Vol. 3 No. 2 (2025)

Spectrum of Engineering Sciences

Online ISSN
3007-3138

Print ISSN
3007-312X

An Optimal Diabetic Retinopathy Detection and Classification Approach based on integrated Hybrid Convolutional Neural Networks (CNNs)

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Abstract

Diabetic Retinopathy is a retina disease caused by diabetes mellitus and it is the leading cause of blindness globally. Early detection and treatment are necessary to delay or avoid vision deterioration and vision loss. This research aims to examine the significant importance

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Online ISSN
3007-3138
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of Deep Learning (DL) that shows substantial gain in artificial intelligence applications, particularly in the medical of things (MoTs) and guarantees impactful results in the diagnosis, classification, prediction and categorization of numerous stages of diabetes using applications based on machine Learning (ML). In this study, we have proposed an ML-based diabetic retinopathy mechanism to classify diabetic issues using a Multi-Layer Neural Network (MLNN). We have used the PIMA Diabetes Dataset (PDD) to test and train the proposed ML model. To increase the accuracy of the (PDD) dataset we looked into different activation capacities, learning algorithms, precision and strategies for dealing with lost information and compared the proposed DL model with conventional machine learning approaches, specifically Random Forest (RF) and Naive Bayes (NB), to evaluate the pattern for the results. Our MLNN-based ML model outperformed the other classifiers with a significant increase of 2.27% in classification precision accuracy.

Keywords: Artificial intelligence (AI), neural networks, Multilayer feed-forward neural Network(MLNN), Naive Bayes (NB), Random Forest (RF), pima diabetes dataset (PDD)

Introduction

Diabetes Mellitus is a serious public health problem, affecting 463 million people worldwide and this number is projected to rise to 700 million by 2045. Expanded blood glucose levels have the potential to adversely affect essential organs, including the kidneys and the heart. Diabetes diagnosis is one of these complicated obsessive disarrangements that regularly call for the collaboration of numerous doctors with changing specialties [1]. Since neurotic testing has verifiably been utilized to analyze diabetes, deciding whether an individual has a disorder may be a complex and challenging preparation requiring particular knowledge and abilities. The massive

Spectrum of Engineering Sciences
SPECTRUM OF ENGINEERING SCIENCES
Online ISSN
3007-3138
Print ISSN
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sum of stimulating information, in combination with the small test sizes for obsessive cases, emphasizes how deep learning strategies are precisely classifying and recognizing diabetic issues [2, 3]. Researchers in [4] developed an estimating strategy based on a Multi-Layer Neural Network (MLNN) to classify diabetes. The PID dataset presents noteworthy trouble within the shape of missing values, which has driven us to examine a few techniques to deal with this issue. In neural networks, the determination of the actuation work is additionally imperative [5]. Deep learning (DL) a subset of artificial intelligence (AI) and ML has significant importance in MoTs. Deep Learning (DL) can not only optimize diagnostic issues but also classify medical issues that require labor-intensive strategies using robots that doctors regularly embrace physically by giving reliable and effective results in less time [6, 7]. This work explores deep learning (DL) for the categorization of diabetes as a specific therapeutic condition by utilizing the PID [8, 9]. An input layer one or more hidden layers and an output layer comprise the MLNN, a complete neural network design. MLNN structure that is widely used in MoTs. Because they function internally and are not readily accessible from the outside, the layers are considered the I/O layers as hidden layers. After accepting input signals from earlier handling units, these covered-up layers handle them and send the results to the covered-up layers that come after. A weight coefficient, which signifies the centrality of the connected interior of the neural arrangement, characterizes the association between two neurons [10, 11].

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3007-3138
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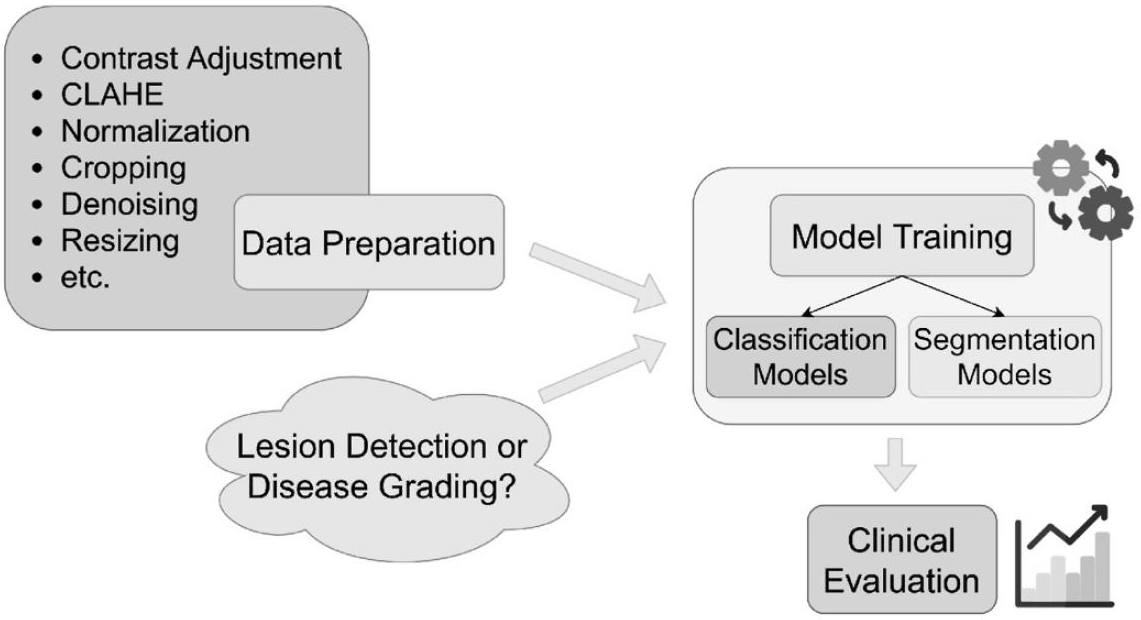

Figure 1: Generalize analysis of DR Images [12]

Recent studies on Diabetic Retinopathy (DR) detection have introduced various methodologies aiming for accurate and automated diagnostic solutions. Investigated the fundamental thoughts of the backpropagation strategy [13]. Artificial neural systems created less-than-ideal results because of their destitute preparation speeds. The backpropagation calculation works using two fundamental stages: the forward proliferation stage and the weight alteration stage. Upon getting an input, the covered-up layers of a neural arrangement are regularly initialized with irregular weight values [14]. The backpropagation strategy was designed to address this issue. The forward engendering and weight alteration stages are the two essential stages of the backpropagation algorithm's operation. The covered-up layers of a neural arrangement are ordinarily initialized with arbitrary weight values upon getting an input In the meantime, each neuron's output is controlled by its actuation work [15, 16].

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Related Work

The author in [17] stated that each layer in Deep Learning (DL) employs characteristics extracted from the yield of the recent layer in a progressive extraction procedure. This various-leveled strategy totals and recombines characteristics from past levels to empower more deep layers to distinguish perplexing designs inside the information. DL algorithms can handle massive datasets with viability, which is much appreciated for this characteristic. MCC is widely used for accuracy calculation rates while significant advancements have been made in IOMTs [18].

$$MCC = \frac{TP * TN - FP * FN)}{\sqrt{((TP + FP) * (TP + FN) * (TN + FP) * (TN + FN))}} \quad \text{Eq (1)}$$

DL algorithms are excellent at identifying patterns and structures in datasets that may lack clear categories or organization [19, 20]. There are two distinct forms of activation functions the Scaled Exponential Linear Unit (SELU) and the Exponential Linear Unit (ELU)—which will be discussed in the next sections.

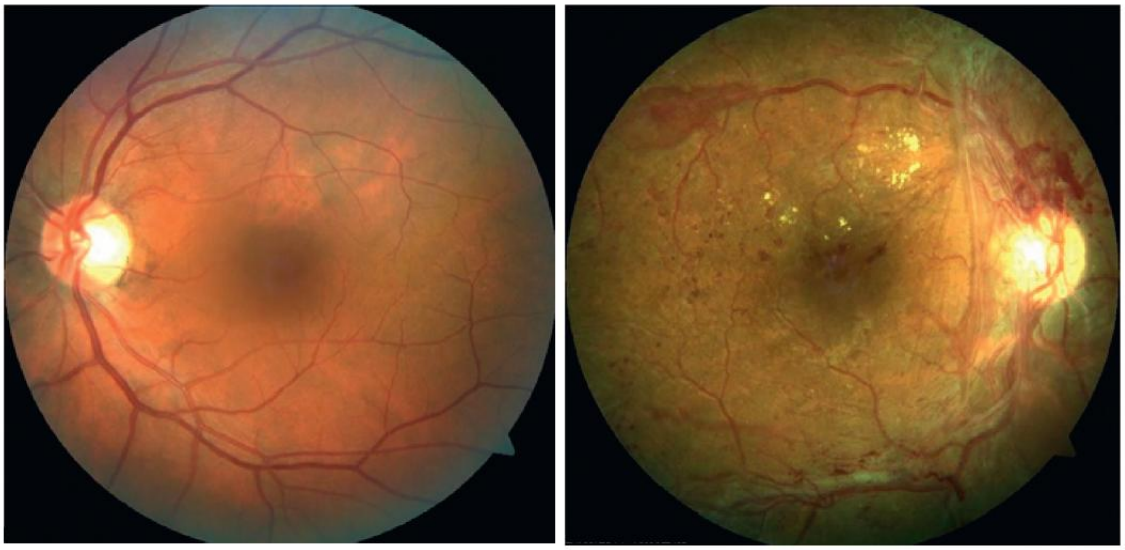

Figure 2: (a) Retinography Patient without DR (b) Retinography Patient with DR [21]

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ELU – E- Linear Unit with 0 < α is

$$f(x) = \begin{cases} \alpha(exp\,(x) - 1) & for\, x < 0 \\ x\ for & x \geq 0 \end{cases} \quad \text{Eq (2)}$$

In [22, 23] the author evaluates a hyperparameter in the ELU controls the saturation level of negative inputs. In deep neural networks, ELU speeds up learning more quickly than other activation functions. Unlike some activation functions, ELU mitigates the vanishing gradient problem by incorporating negative values, which facilitate the adjustment of mean activation towards zero, a feature also observed in batch normalization. Importantly, ELU achieves this with reduced computational overhead [24, 25]. SELU allows for generating mappings consistent with the properties of Self-Normalizing Neural Networks (SNN). Neuron activations in SNNs tend to converge to zero mean and unit variance as shown in Eq 2. This characteristic enables reliable propagation across multiple layers, even in the face of noise and disturbances. As a result, SNNs make it easier to train deep neural networks with several layers by leveraging this effective regularization strategy, which improves learning robustness [26].

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3007-3138
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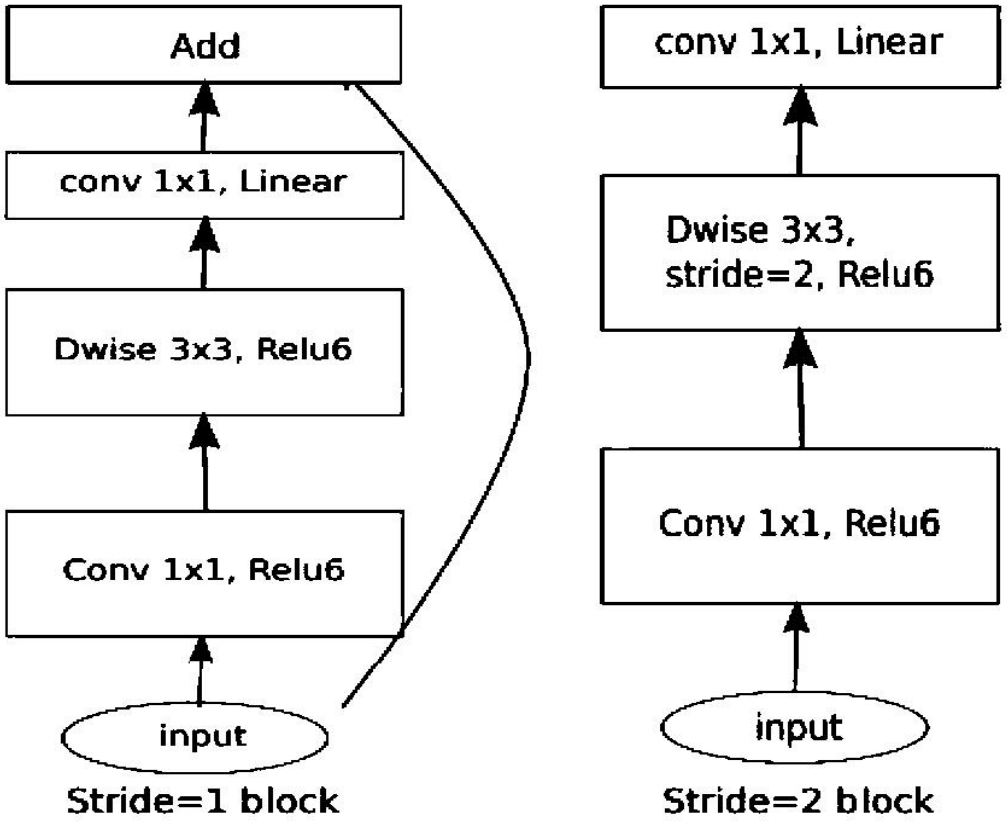

Figure 3: MobileNetV2 Architecture [27]

Two classifiers were displayed within the study, especially Multi-Layer Perceptron (MLP) and Back Vector Machine (SVM), which utilize thirteen restorative components to analyze diabetic issues. MLP classifier showed a 98% accuracy rate, whereas the SVM only managed a slightly lower 96% accuracy. To classify diabetes utilizing the General Regression Neural Network (GRNN) based on nonparametric regression. In preparation, the demonstration appeared to have an accuracy of 82.99%, whereas in testing, it seemed to have an accuracy of 80.21% [28]. The author introduces the Probabilistic Neural Network (PNN) for diabetes prediction. Single covered-up layer. During the preparation, the model gave a max accuracy of 81.49%, whereas, while testing, it was 89.56%. In [29]

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author introduced an open-source dataset named Diabetes Prediction using machine learning through a Naive Bayes radial-based Artificial Neural Network (RBF) and J48 algorithms for diabetes prediction. The classifiers Naive Bayes, RBF, and J48 have detailed accuracies of 76.95%, 74.34%, and 76.5%, separately.

Methods and Materials

The methodology section outlines the process and techniques used to conduct the research and achieve the results discussed in this study. The experiments were conducted using the proposed model by dividing the data into two sections 70% data for training and 30% for testing sets, the dataset was rerun 100 times using various random seeds. The average performance over these iterations reliably assessed the model's stability and efficacy. The main steps include data collection, preprocessing, model selection, and evaluation. Below is a detailed explanation of each step:

Machine Learning-Based Proposed Framework for DR Classification

The proposed model for diabetes classification using deep learning techniques involves the following architecture and training process:

- Input Layer: 10 neurons for eight features plus additional neurons.
- Hidden Layers: Three hidden layers with 60 neurons each, employing ELU and SELU activation functions.
- Output Layer: Single neuron for binary classification.
- Training Algorithm: Backpropagation with forward and backward propagation phases.
- Evaluation: Monte Carlo Cross-Validation over 200 iterations.

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Color Feature Extraction

Color is the significant visual feature extracted from the image. The color feature classification of extraction is performed in the fourth hidden layer by transforming the given RGB color mentioned below:

$$\delta_h = 60^{\circ}\begin{cases} 0 + \frac{(\beta_g - \beta_b)}{(m_x - m_n)}, ifm_x = \beta_r \\ 2 + \frac{(\beta_b - \beta_r)}{(m_x - m_n)}, ifm_x = \beta_g \\ 4 + \frac{(\beta_r - \beta_g)}{(m_x - m_n)}, ifm_x = \beta_b \end{cases} \quad \text{Eq (4)}$$

$$\delta_s = \left(\frac{m_x - m_n}{m_n}\right) \quad \text{Eq (5)}$$

$$\delta_v = m_x(\beta_r, \beta_g \beta_b,),\ \delta_{sv} = m_n(\beta_r, \beta_g \beta_b,) \quad \text{Eq (6)}$$

From the above Equations (4) (5) and (6),$\boldsymbol{m_x}$ represents the maximum pixel while $\boldsymbol{m_n}$ Shows the minimum pixel. The color features are extracted at the hidden layer as shown below in Eq 7.

$$R(t) = \sum_{i=1}^{n} FI_i(t) * \tau_{ih} + [\tau_h * r_{i-1}] \quad \text{Eq (7)}$$

$$Y(t) = \omega[\tau_{ho} * h(t)] \quad \text{Eq (8)}$$

$$\omega = E_f * \frac{1}{1 + e^{-\theta t_f}} \quad \text{Eq (9)}$$

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$$\omega = \begin{Bmatrix} 0; & normal \\ 0 < \omega < 0.25; & Mild \\ 0.25 < \omega, 05; & Moderate \\ 0.5 < \omega < 0.75; & Severe \\ 0.75 < \omega < 1; & Proliferative \end{Bmatrix}$$

Eq (10)

Figure 4 elaborates the flow chart of the proposed MLNN architecture that effectively balances the depth and width by enabling the model to capture complex patterns in the dataset and achieve high classification accuracy.

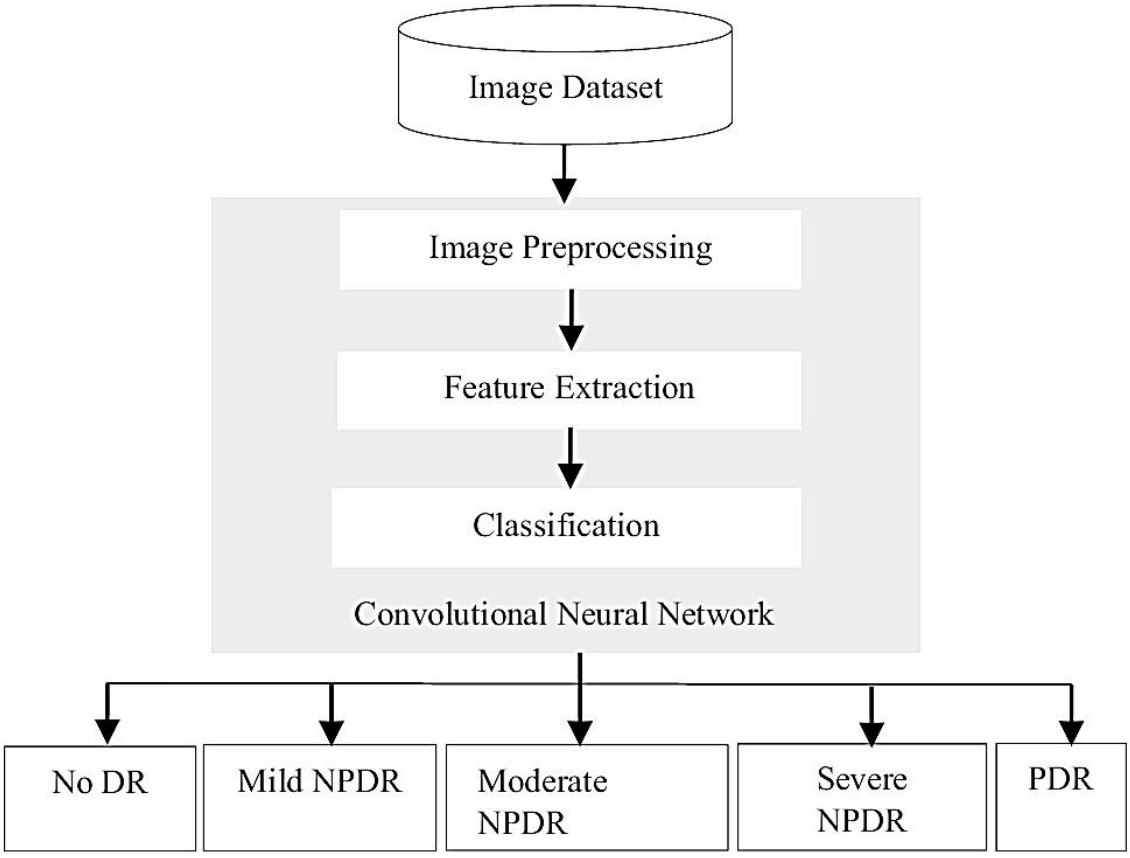

Figure 4: Structure of Proposed ML Framework

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$$z_j = \sum_{i=1}^{n} w_{ij} x_i + b_j \quad \text{Eq (11)}$$

$$a^{(l)} = \sigma\left(z^{(l)}\right) \quad \text{Eq (12)}$$

Data Collection and Model Selection

The data used in this study is the PIMA Diabetes dataset sourced from the Kaggle diabetes prediction repository. PIMA dataset is a free open-source dataset under Universal Common licenses donated for researchers working im the field [30]. Five pertinent features from the dataset including 268 cases of diabetes and 500 cases of non-diabetic were considered.

The below figure 5 illustrates the detection and classification model based on n no of samples by considering the feature matrix (x) and predicting both the diabetic and non-diabetic cases using ML/DL-based architecture. For diabetes classification, we have selected a Multi-Layer Neural Network (MLNN) as our primary model. The architecture of the MLNN includes: I/Layer: 10 neurons corresponding to the eight features of the dataset plus two additional neurons for better handling of non-linearity.Hidden Layers: Three hidden layers with 50 neurons each.O/Layer: Neuron for binary classification (diabetic or non-diabetic). The MLNN model was trained using the backpropagation algorithm, which operates in two phases: Forward Propagation: Initial weights are assigned randomly, and the network output is computed.

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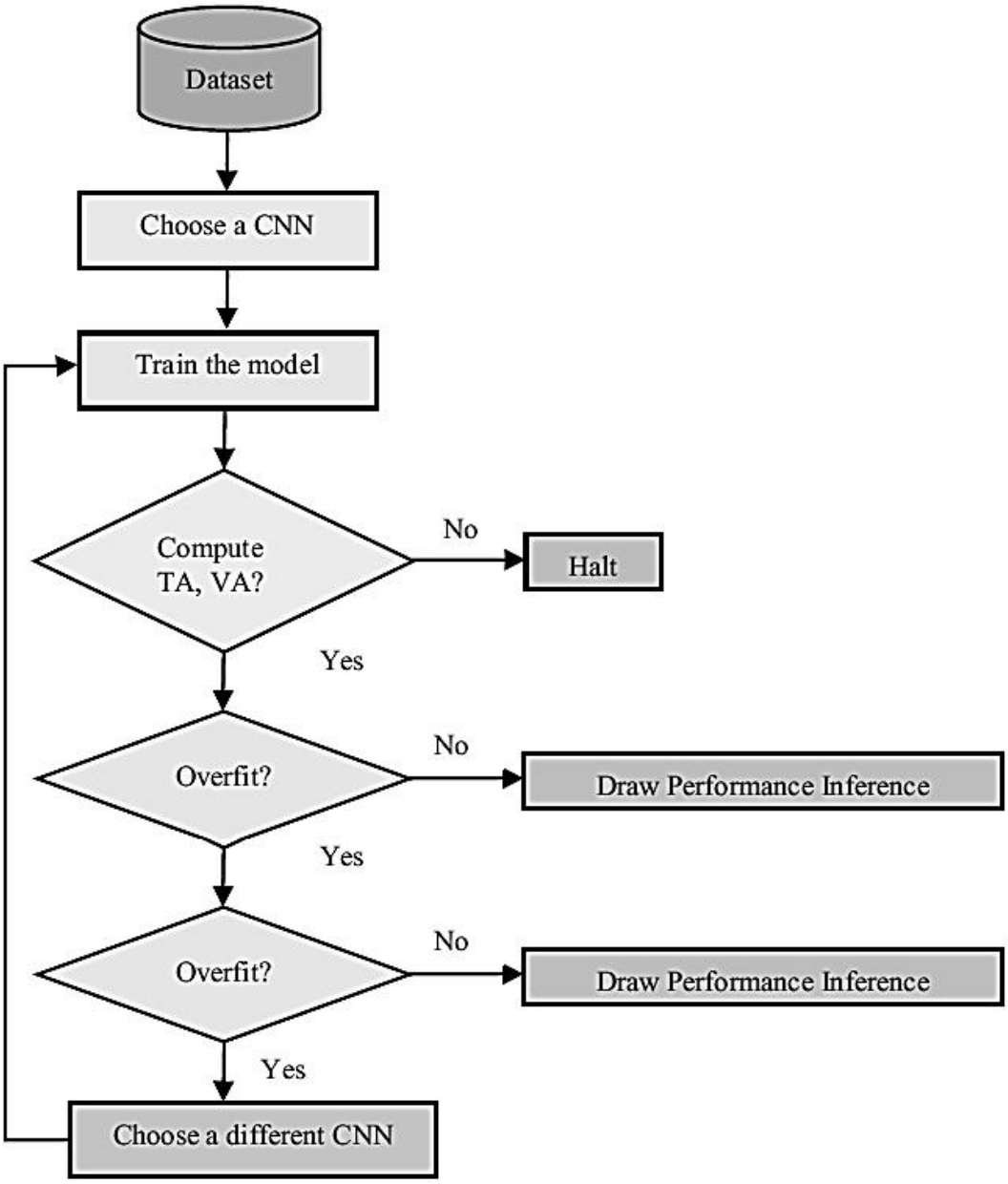

Figure 5: Proposed Flow Chart

The computed resuls are compared using a loss function to calculate the error, which is then propagated backward to adjust the weights iteratively until the error rate reaches an acceptable level.

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$$\boldsymbol{\delta^{(l)}} = \frac{\partial L}{\partial z^{(l)}} = \boldsymbol{\delta^{(l+1)}} \cdot \frac{\partial z^{(l+1)}}{\partial a^{(l)}} \cdot \frac{\partial a^{(l)}}{\partial z^{(l)}} \quad \text{Eq (13)}$$

$$\boldsymbol{\delta^{(0)}} = \frac{\partial L}{\partial z^{(0)}} = \boldsymbol{\delta^{(0+1)}} \cdot \frac{\partial z^{(0+1)}}{\partial a^{(0)}} \cdot \frac{\partial a^{(0)}}{\partial z^{(0)}} \quad \text{Eq (14)}$$

$$\boldsymbol{\delta^{(1)}} = \frac{\partial L}{\partial z^{(1)}} = \boldsymbol{\delta^{(1+1)}} \cdot \frac{\partial z^{(1+1)}}{\partial a^{(1)}} \cdot \frac{\partial a^{(1)}}{\partial z^{(1)}} \quad \text{Eq (15)}$$

$$\boldsymbol{\delta^{(2)}} = \frac{\partial L}{\partial z^{(2)}} = \boldsymbol{\delta^{(2+1)}} \cdot \frac{\partial z^{(2+1)}}{\partial a^{(2)}} \cdot \frac{\partial a^{(2)}}{\partial z^{(2)}} \quad \text{Eq (16)}$$

$$\boldsymbol{\delta^{(3)}} = \frac{\partial L}{\partial z^{(3)}} = \boldsymbol{\delta^{(3+1)}} \cdot \frac{\partial z^{(3+1)}}{\partial a^{(3)}} \cdot \frac{\partial a^{(3)}}{\partial z^{(3)}} \quad \text{Eq (17)}$$

$$\boldsymbol{\delta^{(n)}} = \frac{\partial L}{\partial z^{(n)}} = \boldsymbol{\delta^{(n+1)}} \cdot \frac{\partial z^{(n+1)}}{\partial a^{(n)}} \cdot \frac{\partial a^{(n)}}{\partial z^{(n)}} \quad \text{Eq (18)}$$

To evaluate the performance of our MLNN model, we employed the following metrics:

- Accuracy (ratios): Predicted instances compared to the total instances.
- Recall (ratios): Predicted positives to actual positives.
- Specificity (ratios): Predicted negative observations to the negatives.
- Precision (ratios): Predicted positive to T-predicted positives.

f (x) is *β*-Lipschitz continuous if there exists β≥ 0 such that for all x1,x2 ∈*Rd*

$$|f(x1) - f(x2)| \leq \beta \| x1 - x2 \| \quad \text{Eq (19)}$$

f (x) is L-smooth if f (x) has an L-Lipschitz continuous gradient, i.e., for all x1,x2 ∈ *Rd*,

$$\| \nabla f(x1) - \nabla f(x2) \| \leq L \| x1 - x2 \| \quad \text{Eq (20)}$$

$$f(x1) \geq f(x2) + (x1 - x2)T \nabla f(x2) \quad \text{Eq (21)}$$

(CF): *f (x)* is coercive if lim ‖ x ‖ →∞ f (x) → ∞. The variance of each stochastic gradient ∇fi(x) is bounded if there exists σ∈ R, such that $\text{MinMaxScaler}(\text{feature range} = (\mathbf{0}; \mathbf{1}); \text{copy} = \text{True})$. The change scales all highlight to an extent.

$$X_{std} = \frac{X - X \cdot min}{X \cdot max - X \cdot min} \quad \text{Eq (22)}$$

$$X_{scaled} = X.std * max - min + min \quad \text{Eq (23)}$$

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Analysis of Findings

This section elaborates the results produced after measuring testing and training accuracy using the proposed Multi-Layer Neural Network we utilize for diabetes detection and classification. Training Accuracy (TA) is initially evaluated with the previously implemented techniques MLNN based classification and its performance was evaluated against several machine learning classifiers. Moreover, the results were compared with a few strategies for handling lost values. In conclusion, the classification precision of the MLNN demonstration was scrutinized in terms of distinctive enactment capacities.

Table 1: Comparison of Various Classification Algorithms

	Training					Testing					
Classifier	**Data Type (Training)**				**TA %**	**Data Type (Testing)**				**TA %**	
SVM	75.22	72.34	75.22	72.34	70.58	72.34	91.34	80.62	73.23	82.19	89.89	89.89
CNN	71.45	74.32	75.79	74.32	70.73	74.31	81.30	80.18	76.71	87.34	84.32	74.32
NBB	64.74	73.37	74.72	73.37	70.18	74.32	70.77	89.65	79.89	87.78	77.92	67.92
RF	60.64	75.79	75.79	65.79	61.87	73.37	72.49	72.08	84.32	81.28	70.21	60.21
RNN	57.42	74.72	74.72	64.72	61.53	75.79	72.41	72.01	87.92	86.84	83.68	73.68
DT	75.79	75.79	65.79	73.37	65.79	61.87	73.37	72.49	72.08	84.32	81.28	65.79
ANN	60.64	74.32	75.79	74.32	74.32	73.37	72.49	81.30	80.18	76.71	81.30	60.21
P-MLNN	88.16	74.32	85.79	84.32	81.07	84.72	82.19	71.98	80.21	88.92	97.97	87.97

Assessed the effectiveness of (NB) and (RF) classifiers that is compared to our proposed MLNN based ML model for diabetes classification. Our MLNN model achieved an on the PID dataset, training accuracy (TA) 80.55%, while testing accuracy is 82.73%. The naive Bayes algorithm is known for its simplicity and robustness in classification tasks. In our evaluation, the NB classifier yielded 77.56% for training accuracy and 70.08% for testing accuracy. The NB classifier's classification report can be found in Table II. A Random Forest (RF) supervised classification technique gives more significant results. RF can handle missing values and categorical data. The model achieved an improved training accuracy (TA). Table III highlights the

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MLNN model's classification accuracy superiority over Naive Bayes and Random Forest classifiers. While 92.11% high accuracy. In contrast, Naive Bayes showed consistent performance with a testing accuracy (TA). Model testing accuracy (TA) plays an important role these days due to high dosages of insulin sometimes the effects cause various diseases relevant to the skin, body swelling and high blood pressure the below table elaborates on the accuracy comparison of our proposed MLFN based on ELUP shows a slighter improvement of 0,73% while at the same time, ELU with MLFN outperformed both. The accuracy is defined as:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad \text{Eq (20)}$$

TP: True positives which malicious queries are correctly classified as malicious.

TN: True Negative which benign queries correctly classified as benign.

FP: False positive which benign queries incorrectly classified as malicious.

FN: False Negatives which malicious queries incorrectly classified as benign.

Table 2: Performance Comparison of Training Accuracy

Training (%)	(ELU)	SELU)	(ELU-P1)	(ELU-P2)	(ELU-P3)	(SELU-P1)
Accuracy	90%	85.2%	86.3%	84%	81%	78%
Precision	85.2%	86.3%	82%	90%	85.2%	90%
Recall	86.2%	87.4%	83.3%	85.2%	86.3%	85.2%
F-Measure	88.5%	89.4%	84.5%	88.5%	89.4%	88.5%
Specificity	90.5%	90.3%	87.4%	90.5%	90.3%	90.5%
Sensitivity	95.7%	91.5%	89.4%	81%	78%	85.2%

The precision calculates how many predicted positive instances were positive.

$$Precision = \frac{TP}{TP+FP} \quad \text{Eq (21)}$$

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Recall measures the model's ability to identify the actual positive instances.

$$Recall = \frac{TP}{TP+FN} \quad \text{Eq (22)}$$

The F1 Score is the harmonic mean of the Precision and Recall, Which provides a single metric to balance both.

$$F1 - Score = 2 . \frac{Precision . Recall}{Precision+Recall} \quad \text{Eq (23)}$$

The duration is required for the model to learn from the training dataset while The time taken to make the predictions on the testing dataset, is critical for real-time applications.

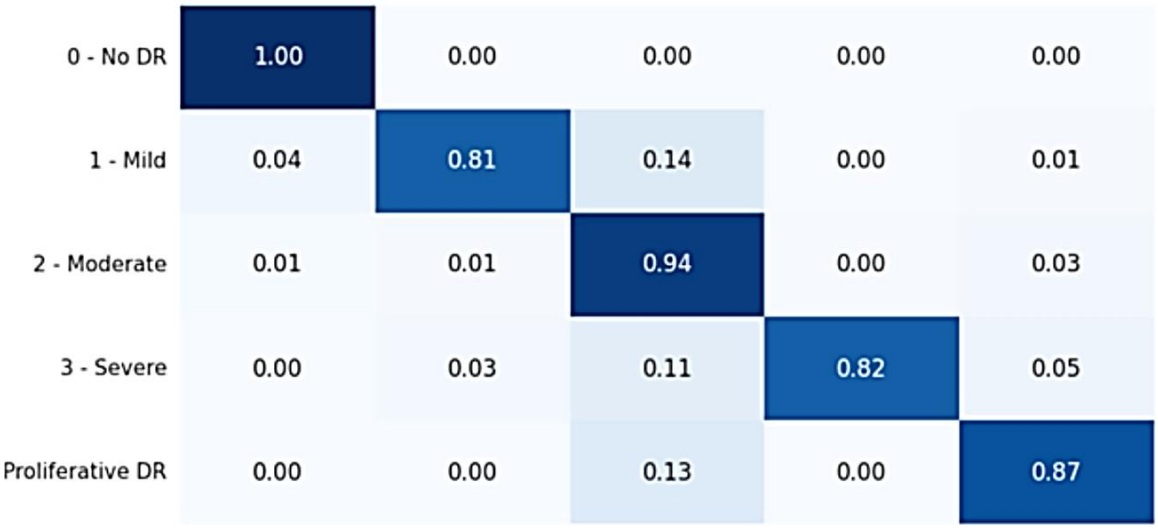

Figure 6: Confusion Matrix on Dataset

Table 3: Comparative Analysis of four classes (no DR, light DR, mod/ severe, and proliferative).

Specialist	Record	Absence	Light	With DR Mod/record	Proliferative
Without DR	Absence	5	1	1	2
With DR	Light	0	3	1	2
With DR	Mod/record	0	1	13	2

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Without DR	Proliferative	1	1	12	2
Without DR	Light	1	1	1	1
With DR	Mod/Record	2	1	1	1
Without DR	Proliferative	0	1	1	3

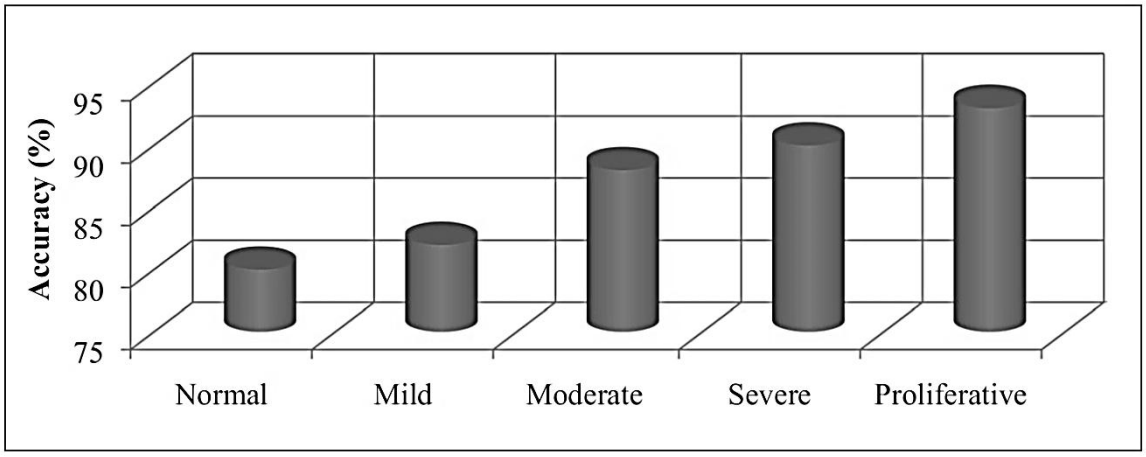

Figure 7: Graph classification for Accuracy using PIMA Dataset

Conclusion and Recommendations

Diabetes stands out as one of the fastest-growing health concerns worldwide, and diabetic retinopathy (DR) is no exception. This condition unfolds through various phases, ranging from mild to severe, culminating in Proliferative Diabetic Retinopathy (PDR). This paper aimed to implement a prediction and classification model for the measurement of diabetes using MLNN using deep learning approaches within MoTs. Medical things MoTs are particularly used in categorizing and classification and detecting various diabetic issues by training and testing the machine learning model. During the testing phase using MLNN, the training accuracy was 84.32% and the testing accuracy of 83.17% was enhanced using the proposed model. The accuracy Accuracy was calculated and compared for the MLNN

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and DL considering parameters for both feature selection and without feature selection. Specifically, the proposed method MLNN outperformed other strategies regarding classification accuracy, such as zero and mean substitutions. The impact of SELU is critical for enhancing neural network performance. After comparing different high-performance activation functions, ELU was shown to be the best fit for the PID dataset. In the future, we are focusing on developing an automated system in the form of a mobile application based on the proposed DL algorithm to help healthcare specialists in the early detection of diabetes. The accuracy measures the proportion of the correctly classified instances both true positives and true negatives out of all instances.

Funding Statement: The authors received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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