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Deep Neural Network–Based Automated Detection and Classification of Diabetic Retinopathy

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Abstract - Diabetic Retinopathy (DR) is a severe complication of diabetes that affects the retina and can lead to vision loss if not detected early. Automated DR classification using artificial intelligence has gained significant attention due to the limitations of manual diagnosis. Traditional machine learning approaches, such as the K-Nearest Neighbour (KNN) algorithm, have been widely used for DR classification, leveraging distance-based similarity measures for image classification. However, KNN struggles with high-dimensional medical image data, leading to suboptimal accuracy, longer computational time, and sensitivity to noise. To overcome these limitations, this study proposes a Deep Neural Network (DNN)-based framework for the automated detection and classification of Diabetic Retinopathy using retinal images. The model integrates Convolutional Neural Networks (CNNs) for feature extraction and a fully connected DNN for classification, ensuring efficient learning of spatial features and robust decision making. The proposed method is evaluated on publicly available DR datasets, achieving higher accuracy, sensitivity, and specificity compared to traditional KNN-based approaches. Results demonstrate that DNN outperforms KNN in handling complex retinal features, reducing false positive rates, and enhancing early-stage DR detection. This study highlights the potential of deep learning in enhancing clinical decision support systems, providing an accurate and scalable solution for automated DR screening. Future work may involve hybrid models combining deep learning with explainable AI techniques to improve interpretability and clinical adoption.

Key Words: Diabetic Retinopathy, Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), K-Nearest Neighbour (KNN), Performance metrics.

1.INTRODUCTION

Diabetic Retinopathy (DR) is one of the leading causes of vision impairment and blindness in working-age adults worldwide. The retina, the light-sensitive tissue at the back of the eye, is impacted by this microvascular consequence of diabetes. Over time, elevated blood glucose levels damage the retinal blood vessels, leading to leakage, swelling, and abnormal vessel growth. If not diagnosed and treated early, DR can progress through various stages. Numerous studies are being conducted in this area of developing deep-learning algorithms for medical applications. All of these studies use a diabetes database either the EYEPACS, MESSIDOR, KAGGLE or some other database.

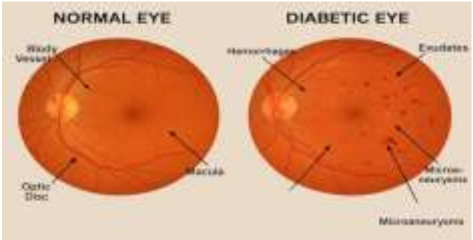

Figure 1: Difference Between Healthy eye and Diabetic eye

Figure 1 shows a contrasts a diabetic eye with diabetic retinopathy with a healthy eye. In the healthy eye, all internal structures such as the retina, optic disc, and blood vessels are intact and functioning normally. The blood flow is smooth, and there are no signs of damage or leakage.

Challenges discussed include high error rates in traditional kNN, bias from imputation techniques, complex data distribution affecting classification accuracy, and limited improvement in CPU processing time despite optimization [1]. A combination of K-Nearest Neighbor (KNN) and Genetic Algorithm (GA) is used for classifying heart disease, where GA helps in selecting and ranking the most relevant features, which are then used by KNN for classification. The efficiency of the fitness function in GA and the selection of the parameter K in KNN both affect the method's accuracy. The paper emphasizes that the right feature selection significantly enhances the performance of KNN [2]. Deep neural networks, specifically max-pooling convolutional neural networks (MPCNNs), are applied for retinal vessel segmentation using the DRIVE dataset. The approach enables automatic detection of blood vessels in retinal images, but faces challenges such as non-uniform illumination, optic disc boundaries, and hemorrhages, all of which can result in false positives and affect segmentation accuracy [3]. A Deep Reinforcement Relevance Network (DRRN) is introduced for reinforcement learning tasks involving natural language, where both the states and actions are described in text. The system uses two separate neural networks to embed the textual representations of states and actions into vector spaces, which are then combined to estimate the Q-value. The paper highlights the difficulty of managing a large and variable natural language action space and suggests improvements through mechanisms like attention to better capture strategic language cues [4]. Different deep learning models including Feedforward Neural Networks (FFNN), Deep Neural Networks (DNN), and Convolutional Neural Networks (CNNs) such as LeNet and VGGNet are compared for medical image classification. The study involves preprocessing of images followed by model training and evaluation. Key issues discussed include vanishing gradient problems in DNNs, reduced performance of CNNs on CPUonly systems, limitations from low-resolution single-band images, and the drawback of using pre-trained models instead of task-specific architectures [5].

2. LITERATURE REVIEW

Diabetes mellitus is a chronic metabolic disease that affects millions of people worldwide, and one of its most serious complications is Diabetic Retinopathy (DR). DR develops gradually and affects the small blood vessels in the retina, leading to visual impairment and even permanent blindness if left untreated. The increasing global prevalence of diabetes has resulted in a growing number of patients at risk of developing DR, creating an urgent need for scalable, accurate, and early diagnostic systems. The following literature survey presents a comprehensive overview of existing approaches for automated DR detection, highlighting their methodologies, advantages, and limitations. This review serves as a foundation for understanding the current research landscape and identifying areas for further improvement and innovation.

In paper [6], a hybrid CNN-RBF model is used for diabetic retinopathy detection, where MS-DRLBP is applied for feature extraction and Otsu's method is used for segmentation. CNN classifies fundus images into five levels, while RBF-SVM refines the decisions. The challenges highlighted include high computational complexity and issues with real-time implementation.

In article [7], an R-FCN model is utilized for diabetic retinopathy grading by combining object detection and segmentation. The model performs well in classifying DR severity levels but lacks support for multimodal imaging, which would allow for more comprehensive diagnostics.

In research paper [8], a comparison is made between BPNN, DNN, and CNN models for detecting diabetic retinopathy. CNN achieves the highest accuracy and fastest processing time. Preprocessing steps such as resizing and data augmentation improve image quality, though deep models still require significant computational power.

In article [9], an ensemble of CNN models is applied to handle data imbalance and improve classification accuracy. This ensemble learning approach enhances detection of minority classes, but it also increases the complexity of the training process.

In paper [10], a CNN-based model is developed to predict the progression of diabetic retinopathy using longitudinal data. This helps in early identification of high-risk patients, supporting personalized treatment plans and showcasing the potential of deep learning in medical forecasting.

In article [11], handcrafted features are combined with an SVM classifier for diabetic retinopathy stage classification. Techniques like ROI extraction and lesion identification improve performance, but the small dataset size introduces risks of overfitting.

In research paper [12], red lesion localization is combined with CNNs to improve diabetic retinopathy classification. Preprocessing techniques enhance lesion visibility, but the model faces limitations in generalizing across different datasets.

In paper [13],To diagnose diabetic retinopathy, a moth search optimization technique is coupled with a deep neural network. CLAHE is used for preprocessing, histogram-based segmentation is performed, features are extracted using Inception-ResNet V2, and classification is done via a DNN-MSO model. The work addresses optimization issues in DCNNs by improving learning rates using a bio-inspired method.

In article [14], a deep neural network with Recursive Feature Elimination is used to predict diabetic retinopathy from individual risk factors. The model eliminates irrelevant features and classifies disease presence. It is compared with traditional ML models and highlights challenges like limited dataset size, need for clinical validation, sensitivity to imbalance, and higher computational cost.

In paper [15], multiple models such as CNN, SVM, ANN, and DCNN are used to classify diabetic retinopathy. The study emphasizes the need for validation on more diverse datasets due to the limited sample size collected from a specific regional population.

In research paper [16], the CNN512 model is used for classification and YOLOv3 for lesion localization in diabetic retinopathy detection. The study addresses a gap in DR lesion detection and points out the limited number of high-accuracy localization studies.

In article [17], a model named VGGNIN is developed by combining VGG16, Spatial Pyramid Pooling, and Network-in-Network layers. It processes variable-scale images and enhances classification through added non-linearity. The model classifies DR into five stages using the EyePACS dataset, but struggles to distinguish early stages due to subtle image features.

In research paper [18], a hybrid classification strategy is employed using SVM, KNN, and Binary Trees with majority voting. It includes preprocessing and feature extraction steps, and discusses challenges like high computational load, classifier sensitivity differences, and the necessity for broader clinical validation.

In paper [19], a CNN-based model using 26 architectures is evaluated for DR classification. The most successful network is EfficientNetB4, which is followed by InceptionResNetV2 and DenseNet169.. Issues identified include overfitting, the need for clinical validation, class imbalance handling, and the high computational demands of CNN models.

In research paper [20], Two deep learning models—a DenseNet121 model and a mix of VGG16 and XGBoost—are investigated.The study uses the APTOS 2019 dataset with data balancing and finds DenseNet121 significantly more accurate. Limitations include subpar hybrid model performance and the need for real-world testing.

In article [21], the DRG-Net approach is proposed, which applies SMOTE for data balancing, uses ResNet50 for feature extraction, and applies graph-based KNN for classification. It highlights challenges such as computational cost from graph construction, need for extensive tuning, and reliance on dataset quality.

In article [22], authors explained the classification of diabetes using CNN method through alerts.

In article [23], author developed a machine learning based diabetes classification system for remote area patients also.

In article [24], www.ijitjournal.org--in this researcher developed an IoT based health monitoring system for diabetic patients using different sensors and measured different health parameters.

In article[25],authors developed an IoT based health monitoring system for remote area patients to measure their health parameters and communicated to doctor as well as to the patient also.

3. K-NEAREST NEIGHBORS (KNN)

For classification and regression problems, K-Nearest Neighbors (KNN) is a supervised machine learning technique. According to a selected distance metric (such as the Euclidean distance), it locates the K data points that are closest to a new sample and makes predictions based on the majority of those data points either average values (for regression) or class (for classification). KNN is a lazy learning algorithm, meaning it does not require a training phase but stores the entire dataset and performs calculations at prediction time. KNN is widely used in automated diabetic retinopathy screening due to its simplicity and effectiveness in pattern recognition. However, in modern DR detection, deep learning models like Convolutional Neural Networks (CNNs) are often preferred for better accuracy and scalability. Combining KNN with deep learning (hybrid models) can improve performance in medical image classification. The existing KNN method is useful in DR detection because of its simplicity, efficiency for small datasets, and effectiveness in pattern recognition. However, modern hybrid models combining deep learning (CNNs) and KNN are becoming more popular for better accuracy and scalability.

Training Phase: KNN is an instance-based learning algorithm, which implies that a model is not particularly developed during training. As an alternative, the training dataset is stored in memory.

Prediction Phase: When a new data point (test sample) is given, the algorithm finds the K nearest neighbours from the training data based on a distance metric (e.g., Euclidean distance).The data point is then either classified based on the majority class of its neighbors (for classification) or averaged by its neighbors (for regression).

KNN Architecture Overview:

KNN doesn't have a conventional "layered" architecture like neural networks. Figure 2 shows an architecture of KNN .Instead, it is a lazy learning algorithm that stores all instances of the training data. Typically, the procedure consists of three steps.

Input Layer (Data & Features)

- Consists of labeled training examples (X,Y) where X is a feature vector and y is the class label.
- Points in an n-dimensional space are used to represent the feature space.

Similarity Computation Layer (Distance Calculation)

- The model calculates the distance between each training data point and the query point when one is supplied.
- Common Distance Metrics: Euclidean, Manhattan, Minkowski

Decision Layer (Voting or Averaging)

- Determines the query point's top K closest neighbors.
- For classification: Majority voting from neighbours.
- For regression: Averaging the neighbours values.
- Tie-breaking: Handled by adjusting K or using weighted voting (closer points have more influence).

4. DEEP NEURAL NETWORK (DNN)

A Deep Neural Network (DNN) is an advanced type of artificial neural network with multiple hidden layers, allowing it to learn complex patterns from data.It uses activation functions and weights to capture relationships as it analyzes inputs through layers of neurons.. Using backpropagation and gradient descent, it adjusts weights to minimize errors over time

DNNs are widely used in image recognition, natural language processing, healthcare, and finance due to their ability to handle large, unstructured data. However, they require high computational power and large datasets for effective training.

The step-by-step workflow involved in using a Deep Neural Network (DNN) for classifying Diabetic Retinopathy (DR) stages based on retinal fundus images. The following are the key stages in this pipeline

Start: The process begins with initializing the system and setting up the environment for model development and deployment.

Load Datasets: A retinal image dataset, such as the Kaggle EyePACS dataset or DIARETDB1, is loaded into the environment. These datasets contain labeled images categorized into DR stages ranging from No DR to Proliferative DR.

Preprocess Data: Raw images are preprocessed to remove noise, normalize intensity, resize images to a standard dimension, and enhance important features such as blood vessels, microaneurysms, and exudates. In order to decrease computational complexity and enhance model performance, this step is essential.

Feature Extraction: Although DNNs can automatically learn features, this step may optionally include techniques to extract relevant texture, color, and morphological features, which help the model focus on disease-specific patterns.

Build Deep Neural Network Model: A DNN architecture is designed, typically composed of multiple hidden layers including convolutional layers (for spatial feature extraction), fully connected layers, and activation functions (like ReLU or Softmax). The model is compiled with an appropriate loss function(e.g., categorical cross-entropy) and optimizer (e.g., Adam).

Train the Model: Labeled data is used to train the DNN. During this phase, the model learns to distinguish between the various stages of DR by minimizing the prediction error on the training dataset through backpropagation and weight updates.

Evaluate Model: The trained model is evaluated on a validation/test dataset using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC. This step helps in assessing the model's generalization ability and identifying overfitting or underfitting issues.

Predict New Cases: Once validated, the model is used to predict the DR stage of new, unseen retinal images. The model assigns a classification label such as No DR, Mild, Moderate, Severe, or Proliferative DR.

End: The workflow concludes with the deployment of the trained model for practical usage in clinical decision support systems or tele-ophthalmology applications.

5. RESULT AND DISCUSSION

The experimental evaluation of diabetic retinopathy (DR) detection models reveals important findings when comparing traditional KNN (K-Nearest Neighbors) with the proposed Deep Neural Network (DNN) approach. The findings highlight how KNN and DNN have different advantages for DR classification. While KNN performs well in terms of recall, making it suitable for minimizing false negatives (missing actual DR cases), it struggles with overall accuracy and precision due to its sensitivity to noise and imbalance. DNN, however, demonstrates high precision, which is vital in medical diagnosis to avoid unnecessary alarm or treatment due to false positives.

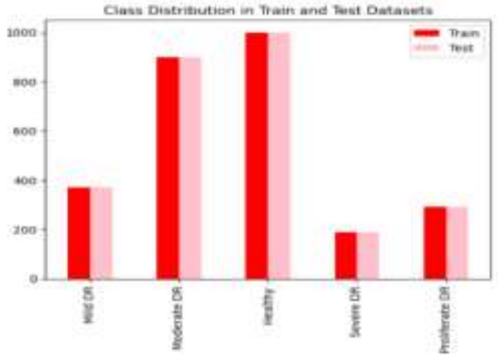

Figure 2: Test and Train Data Visualization

Figure 2 shows the test and train datasets It is evident that the Healthy and Moderate DR classes are dominant, with over 900 and 1000 images respectively, while the Severe DR and Proliferate DR classes are underrepresented. This imbalance may lead to biased performance and reduced sensitivity for minority classes.

Figure 3 shows a specific test image, correctly classified by the model as Severe DR. This supports the model's ability to identify important pathological features despite class imbalance.

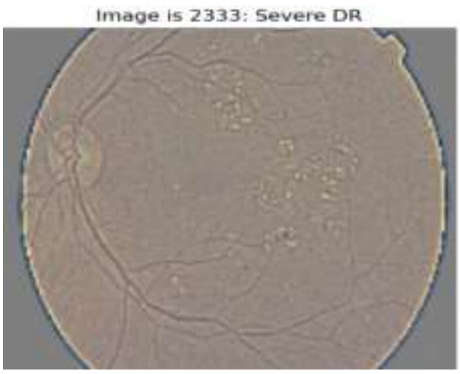

Figure 3: DNN Output

6. CONCLUSIONS

This study presents a comparative analysis of diabetic retinopathy detection using KNN and DNN. While KNN shows promising recall and is easier to implement, DNN demonstrates superior precision, making it more suitable for clinical applications where accuracy in detecting DR is crucial. Future improvements may include advanced architectures, larger balanced datasets, and image preprocessing to further increase classification accuracy and real-world applicability. The encouraging results indicate that deep learning has significant potential in assisting ophthalmologists for early and accurate DR diagnosis.

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