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AN APPROACH TOWARDS DIABETIC RETINOPATHY DETECTION AND ANALYSIS THROUGH COGNITIVE COMPUTING

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ABSTRACT

Diabetes is a common chronic condition that significantly impacts patients' daily lives. Although it cannot be cured, if left unmanaged, diabetes can progressively damage vital organs. Without early and appropriate care, it may lead to multiple adverse effects. To ensure proper care, diabetic individuals typically require regular visits to healthcare professionals. This study proposes a predictive method that empowers diabetic individuals to monitor and manage their blood sugar levels without frequent doctor visits. The central objective of the proposed approach is to reduce the dependence on physician consultations and diagnostic center appointments.

To analyze diabetic retinopathy datasets, the proposed system employs Deep Predictive Neural Networks (DPNNs). Retinal lesions are identified using the Region Convergence Algorithm (RCA), and features are extracted using the Strong Intensity Extractor (SIE), which captures significant pixel-level information. Cognitive Computing (CC), integrated with DPNN, is applied to optimize classification accuracy. The model's performance is evaluated using metrics such as Accuracy, Precision, Recall, and the Confusion Matrix. Numerous experimental inputs are provided to the system based on the developed model to verify and predict potential abnormalities.

Key words*: Diabetes prediction, machine learning, predictive analysis, data analytics, chronic diseases.*

INTRODUCTION

Diabetes is one of the most prevalent chronic illnesses, primarily characterized by elevated or persistently high blood glucose levels. The human body derives energy from glucose, which is obtained through food. The pancreas produces insulin—a hormone that facilitates the absorption of glucose into cells for energy production. When the body does not produce sufficient insulin, glucose accumulates in the bloodstream instead of being absorbed by the cells. Over time, this excess glucose adversely affects the body's vital systems. Although diabetes currently has no permanent cure, early intervention and proper management are essential to maintaining health. Diabetes is broadly classified into Type 1, Type

2, and gestational diabetes. Less common forms include cystic fibrosis-related and monogenic diabetes [1][2]. Diabetes is closely linked to other chronic illnesses and has become increasingly widespread in modern society, impacting nearly every aspect of daily life.

This study focuses on evaluating a robust predictive framework that enables diabetes management without the constant need for medical supervision. The proposed technique leverages patients' historical medical records—including laboratory results, blood glucose levels, and other physiological indicators—gathered over time through clinical visits. This information is used to build a predictive system capable of detecting irregular patterns and anticipating complications. Our system utilizes various machine learning algorithms and selects the most effective model for accurate diabetic prediction [21]. Pregnant women may experience a temporary condition called gestational diabetes, characterized by heightened blood sugar levels during the second trimester. Usually, this form resolves after childbirth. Obesity [3][4] is a significant risk factor for Type 2 diabetes. Diabetes is a chronic condition affecting millions; predictive models can provide timely medical insights. A web-based portal was developed by integrating various machine-learning algorithms to provide accurate assessments for diabetic patients [22][10]. Several deep-learning methods classified the prediction of diabetic retinopathy. The models built with attention networks and adaptive encoding have improved classification performance. This integrated fusion model improves accuracy by extracting the relevant information after the detailed scrutiny of textual and spatial image data [5][6]. The proposed framework has a two-fold feature augmentation framework applied to the data stream derived from the Region Convergence Algorithm (RCA) and the single-modality Messidor dataset. Using the KHUMU diabetic retinopathy dataset achieved a quadratic Kappa score of 90.2%. A cross-dataset comparative analysis used feature fusion to check for the existence of diabetic retinopathy [24][8].

The proposed model was tested using retinal fundus images on Kaggle, a well-established dataset platform. The KNN Germany dataset was selected for disease classification, and images were processed using a Strong Intensity Feature (SIF) based method. A Region Convergence Algorithm (RCA) was employed to isolate diseased areas. Critical features such as entropy, pixel intensity, average grayscale, and deviation metrics were extracted and normalized before splitting into training and testing sets. Our proposed model, a Deep Predictive Neural Network (DPNN) architecture, was then implemented to generate diagnostic predictions. The model used key metrics: accuracy, precision, recall, F1-score, and experimental error rates [14].

This paper is structured as follows: Section III provides background research and explains the rationale for system design. Section IV presents the results and discussion. Section V outlines the proposed model's setup, and Section VI concludes the study with insights into future enhancements.

BACKGROUND STUDY

S. Wang et al. (2021) introduced a multilayer recurrent neural network for detecting diabetic retinal degeneration. The model uses features associated with diabetic retinopathy that can lead to blindness. A significant benefit of this approach is its ability to eliminate residual symptoms of retinal disease. High-resolution fundus images are fed into the model and compared against training metrics to ensure high accuracy. The authors employed a Multi-Channel Generative Adversarial Network (MGAN) architecture to implement a supervised learning model for grade-based classification of diabetic retinopathy. However, a significant limitation of this system is the lack of sufficient labeled data, which negatively affects the quality of analysis. Additionally, processing fundus images without compression requires high-performance graphical processing units [7][12][13].

D. Wang et al. (2021) introduced a low-cost footwear-integrated monitoring system designed to identify early signs of foot ulcers in diabetic patients. The system analyzes plantar pressure patterns and uses a Random Forest algorithm to classify individuals into risk categories. Their findings demonstrated a classification accuracy of 94.7%. Data was transmitted via Bluetooth, supporting live feedback for users. However, although effective in lab conditions, the practicality of long-term daily use remains a concern.

Sisodia et al. (2018) explored diabetes prediction by comparing three classic classifiers SVM, Naive Bayes, and Decision Trees using the Pima Indian Diabetes Database. Their best result achieved a predictive reliability of 76.03%. The study demonstrated the value of historical patient data for identifying disease patterns. However, the authors acknowledged limitations in raw data usage and proposed further improvements in feature selection and dimensionality reduction for future work [9].

He et al. (2021) introduced a deep learning model for diabetic retinopathy classification that incorporates a Category Attention Block (CAB) into a Convolutional Neural Network (CNN). Their model emphasized region-based attention to enhance category-specific features and was benchmarked against standard classification methods. With an overall classification reliability of 78.13%, the approach showed promise in managing class imbalance issues often present in real-world medical datasets [25].

C.Novara et al. (2006) have suggested a blind non-linear detection model to rapidly and effectively detect diabetic patients. It identifies Type I diabetes through a bling, non-linear method and suggest proper recovery strategies. The model also considers real world parameters like diet, emotional transformation, and physical exertion during the diabetic phase. They are supposed to increase the accuracy of predictions.

The new technique focuses on individualized treatment planning using the patient's condition [11]. Some current state-of-the-art methods were also overviewed to compare parameters applied in diabetic retinopathy detection and tackle the pitfalls in classification models [26][20].

SYSTEM DESIGN

A predictive evaluation strategy was used to implement the system model for this study. The dataset was sourced from Kaggle.com, a widely used platform for machine learning and image datasets.

Dataset Description:

The fundus images in the dataset were captured using various camera models and settings, which resulted in variations in orientation and image quality. In some images, the macula and optic nerve appear reversed (i.e., the macula is positioned above the optic nerve), depending on the eye (left or right) and camera configuration. In other cases, the images may appear as they would during an eye examination conducted using a condensing lens with a microscope. Determining whether an image is flipped typically involves identifying whether the macula (the dark central region) is located above or below the optic nerve's midline. If the macula is higher than the optic nerve, the image is likely reversed; if it is lower, the image is correctly oriented.

Additionally, some images contain notches—squares, triangles, or circles—on one side. The presence of a notch usually indicates the image is correctly oriented. Without these notches, it can be difficult to determine orientation. As with many real-world datasets, the images may also include noise, such as poor focus, overexposure, underexposure, or distortions.

The goal of the proposed system is to build a robust model that can perform accurately despite these inconsistencies and noise. Therefore, image preprocessing and resilient feature extraction strategies are essential components of the design.

METHODOLOGY

Figure 1. shows the proposed cognitive computing-enabled deep predictive neural network (DPNN) model for classifying diabetic retinopathy. The fundus images are pre-processed, feature extracted, and

classified with optimized neural network architecture.

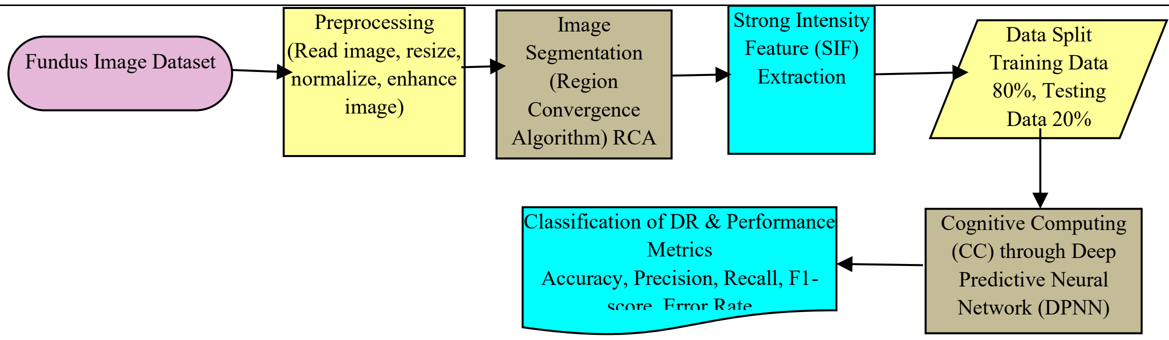

Figure 1. Proposed cognitive computing (cc) – deep predictive neural network (DPNN) model

Implementation Summary:

Reading data from the diabetic retinopathy dataset: The dataset comprises retinal images acquired through fundus photography and is openly accessible for research purposes. The dataset is available online and can be processed using libraries such as OpenCV or Pillow.

Enhancing the image: Techniques for picture enhancement are employed to raise the level of the picture. Sharpening, noise reduction, and contrast improvement are a few standard techniques. A variety of programs and libraries are available to improve images.

Converting the image to grayscale: Turning a color image into a black-and-white image is called grayscale conversion. Utilizing different libraries, such as OpenCV or Pillow is made possible. Creating a region convergence algorithm: A region convergence algorithm divides a picture into regions according to a set of parameters. Various techniques, such as thresholding, edge detection, and clustering, were used to develop the algorithm.

Feature extraction with a strong intensity extractor: This method identifies specific patterns or features in an image that can support classification. A feature extraction technique that detects regions of high intensity is known as a strong-intensity extractor.

A deep neural network comprising multiple interconnected layers is a widely used architecture for image classification tasks. In medical imaging, it is particularly effective for detecting signs of retinopathy in retinal scans. Such a network can be built and trained on curated datasets using machine learning frameworks like TensorFlow or PyTorch.

Segmentation model

Fundus images are segmented into regions of interest based on the Region Convergence Algorithm (RCA) to isolate the diseased areas. This method focuses on segmenting fundus images based on the disease textures within the retina region. The images are selected for the segmentation process using the region convergence approach. The initial value is placed at a random pixel position, where the convergence curve starts growing towards the relative value search. The relative pixels are mapped together to form a converged area segmented from the original data.

The region converged from the overall image is represented by the expression below.

$$Rk = \sum_{i=0}^{n} si \qquad (1)$$

Where Rk is the final segmented region through the complete iteration of i.

Si represents the pixels added into the segmented region, through neighboring sets.

The segmentation process continues until convergence criteria is getting completed.

The convergence is identified through Heterogeneity condition

$$/Ip-\mu R/\leq T \qquad (2)$$

Where Ip is the intensity of the pixel considered from the fundus image under test

μR\mu_μR is the mean intensity of the region extracted from the fundus image.

T is a threshold defining similarity of the extracted region from the segmented area.

The energy minimization for the convergence process is carried out through the below expression.

$$E(R)=p\in R\sum(Ip-\mu R)2 \qquad (3)$$

The region stops growing when the change in **energy function** is below a certain threshold.

Feature extraction model

The proposed approach considers a Strong Intensity Feature extraction (SIF) module to obtain the normalized pixel intensity. The mean intensity extracted from the region of interest (the converged area) denotes the average intensity spread across the segmented region. The SIF mean is denoted by the expression below.

$$\text{Imean} = \frac{1}{N}\sum_{i=1}^{N} I \qquad (4)$$

Where, I denote the all the intensity values extracted after the segmented area.

N denotes the total number of pixels under process

The intensity feature provides the overall brightness of the image region under test. The intensity looks different than that of the original image intensity.

The features extracted from the SIF method also considers extracting the Standard deviation (SD) of the intensities, denoted by the expression below.

$$ISD = \sqrt{\frac{1}{N}\sum_{i=1}^{N} I - Imean} \qquad (5)$$

Entropy is the scalable parameter which measures the randomness and complexity present in the collected intensity values in the region extracted Imean. The higher value extracted from the entropy denotes the complex and detailed image. The entropy is further considered for classification and edge detection.

Energy is considered as one of the important parameters to get measured that denotes the pixel intensities. Energy is denoted by E, expressed by the formula below.

$$E = \sum_{i=0}^{L-1} p(Ii)2 \qquad (6)$$

Higher the energy value denotes the uniform intensity available in the extracted region. Low energy indicates the high texture variations present in the region of interest segmented from the original image.

Cognitive computing (CC)- Deep predictive neural network (DPNN)

The proposed cognitive computing enabled deep predictive neural network (DPNN) model is composed of an adaptive approach to treat the multi-scaled features extracted from SIF of the RCA model. The extracted features are normalized and mapped as training data 80% and testing data 20%. The structure of CC-DPNN architecture is formulated as below.

Table 1. CC-DPNN layers

Layer Name	Function	Processing Mechanism
1. Input Layer	Receives raw data (sensor, text, image, etc.)	Normalization, feature scaling
2. Cognitive Preprocessing Layer	Enhances data with cognitive reasoning	Knowledge graphs, ontologies, attention-based weighting
3. Feature Extraction Layer	Learns hierarchical features	CNN (for spatial), LSTM/Transformers (for temporal), Autoencoders (for unsupervised learning)
4. Predictive Encoding Layer	Captures long-range dependencies in data	LSTM, GRU, Transformers, RNNs
5. Deep Representation Layer	Converts extracted features into meaningful representations	Self-supervised learning, attention mechanisms
6. Decision Optimization Layer	Makes high-level predictions or classifications	Reinforcement learning, Bayesian networks
7. Output Layer	Provides final predictive results	Softmax (classification), Regression (forecasting)

Table 1. presents the detailed architecture of the CC-DPNN, outlining the design of each layer based on multiple iterations of testing and evaluation performed on segmented fundus images. The cognitive computing approach enhances the data by incorporating attentional weights derived from the segmented regions of the fundus images. These weights serve as a strong influencing factor in determining the presence of affected intensities. The representation layer contains the core neural network model, while the decision-making process is optimized through an iterative loop that incorporates a Bayesian neural network. Finally, the output layer completes the network by producing the final classification decision.

RESULTS AND DISCUSSIONS

Simulation results of proposed analysis model

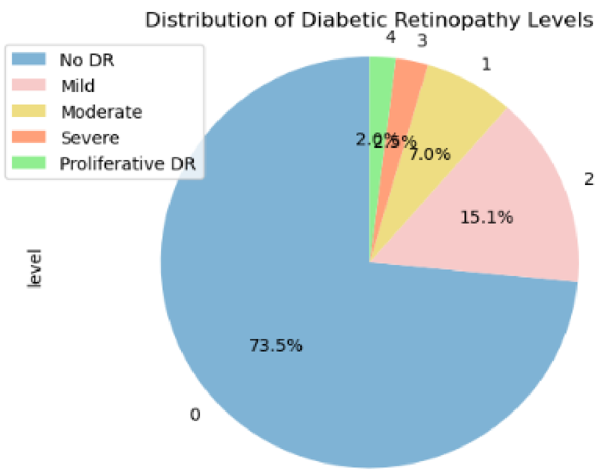

Figure 2. Analysis chart

Figure 2 shows the analysis chart on data given to explore the presence of diabetic retinopathy. Various classifications of DR are exposed here. It can be categorized as No DR, Mild, Moderate, Severe, Proliferative DR etc.

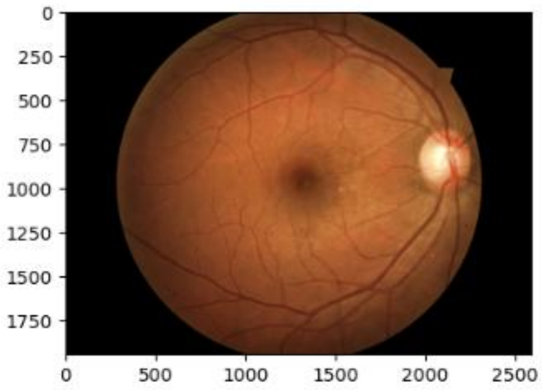

Figure 3. Input test image

Figure 3 shows the input test image taken from the database for detection of DR using CC-DPNN model. The images are resized into fixed size of 1000x1000 before fetching it into the processing model.

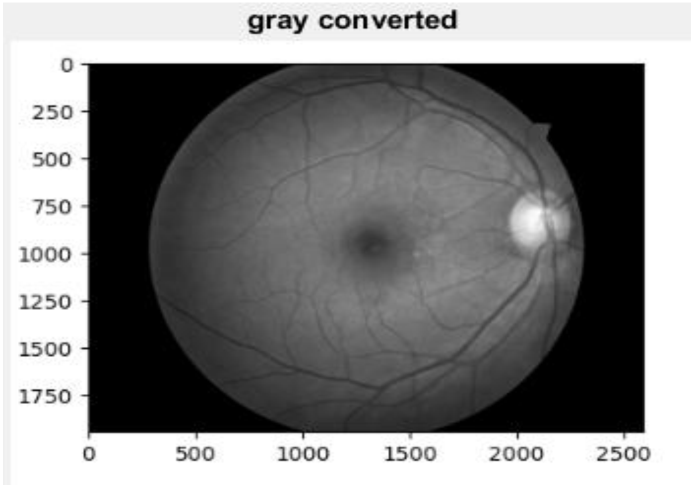

Figure 4. Gray converted

Figure 4 shows the gray converted model where the input RGB image is converted into gray image. From the gray pixels the intensity features are extracted using SIE model and RCA technique.

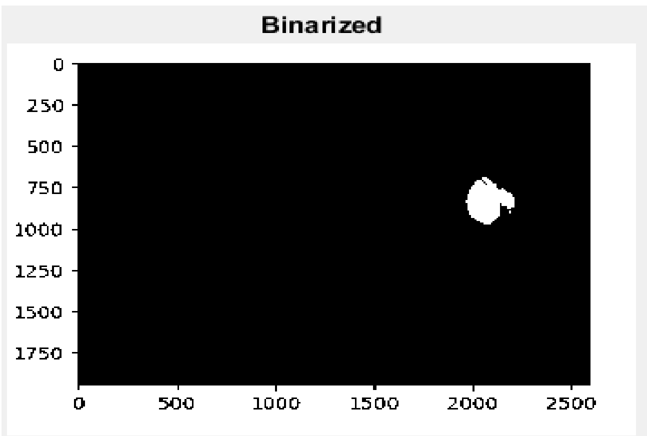

Figure 5. Binary converted

Figure 5 shows the binary converted input image where the gray region is completely converted into binary image. The segmented region with gray pixel is applied parallelly to the SIF process. The strong features such as mean, standard deviation, entropy, intensity mean are evaluated.

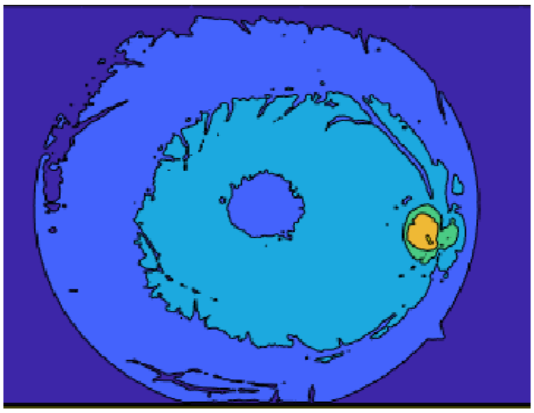

Figure 6. Segmented region

Figure 6 shows the region segmented HSV mapped pseudo image. The region convergence algorithm estimates the area of the retinal lesion. The HSV mapping is used to visually map the affected area.

Table 2. Performance measure of proposed CC-DPNN

Parameters	Values
Accuracy	98.20%
Precision	97.90%
Recall	98.05%
F1score	97.88%

Table 2. shows the performance measure of the proposed CC-DPNN model where accuracy of 98.02% is achieved, precision score of 97.9% is achieved, recall of 98.05% and F1score of 97.88% is achieved. The overall error rate of the process comes around 0.001254 which is a nominal range.

Table 3. Comparison of proposed work with existing and proposed model

References	Research Description	Dataset	Techno- logy	Methodology	Quantitative Measures	Challenges
M.M.Dharmana et al.,[15]	Pre-diagnosis of DR	Clinical data, Images (Fundus)	ML	Blob detection	Accuracy= 83%	Patient Condition need to be monitored
N.Eladawi et al.,[16]	Early detection of DR	OCTA images	DL	3DCNN+ Random Forest	Accuracy= 98%	Computing time is more
N.Islam et al.,[17]	Image guided DR detection	Kaggle	DL	ABCNN+ InceptionV3	Accuracy= 90%,	Imbalanced Data, Noisy Data
C.D.R.Wulandari et al.,[18]	Classification of DR	MESSIDOR	DL	SRM + CNN	Accuracy= 81.25%	Hybrid algorithms are recommended
Proposed system	Classification of DR	Kaggle	ML, NN	CC-DPNN+SIE+RCM	Accuracy=98.2%	Dataset tuning need to be explored more

Table 3 shows the performance comparison of existing and proposed models for diabetic retinopathy (DR) classification. Reference [15][23] utilized a blob detection method on clinical fundus images and achieved an accuracy of 83%. Reference [16][19]employed a deep learning model combining convolutional architecture with a random forest algorithm, achieving an accuracy of 98%. Another image-guided DR technique used a CNN algorithm and obtained 90% accuracy. Reference[17][18] reported an accuracy of 81.25% on DR classification using a CNN method with the MESSIDOR dataset.

The proposed CC-DPNN model, incorporating SIE and RCM techniques, achieved an accuracy of 98.2% on the Kaggle dataset. Further improvements could be achieved by exploring multiple datasets and integrating fusion strategies with various machine learning techniques.

CONCLUSION

Diabetes is a chronic condition that affects many people and requires ongoing medical care. The identification and monitoring of chronic diabetics must be constant. If a disease is not addressed, it will ultimately impact other parts of the body continuously. The model that has been suggested centers around creating a solid architecture that first chooses an effective algorithm model for evaluating the input. Images of retinopathy sufferer eyes were gathered from kaggle.com. On the Kaggle dataset, the proposed CC-DPNN with SIE and RCM technique achieved an accuracy of 98.2%. In addition, the system dataset must be investigated using multiple datasets and machine learning techniques combined.

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