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Empowering healthcare innovation : IoT-enabled smart systems and deep learning for enhanced diabetic retinopathy in the telehealth landscape

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Abstract

Background: Among prevalent medical complications, Diabetic Eye Disease (DED) stands as a significant contributor to vision loss. To forecast its progression and accurately assess the various stages, diverse methodologies have emerged. Machine Learning (ML) and Deep Learning (DL) algorithms have become essential tools in this endeavor, primarily through their adept analysis of Diabetic Retinopathy (DR) images. However, there is still a need for a more efficient and accurate method to predict DR performance. Method: We have developed an innovative method for classifying and predicting diabetic retinopathy. The novel idea in this research is to combine several techniques, including ensemble learning and a 2D convolutional neural network; we utilized transfer learning and a correlation method in our approach. Initially, the Stochastic Gradient Boosting process was employed for predicting diabetic retinopathy. We then used a boosting-based Ensemble Learning method for predicting images of diabetic retinopathy. Next, we applied a 2D Convolutional Neural Network. We successfully employed Transfer Learning to classify different stages of diabetic retinopathy images accurately. This research explores the role of artificial intelligence in

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identifying and categorizing diabetic retinopathy at an early stage, using techniques such as machine learning and deep learning. It also use techniques like transfer learning, domain adaptation, multitask learning, and explainable AI to accurately classify different stages of diabetic retinopathy images. Our proposed technique achieves impressive results through experiments, with a 97.9% accuracy in forecasting DR images and a 98.1% accuracy in image grading. Additionally, sensitivity and specificity metrics measure 99.3% and 97.6%, respectively. Comparative analysis with existing methods underscores the high predictive accuracy achieved by our proposed approach.

Subject Classification: *70E99.*

Keywords: *Diabetic retinopathy prediction and classification, Retinal fundus mage analysis, Cross-domain knowledge transfer, Explainable AI, Hybrid ensemble learning and 2D convolutional neural networks, Managing diabetic eye disease.*

1. Introduction

In cases of diabetes, individuals can develop eye diseases, collectively referred to as diabetic retinopathy (DR). While elevated blood sugar levels contribute significantly, a complex interplay of factors underlies the development of this condition, leading to blood vessel damage. This, in turn, results in vision loss and blurred vision due to impaired eye function. Diabetic individuals are susceptible to various eye conditions, including Diabetic Retinopathy (DR), Glaucoma, and Macular Edema, leading to vision impairment. DR can be classified into Proliferative and Non-Proliferative stages. During this, blood vessels within the retina deteriorate, leading to leakage of blood and fluids. Eye ailments are the predominant cause of blindness, particularly among older people. These techniques enhance accuracy by considering texture, morphological features, optic disc attributes, and more. This research study's main achievements and advancements can be condensed as follows: The hybrid approach combines Ensemble Learning (EL), and our approach to this task includes using 2D-CNN and Correlation methods and also Transfer Learning (TL). The techniques used for predicting DR include Stochastic Gradient Boosting, EL, 2D-CNN, Transfer Learning, and subcomponents. These methods effectively accurately categorize DR image stages and incorporate new features, improving predictive performance.

2. Related Work

The proposed work uses a Deep Learning algorithm to predict DR using color fundus photographs. The Inception-v3 module is used for processing images from the three-field approach. Internal validation shows effective calibration and sensitivity to early-stage DR. Researchers label various DRs into four stages. Bhattacharya et al. [2] developed an automated object localization technique using Fast Region-CNN and Fuzzy K-Means clustering for segmentation. The system enhances risk stratification for developing DR. FRCNN is a technique used to localize annotated images, detect anomalies, and link segmented portions to ground truths in DR, DME, and Glaucoma Regions. SVM classifiers evaluate DR severity using surface characteristics and texture features. Figure 1 depicts the object detection and segmentation process achieved through a CNN algorithm. During this process, preprocessed images undergo feature extraction with the help of the FRCNN algorithm, and CNN-based feature maps are created. The BPSO technique enhances classification accuracy, reducing misleading features. Moradi, Mousa, et al. [1] used Deep Learning frameworks like AlexNet and GoogLeNet to detect diabetic retinopathy in smartphone-based retinal images. AlexNet achieved high prediction accuracy, while GoogLeNet achieved classification accuracy. D-Eye and Peek Retina outperform iExaminer with 70% and 71% success rates, respectively.

Diabetic retinopathy (DR) progresses due to the emergence of delicate blood vessels, leading to visual impairment. Symptoms include blurred

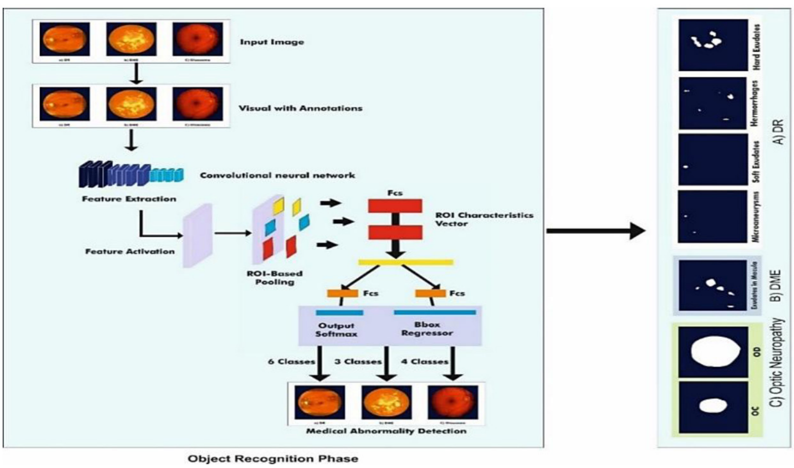

Figure 1

Deep Learning-based Retinal Image Analysis: FRCNN for Lesion Detection and FKM for Segmentation

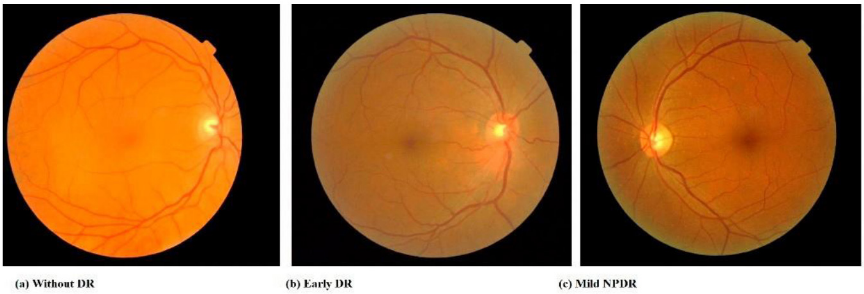

Figure 2

Classification Spectrum of Diabetic Retinopathy

vision, reduced color perception, dark spots, floating threads in sight, and altered vision.

Mild NPDR may show microaneurysms, hemorrhages, exudates, and cotton wool spots, while severe NPDR may have bleeding in all four retinal regions. PDR diagnosis relies on the presence of characteristic DR signs alongside enlarged elements, including the optic disc, cup and blood vessels and also pre-retinal vitreous. There is an urgent need for automated technologies to quantitatively evaluate DR on a huge dataset and decrease inconsistencies. Hossain et al. [3] developed a model for detecting DR involving seven phases, including contrast-limited adaptive histogram equalization, open-close watershed transformation, Gabor filtering, top hat transformation and grey level thresholding and also Deep Belief Network.

Zeng et al. [20] introduced a CNN model for predicting DR progression using the Inception V3 architecture but faced challenges due to the absence of paired fundus images. Figure 2 Classification Spectrum of Diabetic Retinopathy, J.Wang et al. [11] tested various annotation techniques for predicting diabetic retinopathy using logistic regression. They found the ADDA method had the best prediction performance but did not align with commission reduction accuracy. Sengupta and colleagues developed a method for identifying severe cases of DR using a deep learning classifier technique, achieving a sensitivity rate of 97% and a specificity rate of 93.5%. Ahmed, S., et al. [19] introduced a model to identify early-stage glaucoma, focusing on the Optic Disc Region. Giles and colleagues proposed a novel approach to determine the advancement of DR by assessing microaneurysm turnover. Decencière et al [8]. employed five Deep Convolutional Neural Network models to enhance DR classification.

Table 1

Diabetic Retinopathy Implementation Dataset

S. No	Dataset	Year	Number of Images
1	RetinaInsight	2009	80 images
2	MediScanRetina	2016	1350 images
3	OcuVisionAtlas	2018	49 images
4	GlaucoGenX	2022	58 images
5	IrisScopeData	2019	292 glaucomatous
6	VisionDiversitySet	2023	619 Image

2.1 *Evolution of DR Using AI*

The research at Saveetha School of Engineering in Chennai used the MESSIDOR Dataset to classify, train, and test features on 1200 fundus color images. The study classified diabetic retinopathy into distinct stages (Y0, Y1, Y2, and Y3) and categorized the impact based on Y0, Y1, Y2, and Y3, with R0 indicating unaffected, Y1 mild, Y2 severe, and Y3 most severe. The datasets utilized for training, testing, and validation throughout this research are meticulously outlined in Table 1. This comprehensive table provides a detailed breakdown of each dataset, including its size, composition, and key characteristics. By employing diverse and representative datasets, we ensure the generalizability and robustness of our findings.

3. Methodology

This research aims to use a range of features to predict Diabetic Retinopathy, classify its different stages, and identify pre-DR images from large datasets. To achieve this, the methodology proposed comprises advanced techniques such as Ensemble Learning, Deep Modeling, and correlation techniques for DR prediction and classification.

3.1 *Stochastic Gradient Boosting*

Ensemble Learning enhances image prediction accuracy by combining boosting and bagging techniques with a Hybrid DL approach, Figure 3 displays the different stages of DR while Stochastic Gradient Boosting enhances binary prediction accuracy. The summarized breakdown of all DR stages is presented in Table 2.

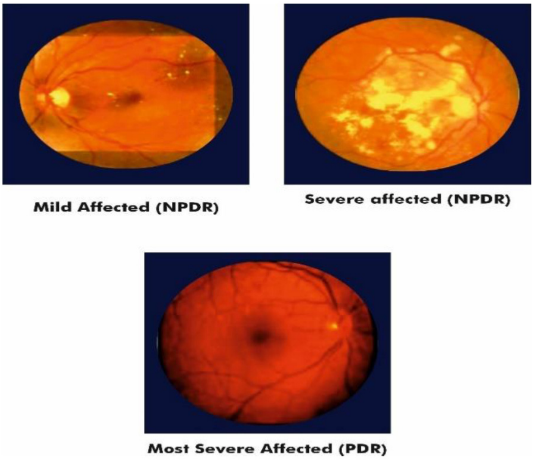

Figure 3

Progression of Diabetic Retinopathy: A Visual Journey

Table 2

Feature Descriptions

Features	Descriptions and reasons
Edema	This refers to the accumulation of excess fluid within the central region of the retina.
Fovea	The sharpest central vision of the retina
Blood vessels	White tissue covers the blood vessels; their total count is 37230. However, in individuals with DR, these values tend to decrease.
Optical distance	The human eye has 1 million optical neurons that transmit visual information to the brain.
Dot or Blot hemorrhages	Red lesions occur in the macular and deeper layers of the retina.
Blood vessels	White tissue covers blood vessels, which range in number—DR patients show decreasing values.
Shannon entropy	The collected information in each region was aggregated by calculating the mean value. Eye.LBP
Entropy	This provides information about textual features.
Exudate number	Exudate refers to the fluid that filters from the affected area.
Renyi's entropy	This technology was utilized for detecting artifacts and instances of eye blinking.
Micro aneurysm diabetes patients	Retinopathy may manifest as microaneurysms near the retinas in diabetes patients.

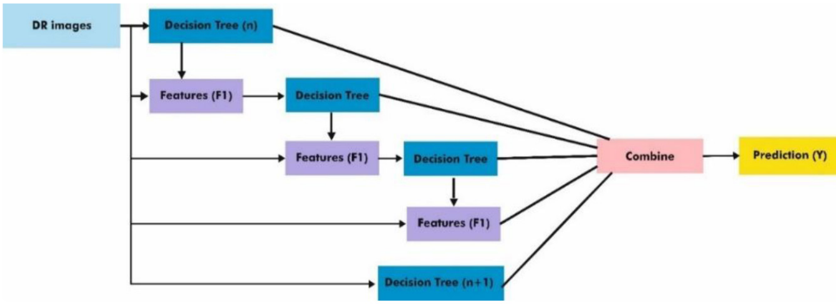

Figure 4

Stages of Boosting: An Ensemble Technique

In Figure 4 Stochastic Gradient Boosting (SGB) is showcased as a powerful tool for binary prediction.

3.2 *Unveiling Subtleties in Diabetic Retinopathy Images for Deep Learning*

Our approach harnesses the inherent strength of convolutional neural networks (CNNs) – masterful explorers of intricate image features and strategically hones their performance through meticulous parameter tuning. A specialized 2D-CNN enhances accuracy and precision through hyper-parameter tuning, random cropping, and image size adjustment. Transfer learning refines pre-trained models.

3.3 *Operation of the Model*

The model operates by combining Figure 5, which depicts the well-defined operational structure of the DR prediction system. It comprises pre-processing, DL modeling, and prediction correlation, all working in unison to provide accurate predictions.

The operational sequence of the proposed working model is delineated in a step-by-step manner as outlined below. The collection of provided input images is represented as follows in Equation (1):

$$X = \{X1, X2, X3, \ldots, X4\} \tag{1}$$

In the methodology provided, "X" represents the number of input images, and the set {X1, ..., Xn} represents the diverse images in the datasets. Equations (2) and (3) Please explain the steps involved in training, testing, and predicting with the photos.

The set D contains n pairs of values (Xi, Yi).

Here, "D" The input images are represented by "X1", while the trained and predicted images are "Y1". The overall prediction ratio is expressed using Equations (1) to (3):

$$Y = \{D(X1, Y1), ..., D(Xn, Yn)\} \quad (3)$$

To make an initial prediction of diabetic retinopathy, we first process the images through segmentation. Feature Equations (4) to (6) are powerful tools for forecasting DR, as they aid in the initial round of training and testing, as well as feature ranking. We use threshold values to process the pixel values of the images. To distinguish initial differences between images, we use Gaussian Pixel Density. Equation (4) governs the predicted performance of the photos.

$$P(Z) = p1 * e\text{^}(z - \mu 1) / \sigma 1 + p2 * e\text{^}(z - \mu 2) / \sigma 2 \quad (4)$$

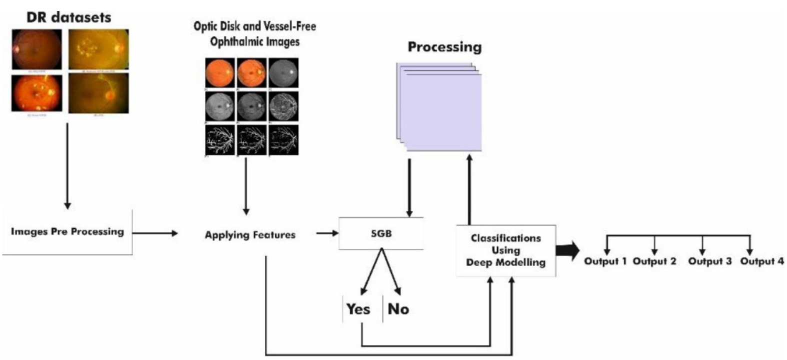

Figure 5(A)

Predictive Model Framework for Diabetic Retinopathy

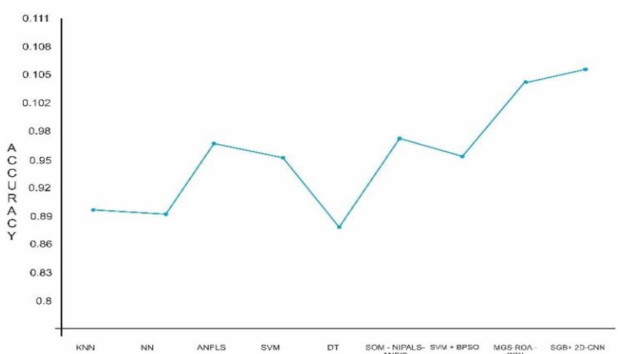

Figure 5(B)

Comparative Analysis of Different Methods

Equation (5) encapsulates various input image features using "P1." When calculating probability density, it is recommended to utilize "P2" as the prior probability density. Additionally, "σ1" and "σ2" should be employed to determine the standard deviations of the density regions.

$$F = P(F1) + P(F2) + ... + P(F10) \tag{5}$$

Before implementing the Equations (2) and (5) serve as reliable initial estimation techniques for our prediction process. "P" indicates the prediction probability of each feature, and "F" sums up all features derived from training.

$$Y1 = D + F \tag{6}$$

In Equation (6), "Y1" predicts DR. The utilization of the EL and SGB-based learning parameters on feature, training, and test data can be accurately expected by utilizing Equation (7).

$$L(xt+1) = cxt - \alpha rv\ J(xi, yi, v) \tag{7}$$

In this equation, the symbol "L" denotes different categories of DR images, while "x" represents the input image and "y" the predicted classification. Equation (5) calculates the predicted classification considering various factors, including learning rates ("α"), initialized learning weights ("t"), and image features relevant to the categorization ("γ"). Equations (4) to (7) successfully classify the different stages of the image, with the assistance of a 2D-CNN for diversity, and its representation can be found in Equation (8).

$$v + vi - vk + 2p(v)\ /\ sv$$

$$hi + hi - hk + 2p(h)\ /\ sh \tag{8}$$

Here, (wi, hi) represents the input array, (wk, hk) stands for the kernel array, and (wo, ho) indicates the output array. Employing Equation (8), diverse classifications are executed, and the classifications are represented by Equation (9):

The values of Y are as follows: Affected with R0, Mildly Affected with NPDR and R1, Severely Affected with NPDR and R2, and Most Severely Affected with PDR and R3. This information is represented by the number 9.

Equations (7)– (9) predict and classify "Affected" (A) and "Severe" (S) cases. Of DR ensue, and the anticipated result is forwarded to Equation (7) to improve precision. As a result, a fresh forecast will be made. Classification is refined through Transfer Learning (TL), facilitating continuous prediction through TL-guided insights.

4. Experiments & Result

In this section, we will discuss the results of experiments on various parameters of the DR Datasets. When selecting parameters to achieve optimal results in model training, it is crucial to carefully evaluate the appropriate number of epochs, learning rate, and regularization level. Requires expertise in the field. Therefore, implementing automated optimization techniques for different aspects of DL architectures tailored to specific medical datasets and additional clinical data could be a potential solution. The features mentioned above are extracted across multiple iterations of the experiment, and the resultant averages of the outcomes are computed by amalgamating the influence of diverse features through various iterations—the prevailing accuracy of predictions, as well as the projections, was achieved through the proposed methodology.

In Figure 6, The research compares different algorithms for predicting DR images and finds our proposed approach highly effective. It uses ensemble boosting models, reducing prediction errors and improving accuracy. The method involves two sets of features, achieving an impressive 97.8% accuracy.

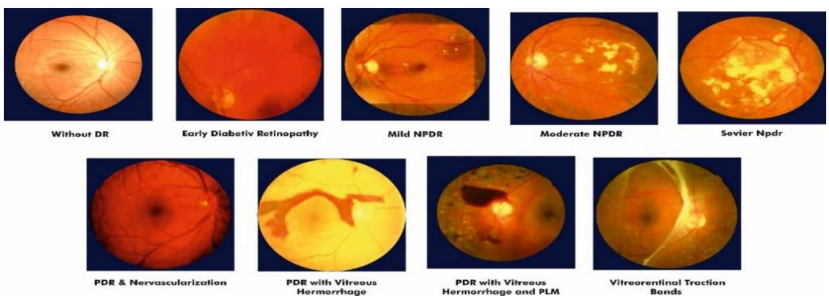

Figure 6

Accuracy Metrics Across Models

This research evaluates machine learning and deep learning techniques for detecting diabetic retinopathy (DR) using a hybrid approach. Figure 7 illustrates the significant progress in DR that has been achieved through the integration of artificial intelligence. The evaluation of sensitivity and specificity predictions for images constitutes two additional essential parameters. Sensitivity is employed to identify accurately matched features within DR images the method combines EL and 2D-CNN algorithms, demonstrating its effectiveness. The proposed

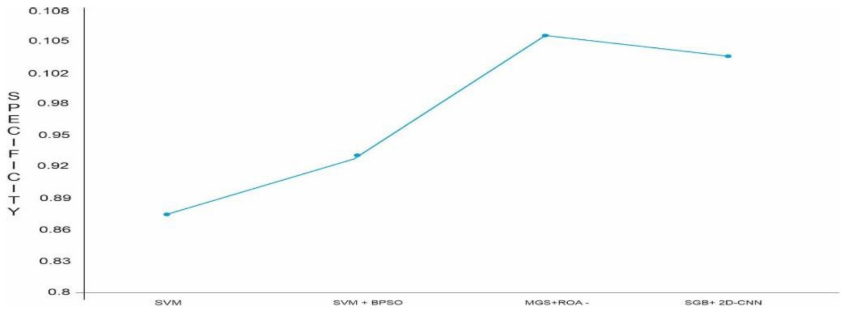

Figure 7

A Comparative Study on Specificity Among Different Methods

method has a specificity of 97.8%, surpassing other algorithms. Performance measures are used to gauge research quality and accuracy, enabling better follow-up strategies and mitigating vision loss risk. The algorithm's sensitivity of 98.9% outperforms other ML and DL approaches.

6. Discussion and Conclusion

Our study introduces a hybrid approach integrating a novel ensemble technique and a 2D-CNN-based prediction model for the finding and classify of diabetic retinopathy (DR). This innovative strategy holds promise for real-time chip-based diagnosis systems, presenting a valuable contribution to the field of DR detection. In experimental settings, our proposed technique demonstrated remarkable performance, achieving a 97.9% accuracy in forecasting DR images and an impressive 98.1% accuracy in image grading. Sensitivity and specificity metrics further supported the robustness of our model, recording rates of 99.3% and 97.6%, respectively. Comparative analysis against existing methods highlighted the superior predictive accuracy of our hybrid approach, positioning it as an advancement in DR detection.

In conclusion, our hybrid approach, combining a novel ensemble technique with a 2D-CNN-based prediction model, offers a significant contribution to DR detection. The promising experimental results and superiority over existing methods emphasize its potential for real-world applications. As we anticipate future developments, the exploration of automated video-based RD detection systems emerges as a logical progression, holding the promise of advancing the timely and accurate diagnosis of diabetic retinopathy.

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