Neural network-based diagnosis of type 2 diabetes using an iridology approach

Alaa Abdulkareem Ahmed[1], Mohammad Tariq Yaseen[1,2]
[1]Department of Electrical Engineering, College of Engineering, University of Mosul, Mosul, Iraq
[2]Department of Communications and Intelligent Digital Systems Engineering, College of Engineering, University of Mosul, Mosul, Iraq

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ABSTRACT

The growing global occurrence of type 2 diabetes requires the development of non-invasive and effective diagnostic methods. This work proposes a novel approach to detecting type 2 diabetes using iridology and machine learning (ML) techniques. By analyzing the iris of the right eye, a single region of interest (ROI) corresponding to the head of the pancreas is recognized for feature extraction. A total of 112 statistical and texture features are extracted using gray-level co-occurrence matrix (GLCM) and discrete wavelet transform (DWT) algorithms. Five neural network (NN) models- narrow, medium, wide, bi-layered, and tri-layered are deployed to classify healthy and diabetic people. The models are trained and assessed using a range of k-fold values (2 to 20) to optimize performance. The highest classification accuracy of 83.2% was reached using the narrow neural network (NNN) model at 7-fold cross-validation. This work exhibits the potential of iridology-based ML approaches for non-invasive diabetes diagnosis, providing a promising substitute to traditional blood tests.

Corresponding Author:

Mohammad Tariq Yaseen
Department of Communications and Intelligent Digital Systems Engineering, College of Engineering
University of Mosul
Mosul, Iraq
Email: mtyaseen@uomosul.edu.iq

1. INTRODUCTION

Diabetes is a disease that is prevalent worldwide and its prevalence continues to rise due to unhealthy lifestyle changes of unhealthy diet and lack of exercise [1], which constitutes a significant burden on health care systems and public health. Its complications pose a risk to human health as it may cause kidney failure, heart attacks, amputation of the lower limbs, retinopathy and stroke [2] Diabetes is a chronic metabolic disease that occurs as a result of decreased insulin effectiveness or the inability of the pancreas to secrete insulin properly, which poses a risk to the body's organs [1]. The hormone insulin is responsible for facilitating the absorption of glucose into the body's cells, which in turn is responsible for generating energy. The deficiency in insulin secretion in the body leads to an increase in the level of glucose in the blood as a result of these cells not absorbing glucose. This makes the human body face challenges in producing or using insulin, which leads to difficulty controlling glucose [2].

The known types of diabetes are type 1 diabetes, type 2 diabetes, and gestational diabetes. Type 2 diabetes known as non-insulin-dependent diabetes [3], is the most common in the world. It occurs as a result of weak insulin production and secretion from the beta cells of the pancreas in addition to insulin resistance in the peripheral tissues. The occurrence of type 2 is linked to a change in lifestyle from an unhealthy diet. The increased risk of developing this type increases as a result of increased intake of high-calorie foods in large quantities, lack of exercise, obesity, high blood pressure, hyperlipidemia, heart disease, aging, in addition to a family history of predisposition to diabetes as well as race (such as Asian, African, etc.) [1]. The severity of symptoms of type 2 diabetes varies depending on the condition and duration of infection, as people with early diabetes may not show obvious symptoms [3]. Sometimes, diabetics avoid using needles to check their blood sugar levels, which can lead to more complex health problems. Between 3.5% and 10% of the population suffers from anxiety about needles, known as needle phobia. Therefore, iridology is the most suitable choice for these people [4].

Iridology known as iridodiagnosis or iridiagnosis [5]. Iridology is a science that has gained wide attention recently because it is a non-invasive method of diagnosing diseases through the iris. It is a diagnostic approach to diseases considered a complementary and alternative medicine science that links iris tissue weaknesses, fractures, patterns, and colors, which provide clues to the health of human organs, by observing changes in the texture, color and structure of specific areas in the iris, which represents a reflection of the health status of an organ in the body, as signs appear in the iris tissues long before the symptoms of the disease appear in the body, which makes iris diagnosis useful for diagnosing problems in the body organs [6], [7].

Iridologists work to match the iris chart with their interpretations of diseases. The iris chart according to Bernard Jensen's classification is a division of the surface of the iris into 80 to 90 regions, each representing an organ of the body [8]. The locations of these organs in the left and right iris correspond to their locations in the body [9], as shown in Figure 1 [8]. According to the modern iris chart, diabetes can be diagnosed by three regions of interest (ROIs) in the right and left iris according to the anatomy of the pancreas, which consists of the head, body and tail. In the right iris, there is one ROI representing the head of the pancreas in the region between 7 and 8 o'clock. As for the left iris, there are two ROIs, the first representing the body of the pancreas in the region between 7 and 8 o'clock, and the second representing the tail of the pancreas in the region between 4 and 5 o'clock [7].

Therefore, research is being conducted to develop a non-invasive and immediate iris-based diagnostic system for type 2 diabetes that does not pose a risk of contamination of the examination tools and saves time and effort in visiting health centers. In addition, it is inexpensive and useful for early detection of type 2 diabetes, whose symptoms may appear late. Using artificial intelligence (AI) algorithms commonly used in medical applications, including diseases diagnosis.

There are many works that diagnose diabetes in different region of interest (ROI), and in addition to the difference in the number and type of extracted features, as well as the difference in classification methods using different types of AI algorithms, whether for deep learning (DL) or machine learning (ML), there some works that dealt with different types of neural network (NN) algorithms.

Hussein *et al.* [8] used iridology and AI technique to diagnose kidney disease using adaptive neuro-fuzzy inference system (ANFIS) which combines fuzzy system with NN. Eight features were extracted from each ROI for both the right and left eyes and these features are energy and entropy for single-level wavelet ecomposition analysis. The evaluation was conducted on two groups. The first group was 172 people suffering from chronic kidney failure and the second group was 168 people without kidney disease. The diagnostic accuracy of the first group suffering from kidney failure was 82%, while the second group without kidney disease was 93%, with 10-fold cross validation.

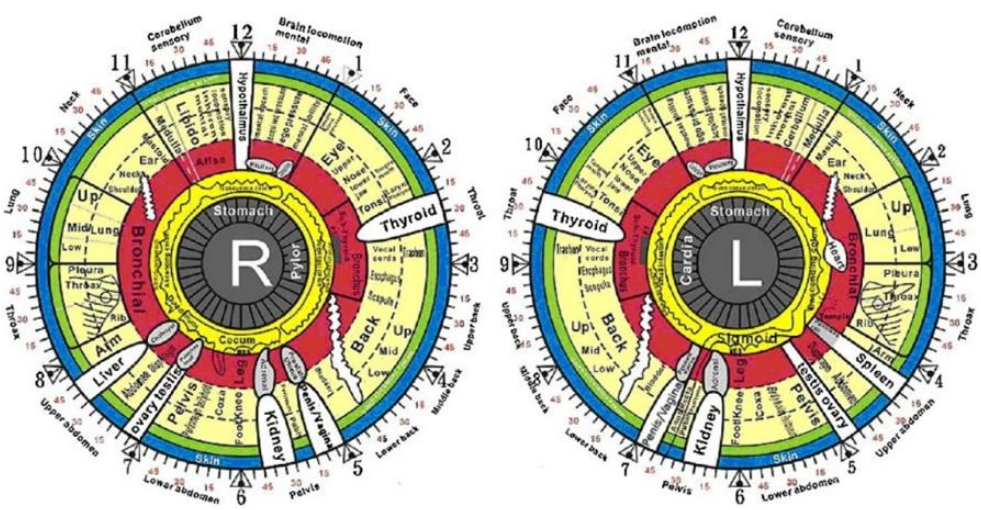


Figure 1. Iris chart for right and left irises [8]

Banzi and Xue [10] used iridology with computer vision to diagnose diabetes. Using a feed-forward backpropagation neural network for classification and training Levenberg-Marquardt backpropagation that updates the network weight and bias. Features were extracted using principal component analysis (PCA) from the ROI in the right eye located between 01:45 to 02:15 o'clock. 800 people were classified, 400 of them were healthy and 400 were diabetic. 8 people were tested and were found to have diabetes and when they were confirmed after insulin testing, they were confirmed to have type 2 diabetes.

Samant and Agarwal [11] used iridology with AI algorithms to diagnose diabetes. 3 ROI were used for pancreatic regions in the right iris between 36'-39' and in the left iris between 38'-41' and 21'-24' with 60 degrees' iris dividing. 63 features were extracted from each ROI, 7 features (Mean Intensity, Standard Deviation, Entropy, Contrast, Correlation, Energy and Homogeneity) directly from the ROI and from each of the eight - 3D discrete waveform transforms. Classification was done on 200 individuals, 100 of them were healthy and 100 were diabetic. The classification process was done using 6 types of ML algorithms, one of which is NN, which had classification accuracy was 67.29% and area under the curve (AUC) was 0.67 with 10-fold cross-validation.

Samant and Agarwal [7] used iridology to detect type 2 diabetes using 6 types of ML algorithms for classification; one of these classifiers is NN classifier. Using image data of 338 people, 158 images of healthy individuals, and 180 images of people with diabetes. Three ROI were used, two regions of the left eye between 7-8 o'clock and 4-5 o'clock and one region of the right eye between 7-8 o'clock, and 180 features were extracted, consisting of 4 first-order statistics features and 4 texture features from the gray-level co-occurrence matrix (GLCM), extracted from the 2D waveforms of the four decompositions, and for all possible combinations of these decompositions from the ROI. The highest accuracy obtained by NN classifier type only was 67.29% at 10-fold for 50 features by t-test feature selection method.

Carrera and Maya [12] used iridology to detect gastrointestinal diseases using 4 types of ML algorithms to classify 100 eye images. One of the classifiers used is NN classifier which showed 83% accuracy by extracting 6 features from the ROI. Rachman and Basari [13] they used iridology to detect high cholesterol levels using the back-propagation neural network algorithm to classify 30 eye images, 10 images of people with high cholesterol and 20 images of healthy people. Four statistical features are extracted from the GLCM of the ROI. The classification accuracy of the proposed system was 96.67%.

Yohannes *et al.* [14] used iridology to detect heart disease using back propagation neural network algorithm to classify 110 eye images, 55 images of healthy individuals and 55 images of individuals with heart disease. PCA and Canny edge are used to extract features from the ROI. The classification accuracy was 95.45% using 50 hidden neurons, 0.01 for error limit, 50 PCA and 0.3 Sigma for Canny edge detection.

Hidayanti *et al.* [15] used iridology to detect upper stomach disorders using the back-propagation neural network algorithm to classify 20 pairs of eye images, 10 pairs of healthy people and 10 pairs of eye images of people with upper stomach disorders. The system's diagnosis accuracy was 55%.

Fernandez-Grandon *et al.* [16] used iridology to detect diabetes using the extreme learning machine (ELM) algorithm, which is a single layer feedforward neural network (SLFN) learning algorithm, with Adam (adaptive moment) optimization with 256 neurons in the hidden layer, learning rate 0.01, and batch size 128 using ReLU activation function, to classify images of the right and left eyes of 124 healthy individuals and 106 individuals with diabetes. The system's diagnostic accuracy was 99.92% at 5- folds.

Özbilgin *et al.* [17] used iridology to detect coronary artery disease using 5 types of ML algorithms; among these algorithms is NN algorithm with its five types (Narrow, Medium, Wide, Bi-layered, and Tri-layered). Eye images of 198 people were used, 104 of whom were healthy and 94 of whom had coronary artery disease. 136 features were extracted from the heart ROI, which were analyzed into 4 wavelet components, from which 34 features were extracted from each component, consisting of 5 statistical features, 7 Gray-Level Run Length Matrix GLRLM features, and 22 GLCM features. The best diagnosis accuracy for the wide neural network (WNN) type only was 92% for the top 50 features selected using the Relieff features selection method.

Ahmed and Yaseen [18] proposed a non-invasive approach for diagnosing type 2 diabetes based on iridology and ML algorithms. The approach is based on extracting 10 features from a single ROI in the right iris located between the 7 and 8 o'clock positions. These features are statistical features such as entropy, GLCM, and Wavelet features. Two classification methods were presented using multiple ML algorithms and a range of cross-validation folds ranging from 2 to 20. The first method is based on a single classification stage with multiple algorithms. This method achieved the highest classification accuracy during training of 78.5% at 5-fold cross-training using support vector machine (SVM) algorithm and Binary GLM Logistic Regression algorithm. The second method aims to increase classification accuracy using two stages of classification based on different types of models selected from a set of multiple MLs models and relying on the use of PCA with a variance ratio ranging from 97% to 100%. The highest classification accuracy reached 82.2% by training predictions in the first stage from two initial classifiers -tree-coarse tree algorithm

(74.8% at 14-fold, and the PCA variance is 97%), and linear discriminant algorithm analysis (77.6% at 9-fold, and the PCA variance is 100%) - before improving the classification using binary GLM logistic regression algorithm (GLM) in the second stage.

Previous works show that the use of five neural network algorithm models and a range of k-fold cross-validation, in addition to a single ROI representing one of the pancreatic organs, has not been explicitly used in the detection of type 2 diabetes.

In this work, a type 2 diabetes detection system is proposed based on iridology, image processing, and AI using ML of the NN type. The proposed method is mainly based on the diagnosis of the right iris with one region of interest (ROI) representing the head of the pancreas. 112 statistical and texture features are extracted from this region; these features are extracted on the principle of duplicate of features from the ROI at each of the four wavelet coefficients and the four directions in the gray-level co-occurrence matrix (GLCM). And then these images are classified into normal images belonging to healthy individuals or diabetic images belonging to individuals with type 2 diabetes by proposing five NN models with a range of k-folds between 2 and 20 folds. The best classification accuracy of 83.2% was obtained by the narrow neural network (NNN) model at 7-fold cross-validation. The stages of building the proposed system will be presented in each paragraph of this research paper based on the proposed methodology, which was done using the MATLAB program.

2. RESEARCH METHOD

The proposed methodology in this work to build a type 2 diabetes detection system based on iridology includes six stages, which include a number of steps that can be observed in the block diagram in Figure 2. The first stage is the input to the system, which is a dataset of images of the right eye. The next stage is the stage of processing those images, which includes a number of steps until obtaining the rubber sheet of the iris. Then comes the stage of extracting the ROI from the iris rubber sheet, followed by the stage of extracting 112 features from this ROI, to finally classify them in the classification stage, in which five types of proposed NN models (Narrow, Medium, Wide, Bi-layered and Tri-layered) are used and then the health status of the owners of these images is predicted and diagnosed, whether they are normal and healthy or have type 2 diabetes. The most widely used software tool for iris diagnostics is MATLAB, due to its ability to process images quickly, efficiently, and accurately to detect and diagnose diseases [19]. So, all the proposed operations in this work were done using MATLAB version R2024a. These stages will be explained in the following paragraphs.

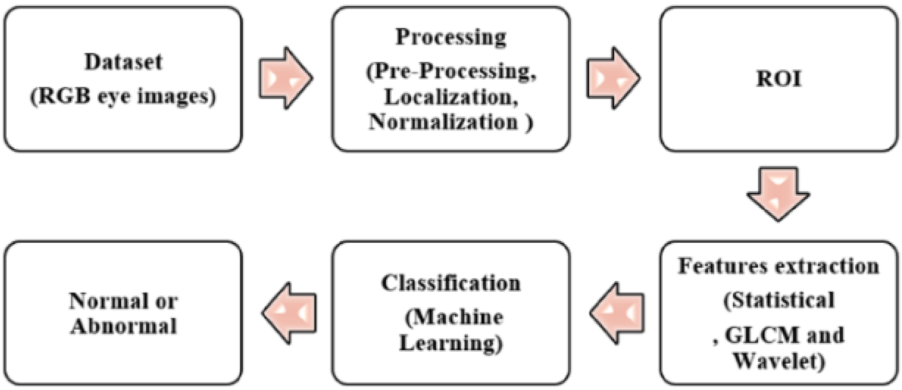


Figure 2. The block diagram of the proposed methodology

2.1. Dataset

The first stage is the image dataset. This data was obtained from a dataset freely available on the GitHub website, as referenced in reference number [20]. The data consists of 193 cases of males and females divided into 104 cases of people with controlled diabetes, i.e. normal people (mean age 57.5 ± 14.2 years), and 88 cases of people with diabetes type 2 (mean age 58.3 ± 10.8 years). In this work, a set of 150 images of the right eye, divided into 107 images (57 images of normal healthy people and 50 images of people with type 2 diabetes) for training and 43 images (24 images of normal healthy people and 19 images of people with type 2 diabetes) for testing the NN models.

2.2. Processing

The task of the processing stage is to convert the eye images entering the system into an iris representation in the form of a rubber sheet. This stage includes several steps, as shown in Figure 3. The first step is to reduce the image size in order to decrease the time required to process each image [12]. The next step is to crop the images to remove unwanted parts and reduce the complexity of the image. The next step is to convert the image from color to grayscale to reduce the simplification of the process [13]. To remove noise and smooth an eye image while preserving edges [21], the median filter is used in the step following the previous steps. The important step for iris detection is edge detection. Canny edge detection method was used in this proposed work with a threshold is 0.05 and sigma is 3. As it is a method used to detect edges in images due to its high detection accuracy and noise removal capabilities [22]. The main and important step in this stage is iris localization by detecting the outer and inner borders of the iris. The outer border of the iris can be determined by the circular edge separating the iris from the sclera, while the inner border of the iris is determined by determining the border of the pupil [8]. The final step in this stage is the normalization step, in which the circular iris is transformed into a rectangular shape to facilitate analysis by standardizing it to a fixed shape. Daugman's rubber sheet model algorithm was used, which is considered the most common method [17]. The benefit of this step is to standardize the size of the iris, which varies in size depending on the intensity of light, to match the size of the typical iris map [8]. After that, the ROI for the pancreas in the eye is determined.

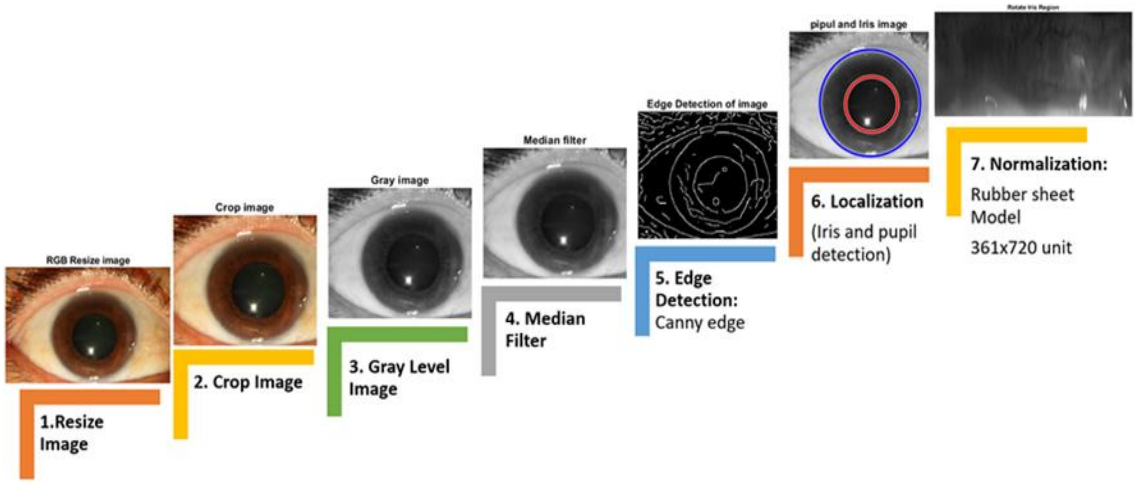


Figure 3. The processing stage

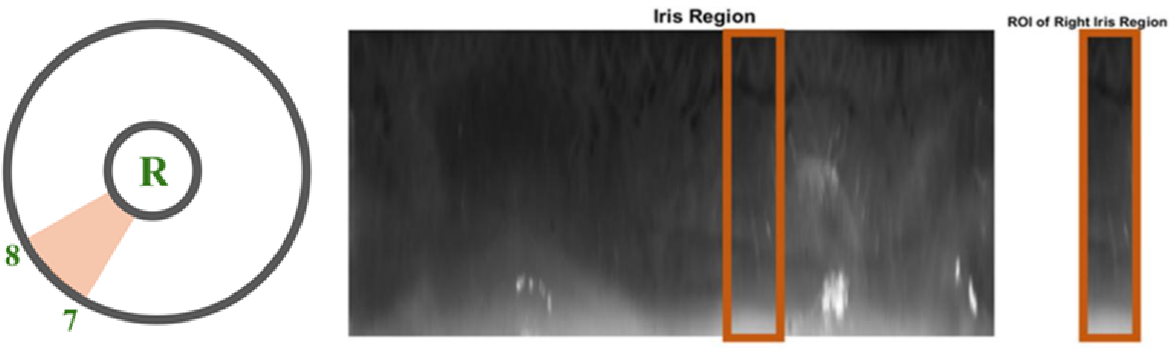
2.3. Region of interest (ROI)

The most important stage in diagnosing type 2 diabetes by iris is selecting and defining the region of interest (ROI) to extract features from it in the next stage. The ROI is a specific region in the iris that represents the pancreas to diagnose diabetes. In this proposed work, one ROI was extracted between 7 and 8 o'clock from the right eye only, which represents the head of the pancreas. Which was cropped from the iris rubber sheet with part 8 specifically out of 12 parts into which the rubber sheet was divided. Figure 4 shows the mechanisim employed to determine and Figure 4(a) extract the pancreas-related region of interest (ROI) from the right iris image. The normalized iris was divided into 12 predefined parts, and Figure 4(b) shows that the ROI relative to part 8 is chosen as the pancreas ROI for feature extraction and analysis.

2.4. Features extraction

After determining the ROI in the right iris, which represents the head of the pancreas to diagnose diabetes, a number of statistical and textural features are extracted from it. The proposed method in this work extracted 112 features from the ROI based on the principle of duplicating the features extracted from the ROI, as shown in Figure 5. Where 8 statistical features were extracted directly from the ROI, namely Mean, Standard deviation, Entropy, Skewness, kurtosis, Number of bins, Number of bins when width=10 and Percentiles of image histogram, and 4 texture features from the gray level co-occurrence matrix (GLCM), namely contrast, correlation, energy, and homogeneity, at all four directions of pixel ($\theta = 0^{\circ}, 45^{\circ}, 90^{\circ}, 135^{\circ}$) at distance (d=1), so that the total becomes 16 texture features. In addition, 2-D discrete wavelet transform

(DWT) are used to extract four coefficients from the first level, namely Approximation coefficient (cA), horizontal coefficient (cH), vertical coefficient (cV) and diagonal coefficient (cD) and from each of these four coefficients, 6 statistical features namely mean, standard deviation, entropy, Skewness, kurtosis, percentiles of image histogram and 4 features from the GLCM are extracted, namely contrast, correlation, energy and homogeneity and at all four directions, so that the total becomes 16 texture features. Thus, the total number of features extracted from the wavelets becomes 88 statistical and textural features. The following is a description of the GLCM and the DWT.



(a) (b)

Figure 4. Determination and extraction of the pancreas related ROI from the right iris image (a) pancreas ROI identified in the right iris and (b) extracted ROI from part 8 of the normalized iris that is divided into 12 parts

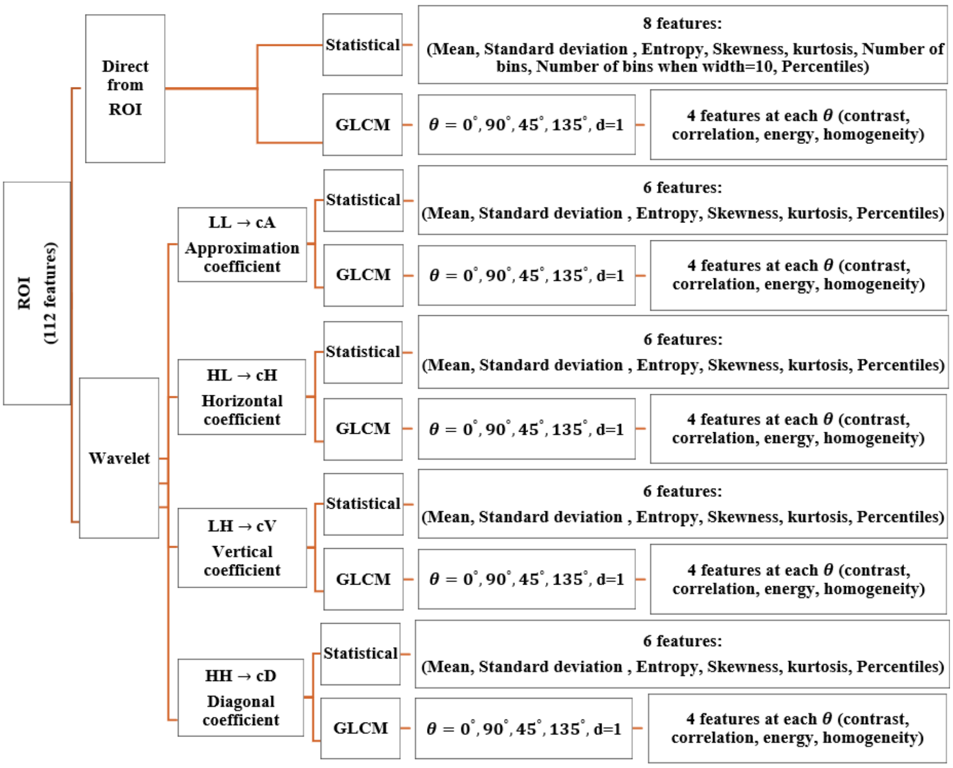


Figure 5. The diagram of extracted features from ROI

2.4.1. Gray-level co-occurrence matrix (GLCM) features

It is a second-order statistical method that calculates the frequency of pairs of pixels that have the same gray level [13]. It is also a spatial gray-level dependence matrix which characterizes, quantifies, and explores the distribution of gray-level intensities. Information about the intensity of the gray level is provided only by statistical features and GLCM-based features extracted from the ROI were extracted to determine the relationship between the inter-pixel. If I (x,y) is the gray-level image and has G gray levels then G×G is the number of possible pairs in the gray level, the frequency of these pairs is calculated and stored in the form of a GLCM Matrix G×G [6].

2.4.2. 2-D discrete wavelet transform (DWT)

The use of DWT in non-stationary image analysis is highly advantageous [11]. Its utility is to perform the extraction of important features from the iris image, where it analyzes the original iris image of size N×N into 4 subsamples of images each of size N/2×N/2 which are approximation (LL), horizontal (HL), vertical (LH), and diagonal (HH) [23].

2.5. Classification

After the feature extraction stage from the ROI, the most important stage begins with the classification stage. The most widely used AI techniques in classification and prediction, include ML techniques that mainly use artificial neural networks (ANN) to try to simulate how living organisms learn.

ML techniques are applied in various medical applications, which involve a number of techniques and approaches [24]. These techniques help analyze and process data, providing solutions with high accuracy and time. These two criteria are the most important criteria in diagnosing diseases that researchers are trying to improve [25]. The method of diagnosing diabetes using iris analysis and ML models has significant potential for reducing patient discomfort during diagnosis [18].

NN are a subfield of ML and form the foundation of deep learning (DL). Their aim is to produce AI by designing computer systems that simulate the human nervous system. ML can perform tasks similar to those performed by humans using NNs whose computational structure simulates human neurons [26]. In this proposed work, five NN models were used, as described:

2.5.1. Narrow neural network (NNN) model

It has a single fully connected hidden layer [27], [28]. Each layer consists of a small number of neurons. One of the problems with this model is that it may limit its ability to capture complex relationships, but its advantages are that it provides a lower probability of overfitting and faster training processes [29].

2.5.2. Medium neural network (MNN) model

It has single fully connected hidden layer [27], [28]. Each layer consists of a moderate number of neurons. The benefits of this model architecture are the balance between training dynamics and model complexity [29].

2.5.3. Wide neural network (WNN) model

It has a single fully connected hidden layer [27], [28]. Each layer consists of a larger number of neurons. Its structure is characterized by identifying complex patterns. Its disadvantages include challenges when overfitting occurs [29].

2.5.4. Bi-layered neural network (BNN) model

It has two fully connected hidden layers [27], [28]. The structure of this model consists of two basic layers, which are the hidden layer and the output layer. Its structure is characterized by simplicity of interpretation [29].

2.5.5. Tri-layered neural network (TNN) model

It has three fully connected hidden layers [27], [28]. The structure of this model consists of three layers: the input layer, the concealment layer, and the output layer. The benefits of this model are to enhance the network's ability to learn more comprehensive representations of the input data [29].

To evaluate the performance of ML models, the cross-validation technique is used. Cross-validation is the process of dividing the training data into k-folds or subsets to train the model and evaluate it k times. Each time, one-fold from the set of k-folds is used for testing and the remaining folds are used for training. This process is repeated k times, each time using a different fold in the test to ensure a more robust evaluation of the model, and the final accuracy is the average of the defective accuracy at each iteration [30].

In this work, the range of k-fold from 2 to 20 folds was used to obtain the most appropriate fold with the best performance accuracy for the five classifier models. Supervised ML requires feature data to be a labeled to train algorithms with to complete the classification process and predict the diagnosis of the disease later. In this work, the label (0) is for normal and the label (1) is for diabetic patients.

The performance results of the ML algorithms for classification are evaluated by 6 metrics, namely accuracy, specificity, sensitivity, precision, F1-score and AUC, as shown in Table 1, based on the validation matrix values, namely false positive (FP), true positive (TP), false negative (FN), and true negative (TN) [31], as shown in Figure 6(a). In this work, the NN models available in the Statistics and Machine Learning Toolbox 24.1 in classification learner Application in the MATLAB version R2024, were used.

Table 1. Machine learning classification performance metrics

Metrics	Definition	Formula
Accuracy	It is the ratio of the correctly predicted samples (true positives and true negatives) to the total number of predicted samples [32].	$\frac{TP+TN}{TP+FP+TN+FN} \times 100\%$, [2]
Specificity or true negative rate (TNR)	the number of accurate negative predictions to the total number of negative predictions [6].	$\frac{TN}{TN+FP} \times 100\%$, [2]
Sensitivity or true positive rate (TPR) [6]	Is the number of samples from a certain class that are correctly classified [6].	$\frac{TP}{TP+FN} \times 100\%$, [2]
Precision	It is the number of times the classifier predicts correctly where it gives detailed characteristics of the classifier [6].	$\frac{TP}{TP+FP} \times 100\%$, [2]
False positive rate (FPR)	It is the probability of an error, i.e. when there is a negative value it is reported as a positive value [2]. or is the number of samples that are incorrectly classified [6].	$\frac{FP}{FP+TN} \times 100\%$, [2]
F1-score	Describes the relationship between the accuracy of the classifier and its sensitivity [6].	$\frac{2TP}{2TP+FN+FP} \times 100\%$, [6]
ROC	Receiver operating characteristic curve [31] is between the false positive rate and the true positive rate for the classifiers [11].	-
AUC	Area under the curve (ROC) represents the ability to access the entire operating range of the classifier [11].	$\int_0^1 \frac{TP}{TP+FN}\, d\, \frac{FP}{FP+TN}$, [33]

3. RESULTS AND DISCUSSION

The results of the classification accuracy of the five NN models and their relationship to the change in the proposed k-fold range are presented in this section. It was noticed in Table 2 that the training results for each algorithm model yielde slighty different classification accuracies at each k-fold. Figure 6 the highest accuracy obtained from the NN models was achieved by the NNN model, reaching 83.2% at 7-fold. It can be noticed in the Validation Confusion Matrix in Figure 6(b) for NNN model at the highest accuracy that the number of incorrectly detected images is 18 images out of 107 and the most incorrectly detected are the images of healthy people compared to those with diabetes. As for Figure 6(c), it illustrates the ROC curve, showing the operating areas for both normal (label 0) and Diabetes (label 1), with an AUC of 0.8674.

As for testing the NNN model using 43 images, it was found that the accuracy was 74.41%, where it was noticed that the total accuracy of training with testing for all images was 80.66%, as indicated by the other metrics for each case in Table 3. To compare the current work with previous studies on diabetes diagnosis using NN algorithm models, Table 4 presents a comparison of both the methodology employed and the classification results.

Table 2. The accuracy results of NN models at 107 image (57-Normal, 50-Diabetic), 112 features, and with k-fold

k-fold	NNN accuracy %	MNN accuracy %	WNN accuracy %	BNN accuracy %	TNN accuracy %
2	64.5%	68.2%	68.2%	64.5%	66.4%
3	75.7%	73.8%	73.8%	72%	74.8%
4	74.8%	72%	74.8%	76.6%	72.9%
5	73.8%	74.8%	75.7%	72%	71%
6	77.6%	75.7%	77.6%	77.6%	74.8%
7	83.2%	76.6%	77.6%	78.5%	72.9%
8	78.5%	76.6%	77.6%	72.9%	76.6%
9	76.6%	72.9%	75.7%	74.8%	75.7%
10	79.4%	72.9%	73.8%	73.8%	73.8%
11	72.9%	73.8%	69.2%	72.9%	70.1%
12	79.4%	75.7%	74.8%	72%	73.8%
13	74.8%	77.6%	78.5%	75.7%	75.7%
14	74.8%	79.4%	74.8%	72%	74.8%
15	67.3%	73.8%	72.9%	73.8%	70.1%
16	75.7%	72.9%	74.8%	70.1%	73.8%
17	72.9%	72.9%	72.9%	72.9%	79.4%
18	76.6%	77.6%	74.8%	78.5%	77.6%
19	72%	72.9%	77.6%	76.6%	74.8%
20	76.6%	74.8%	73.8%	78.5%	73.8%

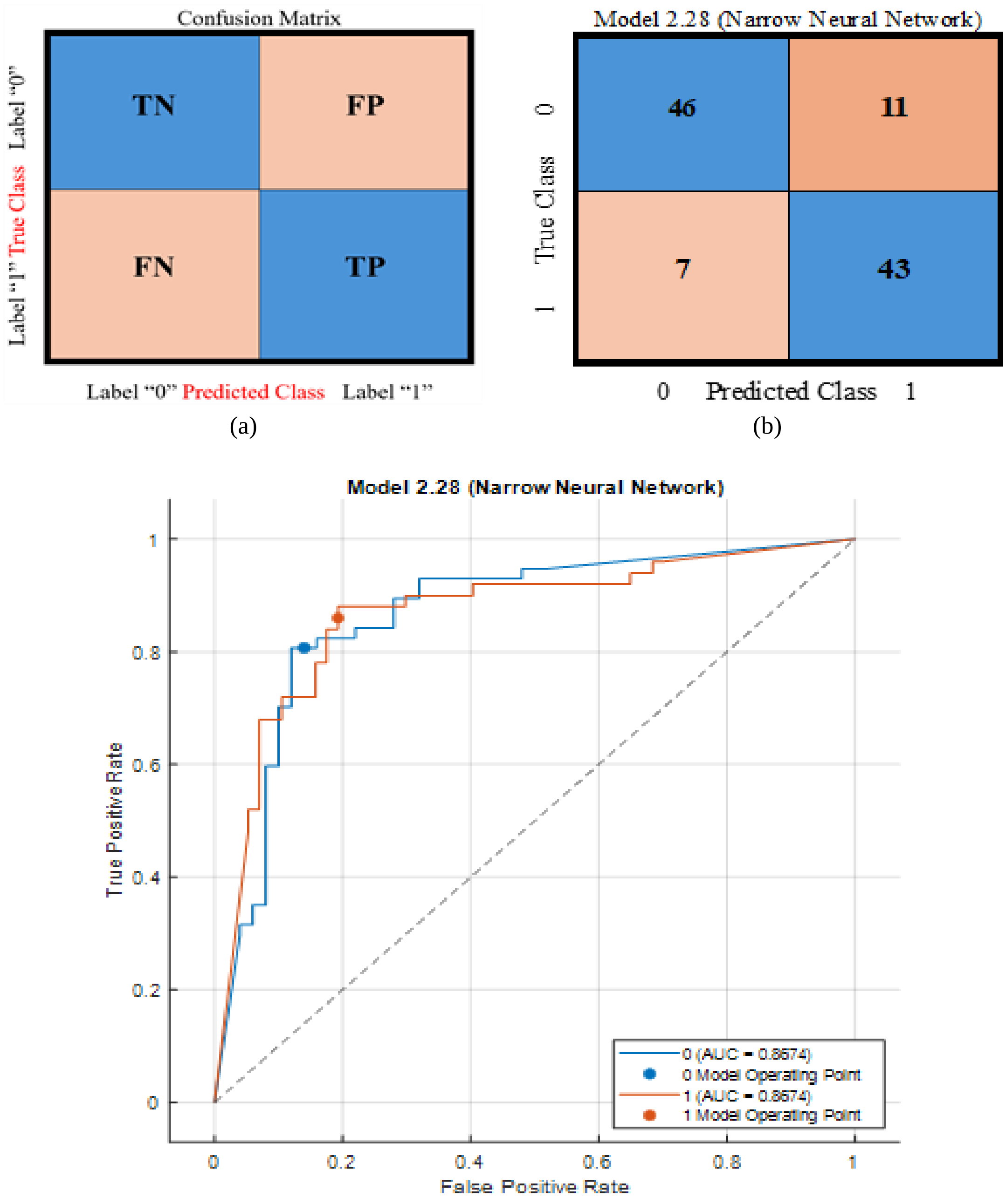


Figure 6. Performance evaluation of the NNN model that accomplish training accuracy of 83.2% using 7-fold cross validation (a) general confusion matrix performance parameters, (b) validation confusion matrix parameters, and (c) the receiver operating characteristic (ROC) curve with the corresponding AUC

Table 3. All metrics results for the highest accuracy of NNN models at 7-fold

Result type	Image no	False predicted	TN	FP	FN	TP	Accuracy	Specificity	Sensitivity	Precision	F1-score	AUC
Training	107	18	46	11	7	43	83.2%	80.7%	86%	79.62%	82.69%	0.8674
Testing	43	11	15	9	2	17	74.41%	62.5%	89.47%	65.38%	75.55%	~0.8947
Training +Testing	150	29	61	20	9	60	80.66%	75.3%	86.95%	75%	80.53%	~0.8695

Table 4. Comparison between current and previous work on diabetes diagnosis based on NN models

Year and Reference	Right iris	Left iris	ROI in right iris (7-8)	ROI in left iris (4-5)	ROI in left iris (7-8)	Sum of the three ROI in both irises	PCA %	Feature selection	Features number and types	k-fold	NN type	Accuracy %
2015 [10]	✓	-	-	-	-	-	✓	-	adaptive histogram equalization	-	feed-forward back-propagation NN	-
2017 [11]	✓	-	-	-	-	-	-	-	63 features statistical and wavelet	10	back-propagation NN	67.29%
2017 [7]	-	-	-	-	-	✓	-	t-test	50 features statistical, GLCM and wavelet	10	NN	67.29%
2023 [16]	✓	✓	-	-	-	-	✓	chi-square	-	5	ELM ((SLFN)) with Adam	99.92%
This work	-	-	✓	-	-	-	-	-	112 features Statistical, GLCM and wavelet	7	NNN	83.2%

4. CONCLUSION

This work exhibits the feasibility of detecting type 2 diabetes via iridology using ML techniques. By extracting statistical and texture features from the right iris and training NN models, the classification accuracy is 83.2% using the NNN model at 7-fold cross-validation. The results show that iridology combined with AI can be an effective and non-invasive diagnostic tool. Future research should concentrate on enhancing model accuracy through advanced feature selection algorithms, deep learning approaches, and more diverse datasets. Integrating this method into clinical practice could improve early diabetes detection, reducing dependence on traditional blood tests.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Alaa Abdulkareem Ahmed		✓	✓		✓	✓	✓	✓	✓	✓	✓			
Mohammad Tariq Yaseen	✓	✓		✓		✓			✓			✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

No conflict of interest.

DATA AVAILABILITY

The images dataset in this study is openly available in GitHub site that in reference number [20].

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BIOGRAPHIES OF AUTHORS

Alaa Abdulkareem Ahmed received her B.Sc. in Mechatronics Engineering. She received her High Diploma in Electrical Engineering/Electronics and Communication Engineering. She is currently M.Sc. Student in Electrical Engineering, University of Mosul, Mosul, Iraq. Her research interests are in artificial intelligence, machine learning, deep learning, electronics, and microelectronics. She can be contacted at email: alaa.22enp39@student.uomosul.edu.iq.

Mohammad Tariq Yaseen received his B.Sc. and M.Sc. in Electronics & Communication Engineering. He received his Ph.D. in Nanotechnology Engineering. He is currently an Asst. Prof. in the Department of Electrical Engineering/Department of Communications and Intelligent Digital Systems Engineering at University of Mosul, Mosul, Iraq. His research interests include nano/microelectronics, smart electronics systems, machine learning. He can be contacted at email: mtyaseen@uomosul.edu.iq.