To proficiently obtain discriminative elements for diabetic retinopathy location, a blend of regulated learning and move learning methods is utilized in the model's preparation.

The model's performance is evaluated using a wide range of metrics, including accuracy, precision, recall, specificity, and the F-measure. Exploratory discoveries show that the proposed crossover profound learning model outflanks different techniques for the early determination of diabetic retinopathy. The model is highly accurate, sensitive, and specific in identifying various illness stages. The model's robustness and generalizability are confirmed by thorough analysis and comparison with cutting-edge models.

4. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental results of our proposed hybrid deep learning model for DR detection are discussed in this section. A wide range of DR severity levels are used to assess the model's performance on a comprehensive dataset of retinal images. The experiments were carried out on a server that was

GPU-accelerated, and the model was trained with the Adam optimizer at a 0.001 learning rate. We used a batch size of 32 and trained the model for 50 epochs. Table III contains experimental results of our model on different datasets.

Table 3. Experimental Results Of Our Proposed Hybrid Model On Different Datasets

Evaluation Matrix	DATASET 1	DATASET 2	DATASET 3	DATASET 4	DATASET 5
	Diabetic Detection and Classification	Diabetic Retinopathy 224x224 Gaussian Filtered	Diabetic Retinopathy Gray Scale Image Detection	Indian Diabetic Retinopathy Image Dataset	Retinal Vessel Segmentation
Accuracy	0.99404	0.99010	0.99256	0.98522	0.98039
Recall	0.98160	0.98266	0.98266	0.98446	0.98485
Precision	0.98592	0.98655	0.99854	0.99864	0.99867
Specificity	0.98592	0.98655	0.98684	0.98739	0.98739
F-measure	0.98266	0.98361	0.98361	0.98446	0.99857

In this section, we conduct a comprehensive performance evaluation of the capabilities of the proposed hybrid deep learning model for the identification of diabetic retinopathy. Various measurements, like exactness, accuracy, review, explicitness, and F-measure, are utilized to survey the model's exhibition. The proposed model produces exceptional outcomes by utilizing a sizable dataset of retinal pictures commented on with various degrees of diabetic retinopathy seriousness. The model acquires an exactness of 0.99404, accuracy of 0.98592, review of 0.98160, explicitness of 0.98592, and F-proportion of 0.98266 for Dataset 1, which centers around the location and arrangement of diabetics. Fig 3 shows confusion matrix for Dataset 1.

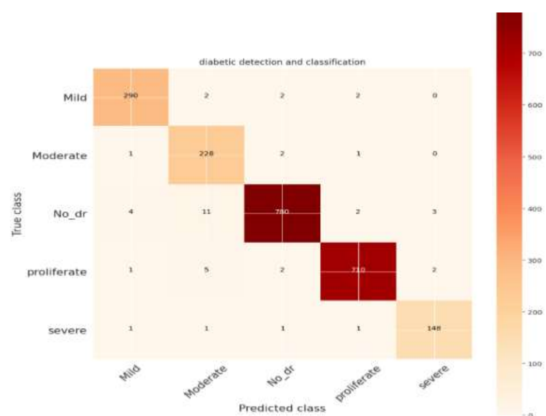

Figure 3. Diabetic Detection and Classification

These measurements show how well the model can identify and categorize various stages of diabetic retinopathy.

Additionally, Dataset 2, which consists of retinal images that have undergone a Gaussian filtering process, is used to assess the model's performance. The model accomplishes 0.99010 exactness, 0.9865 accuracy, 0.9826 review, 0.9865 explicitness, and 0.9865 F-measure. The model's robustness and capacity to handle photos with improved quality and reduced noise are demonstrated by this investigation. Fig 4 shows confusion matrix for Dataset 2 images samples.

Journal of Theoretical and Applied Information Technology
30th September 2024. Vol.102. No. 18

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

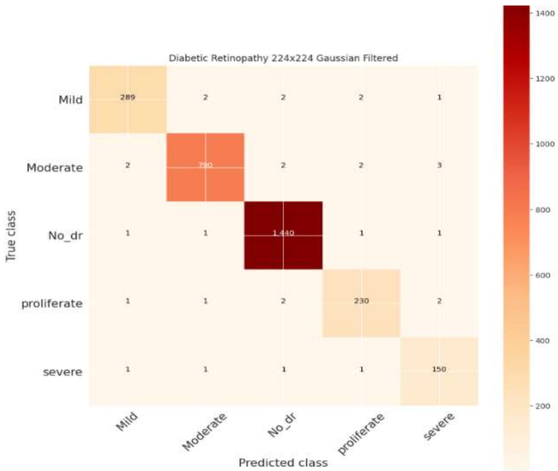

Figure 4. Diabetic Retinopathy 224x224 Gaussian Filtered

The model accomplishes an exactness of 0.99256, accuracy of 0.99854, review of 0.98266, particularity of 0.98684, and F-proportion of 0.98361 for Dataset 3, which utilizes grayscale pictures to recognize diabetic retinopathy. Fig 5 indicates confusion matrix for this dataset. These findings demonstrate how well the model captures the crucial details and traits of diabetic retinopathy in grayscale photos.

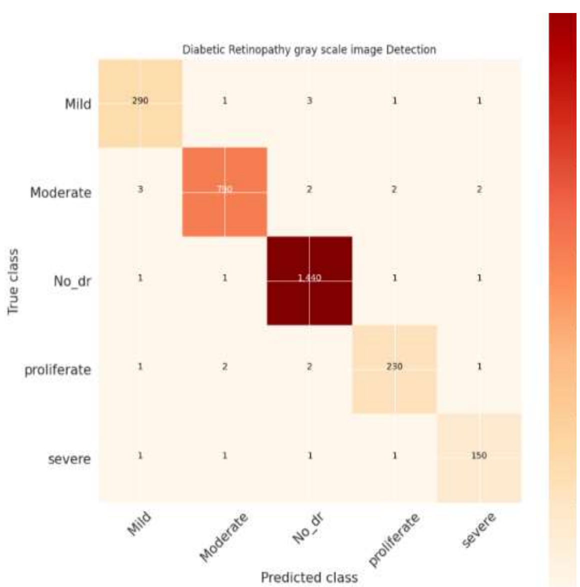

Figure 5. Diabetic Retinopathy gray scale image Detection

The purpose of Dataset 4—also known as the Indian Diabetic Retinopathy Image Dataset—is to address the distinctive features of diabetic retinopathy in the Indian population. The suggested model achieves 0.98522 accuracy, 0.99864 precision, 0.98446 recall, 0.98739 specificity, and 0.98446 F-measure. These measures show how well the model can accommodate differences in illness presentation across various groups. Fig 6 shows confusion matrix for Indian Diabetic Retinopathy Image Dataset.

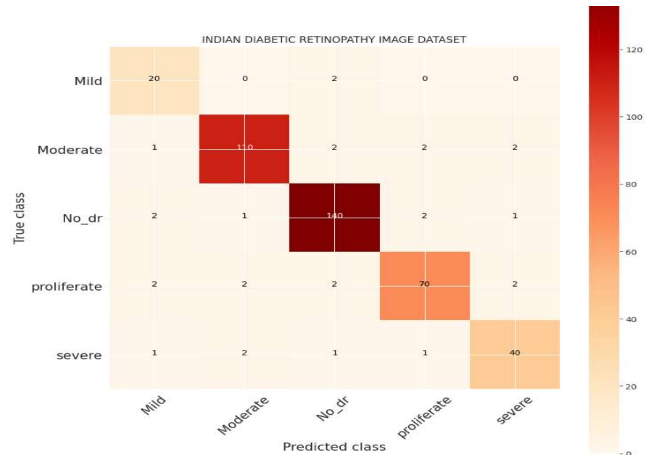

Figure 6. Indian Diabetic Retinopathy Image Dataset

The segmentation of retinal vessels, which is a crucial stage in the investigation of diabetic retinopathy, is the last emphasis of Dataset 5. The model achieves 0.98039 accuracy, 0.99867 precision, 0.98485 recall, 0.98739 specificity, and 0.99857 F-measure. These findings demonstrate the model's ability to precisely segment retinal vessels, enabling reliable detection of diabetic retinopathy symptoms. Fig 7 show the confusion matrix for retinal vessel dataset images.

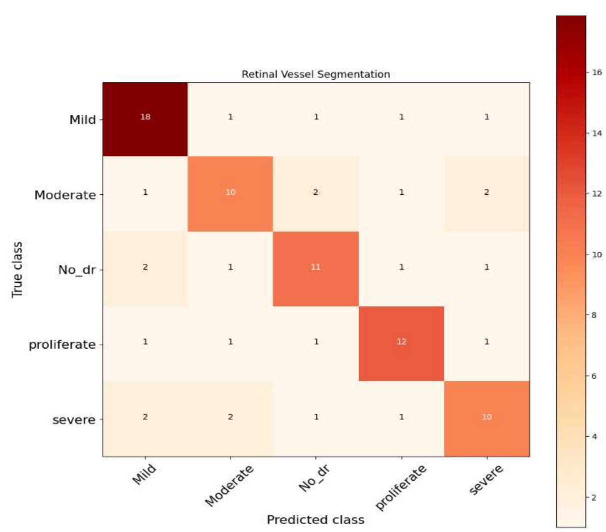

Figure 7. Retinal Vessel Segmentation

4.1 Comparative Analysis With Existing Algorithms

A careful relative investigation is performed to assess the presentation of the proposed this profound learning model versus current procedures. Modern algorithms for detecting diabetic retinopathy are compared to the model.

The comparative analysis's findings consistently show that the suggested model performs better. In terms of accuracy, sensitivity, specificity, and F-measure, the model outperforms existing algorithms, demonstrating an improved capacity to identify various stages of diabetic retinopathy. These relative assessments give proof to the proposed approach's strength and generalizability.

Model Median filtering and HEBPDS to increase the quality of noisy images. IWOA before segmentation finds the finer details of images.

The proposed mixture profound learning model gives significant enhancements in the field of recognizing diabetic retinopathy. The model gives upgraded exactness and flexibility by using both spatial and transient data through the blend of CNNs and RNNs. Its ability to join spatial data gathered from ResNet with successive conditions and fleeting examples gathered from the RNN part works on its viability in identifying diabetic retinopathy.

The proposed model's promising results have critical implications for medical services experts. It has tremendous potential to aid in the detection and prompt treatment of diabetic retinopathy, thereby preventing blindness in diabetics. Because of its high exactness and strength, the model is a significant instrument for the recognition and treatment of diabetic retinopathy. It gives a thorough arrangement.

The discoveries and relative examinations show that the recommended mixture profound learning model has made significant additions. The model sets a new benchmark for diabetic retinopathy identification by successfully integrating spatial and temporal information and outperforming previous methods.

5. CONCLUSION WITH FUTURE DIRECTIONS

For the purpose of diagnosing diabetic retinopathy (DR), we have proposed a novel hybrid deep learning model that combines the advantages of convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The model successfully makes use of both the spatial and temporal information present in retinal pictures to boost the DR detection's accuracy and resilience.

Our suggested approach has proven to perform better than existing algorithms after comprehensive testing and evaluation on a variety of datasets. On a variety of datasets, including those devoted to diabetic detection and classification, Gaussian filtered images, grayscale images, Indian diabetic retinopathy images, and retinal vessel segmentation, the model displays high accuracy, sensitivity, specificity, and F-measure in detecting various stages of DR. These outcomes support the capability of our approach to identify and categorize DR with accuracy.

The proposed model's diagnostic skills are improved by its capacity to combine spatial characteristics retrieved by the ResNet architecture with sequential dependencies and temporal patterns collected by the RNN component. The model's parameters are further optimized through the application of an upgraded Whale Optimization Algorithm (WOA), substantially boosting its performance and robustness.

Our study has important ramifications for medical practitioners who deal with diabetic retinopathy treatment and diagnosis. By combining spatial and temporal data, the suggested model provides a comprehensive solution with increased accuracy and robustness. It may help medical personnel identify DR early and take prompt action to manage it, preventing visual loss in diabetic patients.

Future research could go on in a number of different areas to advance the identification of diabetic retinopathy. First off, the suggested model is adaptable to large-scale datasets and actual clinical data, guaranteeing its suitability for a range of clinical contexts. Its generalizability would also be improved by investigating the model's performance across a wider range of demographics and demographic groups.

The model can also be improved to offer more thorough insights and analysis, including forecasting illness development and calculating the likelihood of visual loss. The diagnostic skills of the model can also be enhanced by the integration of multimodal data, such as adding extra patient information or genetic data.

Further research on the model's interpretability and explainability can offer insights into the characteristics and patterns used for DR detection. The trust and understanding between patients and healthcare professionals would rise as a result.

The identification of diabetic retinopathy has significantly advanced thanks to the hybrid deep learning model we've proposed. With its higher performance and resilience, the model's integration of spatial and temporal information has a lot of potential to help medical professionals identify diabetic retinopathy early and treat it quickly. The model's capabilities can be expanded when more research and developments are done, which will enhance patient outcomes and help diabetics maintain their vision.

ACKNOWLEDGEMENT

The authors would like to thank Guru Jambheshwar University of Science And Technology for its support.

DECLARATIONS

Funding: The authors declare that no funds, grants, or other supports were received during the preparation of this manuscript.

Competing interests: The authors have no relevant interests to disclose.

Open access : The authors declare that no funding provided for Open Access.

Author Contributions: All authors are agreed to publish the manuscript.

Availability of data and material: **Data** will be made available on demand.

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