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Machine Learning-Based Early Detection of Diabetic Retinopathy: A Comparative Study Using BP-ANN and SVM

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ABSTRACT
Preventing vision loss and providing appropriate medical intervention are both made possible by early detection of diabetic retinopathy (DR). This study's overarching goal is to improve upon previous efforts in early DR detection by creating and testing a model that combines prior information with an enhanced Backpropagation Artificial Neural Network (BP-ANN). The model will then be compared to both the classic BP-ANN and Support Vector Machine (SVM) approaches. Retinal fundus images were gathered into a dataset. Essential characteristics of the retina, including the width and tortuosity of blood vessels, were semi-automatically retrieved and utilized as inputs for a priori knowledge.
In addition to conventional BP-ANN and SVM models, we trained an enhanced BP-ANN model that leveraged these attributes. A 10-trial, 5-fold cross-validation procedure was used to assess the generalizability and robustness of the model. In terms of training efficiency, convergence speed, and classification accuracy, the experimental findings showed that the enhanced BP-ANN model outperformed both the conventional BP-ANN and SVM models. The results show that the improved BP-ANN could be a valuable tool for ocular diagnostics and confirm that including domain-specific features into neural networks can improve early DR diagnosis.
Keywords: Diabetic retinopathy, Fundus images, Machine Learning, Artificial Neural Networks, Diabetes.

INTRODUCTION

"Diabetes Mellitus" ranks high among the world's most prevalent and serious diseases. A total of 8.5% of persons over the age of 18 are affected by diabetes, which is also the cause of 1.6 million fatalities globally, as reported by the World Health Organization (WHO) in 2021. The number of deaths caused by diabetes rose again between 2010 and 2016, after a decline from 2000 to 2010 in several developing nations. A significant public health concern, the four primary diseases—cardiovascular disease, cancer, chronic lung disease, and diabetes—kill more than 18% of the world's population. Deaths from diabetes, for instance, increased by 70% in 2000 and are projected to increase by 80% in 2020 among men. Obesity, advancing age, inactivity, lifestyle choices, genetic predisposition, hypertension, poor nutrition, etc., can all lead to diabetes mellitus. Diabetes increases the risk of cardiovascular disease, stroke, renal failure, nerve damage, vision problems, and many other complications over time.

Diabetes is currently diagnosed in clinical practice by gathering data from multiple tests and then administering the proper diagnostic medication (Gadekallu et al., 2020). Many different diseases can be diagnosed using supervised and non-supervised machine learning (ML) methods in the healthcare industry (Haq et al., 2020; Yu et al., 2010). To reduce the expenses associated with detecting complicated diseases and to predict their outcomes, researchers can use ML approaches to explore hidden patterns in medical datasets (Ahamed et al., 2021). To train ML algorithms, real-world medical datasets with varying features and external variables are utilized.

Diabetic complications can be prevented with early detection and proper medical treatment (Dinh et al., 2019). ML methods can aid in the early detection of this disease. A prediction model is built using machine learning techniques. This is because ML approaches enable computers to learn and acquire intelligence from either past experiences or a pre-defined dataset (Gulshan et al., 2016; Vinayakumar et al., 2019). The predictive model can make more accurate decisions, as it can recognize and comprehend the incoming data.

Preventing irreversible eyesight loss requires prompt diagnosis and treatment. Retinal image screening by hand, on the other hand, is time-consuming, prone to inter-observer bias, and sometimes unavailable in underprivileged or rural areas. Due to this difficulty, healthcare providers require rapid, accurate, and automated diagnostic methods to detect early-stage DR effectively.

Recent developments in AI have led to the emergence of machine learning (ML) algorithms as powerful tools for analyzing medical images. The use of support vector machines (SVMs) and artificial neural networks (ANNs) for classifying intricate patterns in retinal fundus images has demonstrated promising results. Among these, BP-ANNs offer a versatile learning capability that can be enhanced by incorporating domain-specific prior information, such as the width and tortuosity of blood vessels.

The goal of this research is to improve the BP-ANN model for early-stage DR detection by using a priori knowledge. It goes on to evaluate this improved model alongside more conventional BP networks and support vector machine classifiers. The research examines the accuracy of classification, training efficiency, and robustness using k-fold cross-validation, utilizing a carefully selected dataset of 240 retinal images. By comparing different approaches, we can see that the modified BP-ANN is effective and that we can build a graphical user interface that is easy for clinicians to use.

REVIEW OF RELATED STUDIES

Dejene, Fitsum et al., (2024). Among the numerous causes of blindness worldwide, diabetic retinopathy (DR) ranks high. Preventing visual impairment caused by DR requires early detection and rapid treatment. It requires a substantial amount of time and effort to screen retinal fundus images manually. A significant disparity also exists between the number of people with diabetic retinopathy and the number of doctors who can treat them. One promising substitute for conventional DR screening methods is the integration of ML and DL algorithms. But there are obstacles, such as a complicated DL model, a lack of a quality-labeled retinal dataset, and a significant demand for computer resources. Consequently, we reviewed the literature on DR screening using ML approaches and analyzed our findings.

Regarding this, our work makes a substantial contribution in various ways. First, we identify publicly available retinal fundus images and describe them. Next, we'll review some of the preprocessing methods commonly used for DR screening. Furthermore, we assess the development of ML methods for DR screening. Finally, we outlined current obstacles and prospective paths.

Usman, Tiwalade et al. (2023). In millions of people around the world, Diabetic Retinopathy (DR) has taken a toll on their vision. Despite the availability of well-respected screening procedures, such as optical coherence tomography and fluorescein angiography, most people are unaware of the condition and do not undergo these tests when they should. Avoiding eyesight loss, which can occur when Diabetes Mellitus (DM) remains untreated for an extended period, requires prompt diagnosis of the condition. Many DL and ML algorithms have been applied to DR datasets for disease classification and prediction; however, most of these studies have failed to address the crucial steps of data preprocessing and dimensionality reduction, leading to biased results. Color fundus photographs (CFPs) underwent data preprocessing as the initial step of this investigation. Principal Component Analysis (PCA) was then used for feature extraction. Based on a pre-trained Convolutional Neural Network (CNN) architecture, a model for Deep Learning Multi-Label Feature Extraction and Classification (ML-FEC) was proposed. The next step was to train a subset of the images using three state-of-the-art CNN architectures with parameter-tuning. These architectures were used to identify and classify the lesions. Transfer learning was then applied to this subset of images. Results showed that ResNet 50 achieved an accuracy of 93.67% with a hamming loss of 0.0603; Squeezenet1 attained an accuracy of 91.94% with a hamming loss of 0.0805; and ResNet 152 achieved an accuracy of 94.40% with a hamming loss of 0.0560. This demonstrates that the model is suitable for use in everyday clinical practice and supports the implementation of large-scale DR screening programs.

Yazid, Rizq & Samsuryadi, Samsuryadi. (2022). Diabetic retinopathy (DR) is a consequence of diabetes mellitus that can cause damage to the eye's retina and can be classified as either normal, mild, medium, severe, or proliferative. Blindness can result from this condition if it is not identified and treated in time. Currently, an ophthalmologist must manually examine a photograph of the patient's fundus to diagnose and categorize this condition. The technique is laborious and requires a specialist in the field, which is a drawback of manual detection. The researchers in this study used Convolutional Neural Networks (CNNs) to identify and categorize cases of DR illness. Studying the features of eye fundus images of DR patients led to the construction of the CNN model based on the VGG-16 architecture. Using the BT-709 (HDTV) approach, 4750 photos were resized to 256 × 256 and transformed to grayscale for the model's training. In terms of detecting and classifying 100 test photos according to five DR severity classifications, the created CNN-based software with VGG-16 architecture achieved an accuracy of 62%. With a sensitivity of 90% and a specificity of 97.5%, this program outperforms all but the most extreme of the mild software classes.
Pradhan, Amnaya & Sharma, Neha. (2022). Diabetic complications affect around 1.5 million people every year across the world. The majority of the 422 million individuals diagnosed with diabetes worldwide live in low- and middle-income nations, which is a very concerning statistic. Worldwide, diabetic retinopathy is the leading cause of blindness. Typically, it strikes individuals between the ages of 25 and 65. It occurs when hyperglycemia damages or blocks the retina's blood vessels, which in turn prevents blood from traveling through the eyes. Treating diabetic retinopathy early is of the utmost importance. In the long run, it can lead to blindness if left unaddressed. The suggested approach for diagnosing diabetic retinopathy is to employ ResNet-equipped Convolutional Neural Networks. To capture images of the retina, doctors use fundus cameras. In areas where medical testing is complex, the goal is to identify and prevent this disease. Following the preprocessing, segmentation, and enhancement steps outlined in the paper, features such as microaneurysms and hemorrhages will be extracted from the images. This is used to classify the condition as mild, moderate, severe, or proliferative. Future applications of this approach may include the detection of glaucoma and macular degeneration.
Hasan, Dathar et al. (2021). A chronic condition, diabetes mellitus, is rapidly becoming a global epidemic. It develops when blood sugar levels rise and leads to issues with the eyes, kidneys, and heart. One ocular complication of diabetes is diabetic retinopathy (DR), which occurs when blood vessels in the retina become damaged or burst. Because it manifests asymptomatically in its early stages, it is thought to be the primary cause of blindness. A critical step in providing the required medical treatment is the earlier detection and classification of DR cases. Thanks to the rapid advancement of its algorithms, machine learning has become an increasingly effective tool in computer-aided diagnosis and medical applications. The purpose of this research is to compare and contrast detection and classification systems for DR that rely on machine learning methods. Several publicly accessible datasets provide large quantities of retina fundus and thermal pictures, which are used to train and evaluate these algorithms. By locating the red flags and determining the degree of DR severity, these algorithms demonstrated their efficacy. Based on the systems we examined, the deep convolutional neural network algorithm ResNet50 demonstrated the best performance in terms of the evaluated indicators. The Resnet50 can analyze retina images and extract valuable information using a series of feature extraction kernels. We conclude that ML algorithms can aid doctors in making accurate diagnoses and providing effective treatment for DR cases.
Amin, Javeria et al., (2016). Microvasculature in the retina, a byproduct of diabetes mellitus, is the root cause of diabetic retinopathy. In extreme and untreated cases of diabetic retinopathy, blindness can develop. It is a laborious and time-consuming process to manually examine fundus images for morphological changes in microaneurysms, exudates, blood vessels, hemorrhages, and macula. With the use of an observer-friendly computer-aided system and intervariability, it can be easily built. The goal of this study is to review various methods for diagnosing non-proliferative diabetic retinopathy, including microaneurysms, hemorrhages, and exudates. Diagnosing proliferative diabetic retinopathy also involves methods for detecting blood vessels. In addition, the article delves further into a review of the studies used by the writers to identify diabetic retinopathy. Researchers and technical professionals interested in applying current research in this field may find this work helpful.

MATERIAL AND METHODS

Dataset and Experiment Design

The same 45° field of view camera captured 240 fundus images, all centered on the macula. For further training, these photos were gathered from a cohort consisting of 120 individuals with early-stage DR and 120 healthy controls. The study was approved by Nantong University's Ethics Committee and conducted under the ethical standards outlined in the 1995 Declaration of Helsinki. To ensure uniformity for further width calculation tests, all image sizes were adjusted to 565 × 584 pixels. Figure 1 illustrates the experimental setup we employed, which integrated a priori information with the conventional BP-ANN process's feature extraction and network development steps.

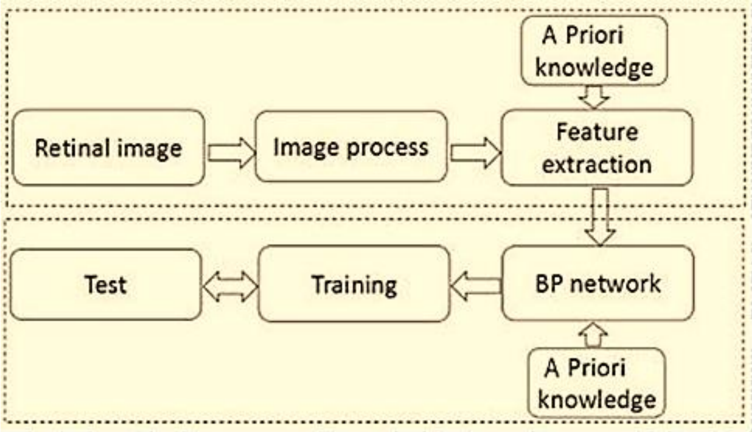

Figure 1: Proposed research model

Retinal Image Processing and Feature Extraction

To ensure consistent lighting, size, and color throughout the imaging procedure, all fundus photos were standardized using multiple cameras. The blood vessels in the retina were automatically segmented using a powerful fuzzy clustering method that relies on textural cues (Figure 2).

The researchers in this study consulted with seasoned ophthalmologists to determine what constitutes a priori knowledge, and they settled on geometric characteristics of blood arteries, including tortuosity and breadth. Using the self-adaptive distance regularized level set evolution method, which was previously proposed, we were able to automatically name the major arteriole and venule trees by detecting the optic disk (OD). Segmenting the OD enabled the automated identification of the OD centroid, facilitating subsequent image processing. To obtain the first seeds, we subtracted the self-adaptive spherical mask from the vessel centerline network; the mask's center was at the OD's centroid. The seed points were categorized into venule seed points and arteriole seed points after they were identified.

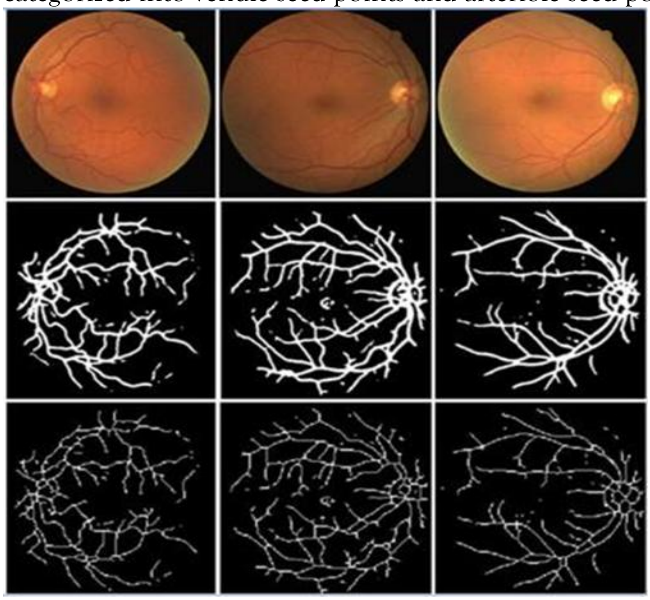

Figure 2: Segmentation Results of Retinal Blood Vessels from Fundus Images

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The entire network of retinal vessels was then annotated as arteriole and venule trees using automatic tracing techniques, as shown in the figure below. Ophthalmologists matched the acquired tracing results with the ones they had previously recognized.

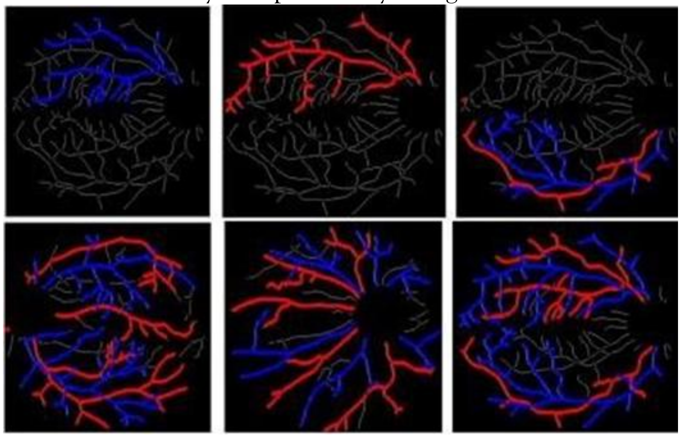

Figure 3: Artery and Vein Classification in Retinal Vessel Segmentation

After that, we labelled and chose the inferior retinal temporal artery (IRTA), inferior retinal temporal vein (IRTV), superior retinal temporal artery (SRTA), and superior retinal temporal vein (SRTV) for additional quantitative analysis. Geometric features, including the thickness and curvature of retinal segments at each order, were retrieved following vascular labeling. To extract features from the retina, a topological order framework for the vessels was employed. The first order segment was defined as the point where the retinal tree starts from the OD outline, two daughter segments were marked as the second order, and the orders of the offspring's topological branches were added until the automatic tracing was finished. This is how the four main retinal vessels (IRTA, IRTV, SRTA, and SRTV) had their 72 features extracted and prepared for analysis, one for each hierarchical order. The commonly used computer vision features, including mean, variance, homogeneity, contrast, dissimilarity, entropy, angular second moment, and correlation features from the gray-level co-occurrence matrix, were also extracted from the same dataset for further classification, allowing for a comparison of the efficiency of our a priori knowledge-based features.

Classifier and Performance Evaluation of an Enhanced BP Neural Network

Here is the blueprint for our BP-ANN (Figure 4):

The input to the hidden layer, denoted as H_{in} (j), in

$$H_{in}^{n}(j) = \sum_{i=1}^{M} \omega_{ij}^{n} x_{i}^{n} + a_{j}^{n}$$

The hidden layer's threshold is represented by a_jThe weights between the input layer's neurons and the hidden layer's neurons are denoted by w_{ij}The input features were represented by x_i.

We controlled w_{ij} to w'_{ij} using our previous regression modeling coefficients of the input features, as opposed to the traditional method of randomly assigning w_{ij} In a traditional BP network. The following is a definition of its estimates:

$$\hat{\beta} = \arg\min_{\beta} \left\| Y - \sum_{j=1}^{p} x_j \beta_j \right\|^2 + \lambda \sum_{j=1}^{p} \left| \beta_j \right|$$

Where λ is a regularization parameter that cannot be negative, x represents the width and tortuosity of the retinal segments at each order, Y stands for the average accuracy of two models, and the βs are the regression model's coefficients.

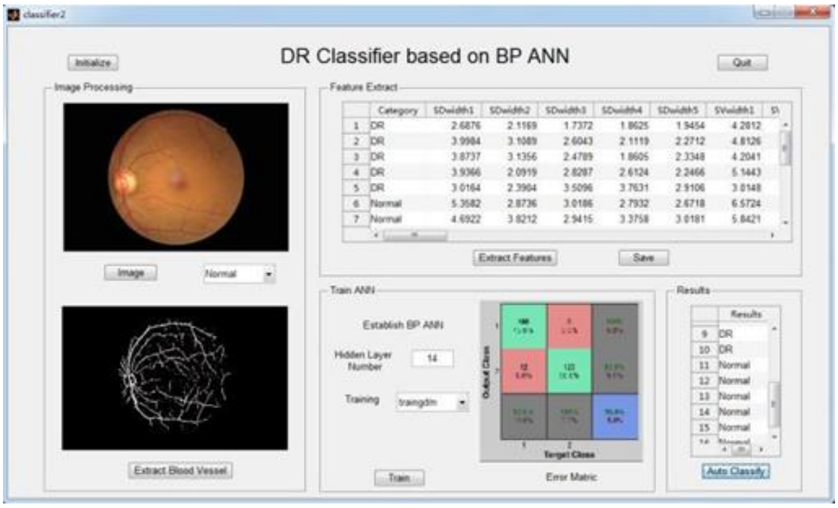

Figure 4: Graphical User Interface of DR Classifier Based on Backpropagation Artificial Neural Network (BP ANN)

The following is a reference to the ideal hidden layer neuronal density:

$$h < -1$$

$$h < \sqrt{(m+n)} + a$$

As a constant between 0 and 10, n denotes the number of neurons in the input layer, h the number of neurons in the hidden layer, m the number of neurons in the output layer, and so on. The parameters used in this investigation were n = 72, m = 2, and h = 11–20. Using the moment gradient descent method, BP-ANN was trained. We kept track of the training epoch, specificity, accuracy, and sensitivity independently for every test.

We compared the outcomes with the improved a priori knowledge-based BP-ANN to those with the conventional computer vision-based feature extraction method. To evaluate the performance of our suggested BP classifier, we also fed the same characteristics into a support vector machine classifier that utilized a radial basis function as its kernel. Additionally, the effectiveness of the suggested procedures was demonstrated through the use of the k-fold cross-validation method.

DR Detection Application Development

Here, we developed a graphical user interface (GUI) for the DR classifier using our enhanced BP-ANN, making it easier to apply our technique to DR screening (Figure 5).

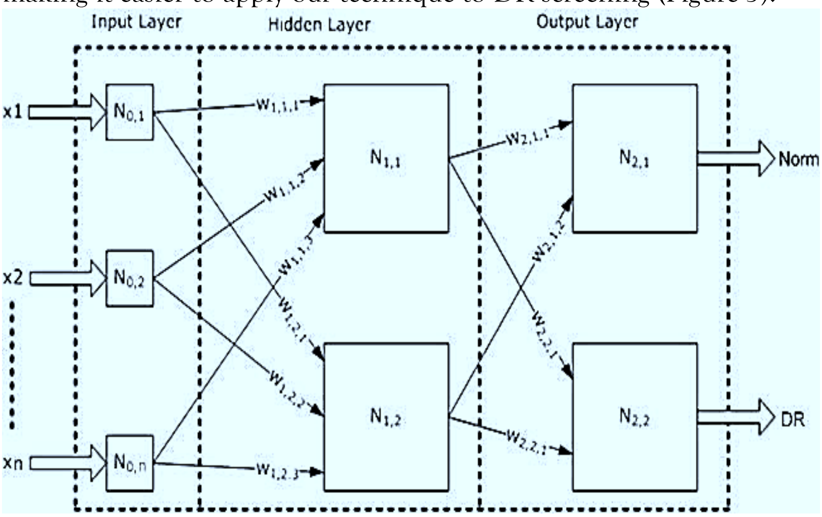

Figure 5: Architecture of the BP Network for Diabetic Retinopathy Classification

Built-in image processing techniques were available for tasks such as automatically categorizing, importing fundus images, segmenting blood vessels, extracting features, and training artificial neural networks. Before any fundus images could be imported, an ophthalmologist would check to see if they revealed DR. Next, the characteristics such as blood vessel width and tortuosity were retrieved, stored, and subsequently

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https://www.theaspd.com/ijes.php

utilized as training input values for BP-ANN. Training parameters were manually configured for BP-ANN construction before pressing the "Train" button. Iterative training was continued until the network reached its peak performance, at which point the training confusion matrix was shown to validate the network's performance. To determine the DR status of fundus images that were not previously identified, the training network structure was subsequently saved. The categorization results would be shown when the "Auto Classify" button was clicked.

RESULTS AND DISCUSSION

To determine if a fundus image was normal or DR, this research used three different methods: support vector machines (SVMs), classic BP-ANN, and our enhanced BP-ANN. For this investigation, 240 labeled original samples were evaluated 10 times for validation results using 5-fold cross-validation, with k set to 5. In Table 1, you can see the outcomes of our ten rounds of randomization and five rounds of cross-validation.

Table 1: K-fold cross-validation results for SVM

No.	1	2	3	4	5	6	7	8	9	10
Accuracy (%)	88.33	90.00	90.33	90.83	91.33	91.67	92.67	92.5	93.17	93.67

In contrast, Tables 2 and 3 present the average accuracy of ten randomization experiments with various hidden neurons for BP-ANN and a priori knowledge BP-ANN, indicating that the latter can achieve superior detection results.

Table 2: Performance of BP-ANN with Varying Hidden Neurons Using K-Fold Cross Validation

Hidden neurons	11	12	13	14	15	16	17	18	19	20
Mean accuracy (%)	88.85	90.77	92.31	93.85	93.46	94.23	94.23	94.62	95.38	96.15

Table 3: Performance of A Priori Knowledge-Based BP-ANN with Varying Hidden Neurons Using K-Fold Cross Validation

Hidden neurons	11	12	13	14	15	16	17	18	19	20
Mean accuracy (%)	92.38	92.62	93.69	93.77	93.85	96.38	96.31	97.31	97.77	98.46

The time cost was shorter when utilizing our improved BP-ANN, as shown in Figure 6, where the epoch was significantly lower in the improved BP group compared to the standard BP group (109 vs. 254), and the epoch decreased as the number of neurons in the hidden layer increased. Both our improved BP-ANN and the conventional BP-ANN showed an increase in accuracy and epoch when the hidden neuron count reached 20; however, our improved BP-ANN outperformed the conventional BP-ANN (Figure 7).

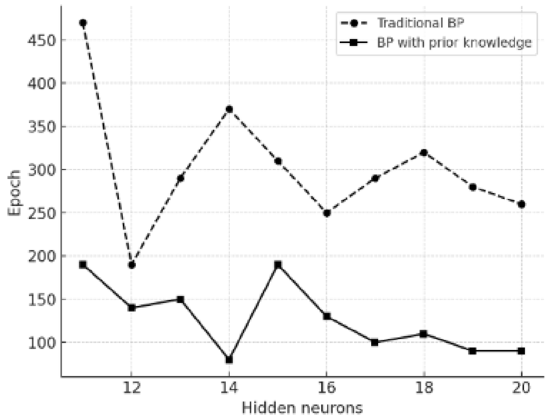

Figure 6. Comparison Between Traditional BP and BP with A Priori Knowledge

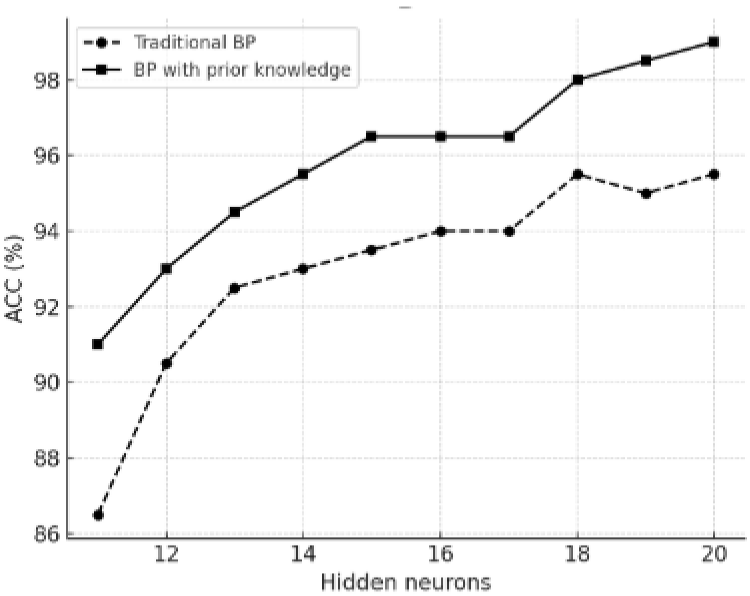

Figure 6. Performance Comparison of Traditional BP and BP with Prior Knowledge Based on Hidden Neurons

This study's classifier was a modified ANN, which is typically thought of as a type of supervised machine learning protocol due to its training procedure. Abràmoff et al. employed a non-supervised k-NN classifier to classify microaneurysms based on three features—hemorrhages, exudates, and cotton wool spots—and achieved a sensitivity of 90% and a specificity of 47.7%, which is different from this sort of supervised classifier. Similarly, Dupas et al. employed a k-NN classifier to detect DRs; their results showed a 72.7% increase in specificity but an 83.9% decrease in sensitivity. However, similar to our study, Shahin et al. employed a supervised ANN classifier to automatically recognize blood vessels, hard exudate microaneurysms, entropy, and homogeneity in retinal images. They then classified the images as either normal or abnormal. They achieved results that were similar to those in our study, in terms of accuracy (over 92% on average), sensitivity (over 88%), and specificity (100%). In addition, Acharya et al. extracted four features—retinal blood vessels, exudates, microaneurysms, and hemorrhages—using support vector machines (SVMs), another well-liked supervised classifier for DR classification. In comparison to our study's 92.19% accuracy, 92.50% sensitivity, and 91.67% specificity, they only managed 86% detection accuracy, 82% sensitivity, and 86% specificity.

CONCLUSION

The study demonstrates that machine learning can aid in detecting diabetic retinopathy (DR) at an early stage, particularly with an enhanced Backpropagation Artificial Neural Network (BP-ANN). The improved BP-ANN outperformed both conventional BP networks and Support Vector Machines (SVMs) in terms of classification accuracy by incorporating prior information into the network architecture. This information included characteristics such as the breadth and tortuosity of blood vessels. A decrease in the number of epochs required for convergence is evidence that including pertinent physiological indicators not only enhanced diagnostic performance but also significantly reduced training time.

Additionally, the suggested model proved dependable and robust when handling medical image data, consistently yielding accurate findings throughout 5-fold cross-validation. Improving the model's usability through the creation of a graphical user interface will make it more useful in real-world DR screening programs, particularly in healthcare settings with limited resources. The results indicate that early illness detection systems can be improved in terms of efficiency, interpretability, and clinical relevance by incorporating domain-specific knowledge into machine learning models.

The next step could be to test the model on larger datasets from multiple centers to assess its performance, incorporate more diverse clinical variables into the dataset, and expand the dataset itself. The findings lay a solid groundwork for the development of innovative screening tools to aid ophthalmologists in detecting and preventing diabetic retinopathy, a leading cause of blindness.

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