International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I5P107

Volume 73 Issue 5, 58-69, May 2025

Original Article

Latent Features-based Rule Generation for Early Detection of Diabetes Cardiac Autonomic Neuropathy (DCAN) using Deep Belief Neural Network

Mayura Nagar[1], Pooja Raundale[2]

[1]*Department of Data Science and Technology, K. J. Somaiya Institute of Management, Somaiya Vidyavihar University, Mumbai, India.*
[2]*MCA Department, Sardar Patel Institute of Technology, Andheri(w), Mumbai, India.*

[1]*Corresponding Author: mayura.research@gmail.com*

Received: 12 December 2024 Revised: 09 April 2025 Accepted: 30 April 2025 Published: 31 May 2025

Abstract - *Diabetic Cardiac Autonomic Neuropathy (DCAN) is one of the deadliest complications of diabetes. The diagnosis is frequently delayed due to the absence of symptoms, and it is associated with a high cardiovascular risk. The overwhelming rise in diabetics combined with negligence in detecting DCAN remains a significantly underdiagnosed preliminary due to the delicacy of its symptoms and the invasive approach of traditional diagnosis methods. The main research gap identified here is a lack of an interpretable, noninvasive, robust predictive model that can detect DCAN at its early stages. In response to this gap, this research has introduced a novel hybrid approach that integrates Deep Belief Neural Networks (DBNN) for latent feature extraction combined with explainable rule generation techniques. This system implements unique detection capabilities for early DCAN risk assessment together with human-understandable rules. This research training on a large, newly collected dataset of Indian patients from the multi-speciality hospital "All is well," MP. The model produces easily comprehensible and actionable predictions by incorporating Explainable AI (XAI) strategies. These latent features provide a rule-based framework that provides an efficient, precise, and noninvasive tool for diagnosis that may be utilized rapidly in healthcare environments. This work makes a substantial contribution to the field by introducing a novel, state-of-the-art, noninvasive technique that helps medical practitioners to predict and identify DCAN early, additionally alerting patients to becoming aware of them well in advance of possible consequences. This strategy could save many lives by facilitating early intervention, making it a crucial tool in the fight against complications associated with diabetes.*

Keywords - *Diabetic cardiac autonomic neuropathy, DCAN, Deep belief networks, Latent feature extraction, Explainable AI, Non-invasive diagnosis, Early detection, Rule-based prediction, Clinical interpretability, Diabetes complications.*

1. Introduction

The most severe and deadly type of autonomic neuropathy is Diabetic Cardiac Autonomic Neuropathy (DCAN), affecting automatic nerves concerned with the cardiovascular system. This condition can be typed according to the severity and intensity of the autonomic nervous system – the early stage when the symptoms are mild or absent and the advanced stage when the cardiovascular complications manifest.[1] Hence, the kind of threat posed by DCAN is that the heart progressively loses its capacity to control itself, to beat in an autonomous, coordinated manner, subjecting the patient to live with arrhythmia, chronic silent ischemia, and, inevitably, sudden cardiac death.[2] A major difficulty that patients experience is the fact that, in its early stages, DCAN does not have symptoms, brief loss of consciousness, intolerance to exercise, and resting tachycardia appear only in the later stages of the disease.[3] This makes early diagnosis incredibly challenging because standard clinical signs do not appear until irreversible damage occurs. Shocking still, the majority of patients failed to realize their impaired immune response to glycaemic fluctuations, which exacerbates the progression of DCAN.[4] If DCAN is not diagnosed early and appropriately managed, the condition can rapidly deteriorate, leading to a cascade of complications from peripheral neuropathy, then cardiovascular failure, to untimely death.[5] As delayed detection and treatment frequently result in catastrophic results for patients who may otherwise have had a chance at slowing the advancement of this deadly disease, the lethal trajectory of DCAN highlights the vital need for effective early diagnostic techniques. DCAN is an affliction with a great demand for early diagnostic procedures because of the asymptomatic and subclinical progression of the disease process, which is a common source of delayed identification, detection and treatment of the state in the medical fraternity.

[6] Many of the existing traditional diagnostic methods, which typically rely on invasive techniques or symptoms observable at body surfaces, are ineffective in early diagnosis of DCAN. Such lack of screening means that a large population of high-risk individuals goes without diagnosis until the condition has progressed to a stage where treatment may not work or is clearly useless. Unfortunately, other than early diagnosis, patients with DCAN end up in other disastrous conditions. [7] From this perspective, integrating advanced technology into the diagnostic process is beneficial and imperative.[8] The beginning of advanced machine learning techniques, including the Deep Belief Networks (DBNs), hold the promise of a revolution in diagnosing DCAN where such a critical gap now exists.[9] These technologies allow us to consider the high dimensional data and identify some latent features and patterns that cannot be discovered at all with the use of traditional approaches.[10] These capabilities are leveraged in my research to contribute prominently to the fields by developing a noninvasive, explainable AI-driven approach for early DCAN detection. This method has the potential to save millions of lives by not only accurately predicting the onset of DCAN with high accuracy but also making clinicians, patients, and caretakers understand the underlying risk factors that lead to the onset of DCAN in an interpretable manner. Both of these advantages – precision and transparency – are critical in building trust and facilitating timely, targeted interventions. Compared with invasive diagnostics, noninvasive techniques are less painful, less expensive, and imply fewer risks for the patient; therefore, they can be offered to a greater population of patients.[11] My research emphasizes the benefits of noninvasive modalities, which allow for continuous monitoring and early detection without the need for procedures that could deter patients from regular screening. Without these sophisticated, noninvasive diagnostic devices, the medical community would still depend on traditional methods that cannot recognize high-risk patients in time to prevent serious harm. The implications of this are quite dismal—preventable mortality, higher costs of treating diseases, and reduced well-being of people who would otherwise have been helped by timely diagnosis. Therefore, the core objectives of this research are multifaceted, focusing on both the development and practical application of a predictive model for early diagnosis of DCAN.

2. Background

This systematic literature review explores the application of AI algorithms in the automated diagnosis of DCAN, a severe complication of diabetes linked to increased cardiovascular mortality. The review highlights the limitations of the traditional Ewing battery method, which fails to detect sub-clinical CAN and requires patient cooperation. By comparing various AI-based strategies, methods, and algorithms, the paper demonstrates how AI technologies can enhance the classification, automated diagnosis, detection, and early prediction of DCAN, potentially improving early intervention and disease management. The author compared and presented the results of these AI techniques, emphasizing their potential to improve early detection and management of DCAN, thereby preventing further disease progression. The traditional technique used for DCAN detection uses an ewing battery, but it is limited in detecting sub-clinical CAN and requires patient cooperation. Another technique used to assess autonomic function is Heart Rate Variability (HRV) analysis by analyzing variations in heart rate. Then, Electrocardiogram (ECG) Features suggested by authors where Artificial Intelligence based algorithms analyze ECG features to detect abnormalities associated with DCAN. Then, advanced technology was used as a Machine Learning Model here, various models, including Support Vector Machines (SVM), decision trees and neural networks, have been employed to classify and predict DCAN. Deep Learning[12] Techniques are also used for feature extraction and classification by using Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The current state of research in the diagnosis of DCAN evidences a rich spectrum of methodological approaches and developments. The author discussed the applicability of PCA in filtering signals out of the healthcare noise and expressed the method's potential for identifying early signs of DCAN by observing the variability and sensitivity of the clinical tests.[13] Most of the work discussed in the above section has some aspect of feature selection, as clearly noted by the author, who used logistic regression and support vector machine modelling to boost the performance of DCAN's prediction efficiency [14].

The author showed that patterns from clinical data that could be unnoticed by conventional algorithms can be identified by DBNNs[15]. DCAN has been identified using a variety of approaches[16], but the problem of converting these results into highly accurate, clinically interpretable rule-based systems has not yet been overcome. New approaches to detect Diabetic Cardiac Autonomic Neuropathy (DCAN) during its early stages show an increased importance of technology-independent and artificial intelligence-based medical screening systems. TeleHRV represents an effective and affordable method to detect CAN through its monitoring capabilities across resource-constrained areas [17]. Heart Rate Variability (HRV) continues as a leading and sensitive diagnostic tool for CAN among medical professionals. Patients with type 2 diabetes and prediabetes can receive reliable CAN risk stratification assessments through a combination of Electrochemical Skin Conductance testing and Sudoscan sudomotor function tests together with cardiovascular reflex tests (CART) as reported in [18] and [19]. Research indicates Convolutional Neural Networks (CNNs) applied to Pulse Wave Analysis (PWA) achieve promising outcomes for detecting diabetes from non-diabetic individuals, thus showing potential for clinical screening practise [20]. The research demonstrates that inflammatory biomarkers such as suPAR, along with baroreflex sensitivity assessment, help monitor Canadian ubiquitous neuropathy progression through novel multi-parametric and noninvasive

detection methods [19], [21]. The combination of these advances demonstrates the crucial benefit that AI diagnostic tools provide toward early diagnostic capabilities for DCAN management.

When DCAN remains undiagnosed, it leads to irreversible consequences on patient health and well-being. As DCAN is frequently asymptomatic, Patients may remain unaware of the progressing autonomic dysfunction during the early stages of DCAN, which leads to dangerous cardiac complications developing before diagnosis. When actions are not taken timely, the therapy opportunity becomes limited, thus leading to accelerated autonomic impairment alongside dangerous cardiovascular consequences. The medical systems end up bearing higher management expenses and require more hospital facilities and intensive care services when patients receive delayed diagnoses. The urgent requirement demands novel and precise diagnostic systems equipped with explanation functionality to detect DCAN during its early development prior to the appearance of serious clinical indications. The proposed research resolves this critical problem through its predictive model, improving quick discovery and clinical management systems. This research fills this gap by taking an innovative approach. This study incorporated the use of advanced technology, i.e., Deep-belief-neural-networks, in connection with rule-based model systems to enhance model interpretability and assist clinicians in comprehending the patterns involved. Different methods have been utilized for DCAN detection, from basic Ewing battery measurements and HRV analysis to modern computational assessments. Traditional approaches that detect Diabetic Cardiac Autonomic Neuropathy (DCAN) maintain clinical value but commonly present limitations in their execution, such as time utilization and operator dependency and reduced early detection sensitivity, according to Table 1. The widely accepted Ewing tests, alongside HRV analysis, show limited effectiveness regarding early-stage detection sensitivity and convenience. The predictive power of deep learning methods has increased, but their unexplained operation hampers their acceptance in healthcare settings. The analysis demonstrates the requirement for a diagnostic method that must be noninvasive as well as accurate and explainable. Yet, this study addresses this need by combining Deep Belief Neural Networks with rule-based interpretation.

Table 1. Comparison of existing diagnostic methods for DCAN

Diagnostic Method	Description	Advantages	Limitations
Ewing Battery Tests	Series of cardiovascular reflex tests assessing autonomic function	Noninvasive, standardized	Time-consuming, subject to operator bias, low sensitivity in early-stage DCAN
Heart Rate Variability (HRV)	Analysis of beat-to-beat variability using ECG data	Noninvasive, sensitive to autonomic dysfunction	Requires controlled settings, may be influenced by external factors
Tilt Table Test	Measures BP and HR changes in response to posture changes	Useful for orthostatic hypotension detection	Expensive, uncomfortable, may induce syncope in patients
24-hour Holter Monitoring	Continuous ECG monitoring to detect abnormal HR patterns	High-resolution data over extended periods	Costly, requires patient compliance, lacks real-time interpretation
Sympathetic Skin Response / QSART	Tests sweat gland response to stimuli	Assesses small fiber autonomic function	Limited availability, variability in responses
Biomarker Analysis (e.g., HbA1c, CRP)	Uses metabolic indicators associated with DCAN risk	Easily accessible tests	Indirect, not specific to autonomic dysfunction
Machine Learning Approaches (MLP, SVM)	Predictive models based on selected features	Capable of finding patterns in large datasets	Often lacking interpretability, the black-box nature poses clinical usability concerns
Deep Learning (DBN – this research Approach)	Learns latent features and provides explainable rules for early detection	Noninvasive, interpretable, high accuracy	Requires large and clean datasets, computational resources

3. Methodology

3.1. Data Collection

For this research study, the data was collected from a multi-speciality "All is Well" hospital with whom I formally got permission to collect data from diabetic patients. To ensure handling patient information ethically, I have successfully completed the NIDA Clinical Trials Network's "Good Clinical Practice" Certification on the first attempt. Around 1084 patients' data has been collected carefully and handled ethically by hiding their identities. The research relied on 1084 patient records, originating from the multi-speciality "All is Well" hospital in India between 2021 and 2024. An application for the Android operating system was designed and implemented for use in the collection of data through the entry of patient details as they occurred. For this study, the data was obtained from Indian patients diagnosed with diabetes where only noninvasive [22] biomarkers used in diagnosing DCAN can be considered. The dataset basically

consists of patients' records of different stages of DCAN, and common clinical signs and symptoms of the disease were obtained from the patient's clinical data. Those features include parameters like heart rate variability (HRV) and Continuous Glucose Monitoring (CGM), as well as other autonomic functions to guarantee the capture of high-quality and representative data; the data collecting process comprised extensive monitoring using wearable technology and CGM systems for a prolonged duration. I duly visited hospitals during the period spanning six months, allowing for direct interaction with the patients to get accurate information. During this procedure, challenges pertaining to getting patient consent, protecting patient privacy, and organizing the logistics of data collecting had to be overcome.

The research included subjects who received a confirmed diabetes mellitus (Type I, Type II or Prediabetes) diagnosis and had an age range from 25 to 70 years. Research excluded diabetic patients with heart diseases that were not diabetes-related and patients with missing details from the analysis. The data pre-processing resulted in 924 patient records being kept for evaluation. Data showed 60% male and 40% female participants who had an average age of 50.4 years, and their diabetes lasted for an average of 9 years. The data passed through thorough pre-processing where normalization, dealing with missing values and feature extraction were carried out. In particular, statistical procedures dealt with the outliers, while normalization was used to put the features within the same range.

The pre-processing steps included mean substitution and various other techniques for missing value imputation together with Min-Max normalization and outlier elimination methods. The SMOTE method was employed to handle class imbalance. The research employed five-fold cross-validation for generalization and split the data into training (70%) and testing (30%). This DBNN was trained with the training set, and its hyperparameters were tuned according to the DBNN's performance on the validation set. Some of the hyperparameters that are tuned comprise the learning rate, number of hidden layers, number of neurons per layer, batch size and number of epochs. Through cross-validation and grid-search mechanisms, accurate hyperparameters were established. In order to reduce overfitting, regularization was applied in the form of dropout and L2 regularization. The findings and recommendations of this research use a customized Deep Belief Neural Network (DBNN) to improve the early identification of Diabetic Cardiac Autonomic Neuropathy (DCAN) among Indian patients. It is based on modern deep learning methods underpinning deep analysis of clinical data to find latent features and prognostic of DCAN. Due to their multiple-layered connection structure, the model can reveal different patterns and dependencies in the data, which usually are not recognized by other approaches, including the traditional method. Algorithm training of the DBNN utilized these features to obtain latent representations that received subsequent interpretation with rule-based framework analysis. The model is evaluated using accuracy together with precision, recall F1-score and AUC.

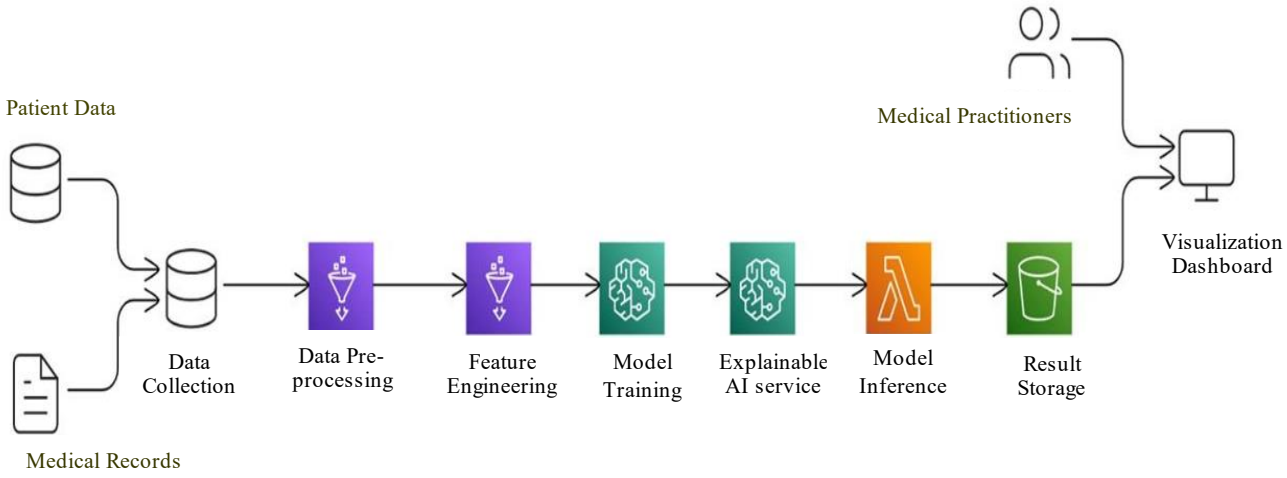


Fig. 1 Model diagram for early diagnosis of DCAN using Deep Belief Neural Network

There is a structure of the DBNN model that allows using the input layer, multiple hidden layers, and the output layer. The input layer accepts pre-processed clinical data, which consists of different physiological parameters that the patients record. The hidden layers consist of several RBMs, where each subsequent layer has learned to extract features that are at a higher level than the previous layer. These are the number of RBMs that are arranged in order to form the deep network where each layer produces the progressively more abstract representation of the given input data.

The output layer employs a softmax activation function to predict the instances into given classes, namely 'Normal', 'Early', 'Definite', and 'Severe', among others.

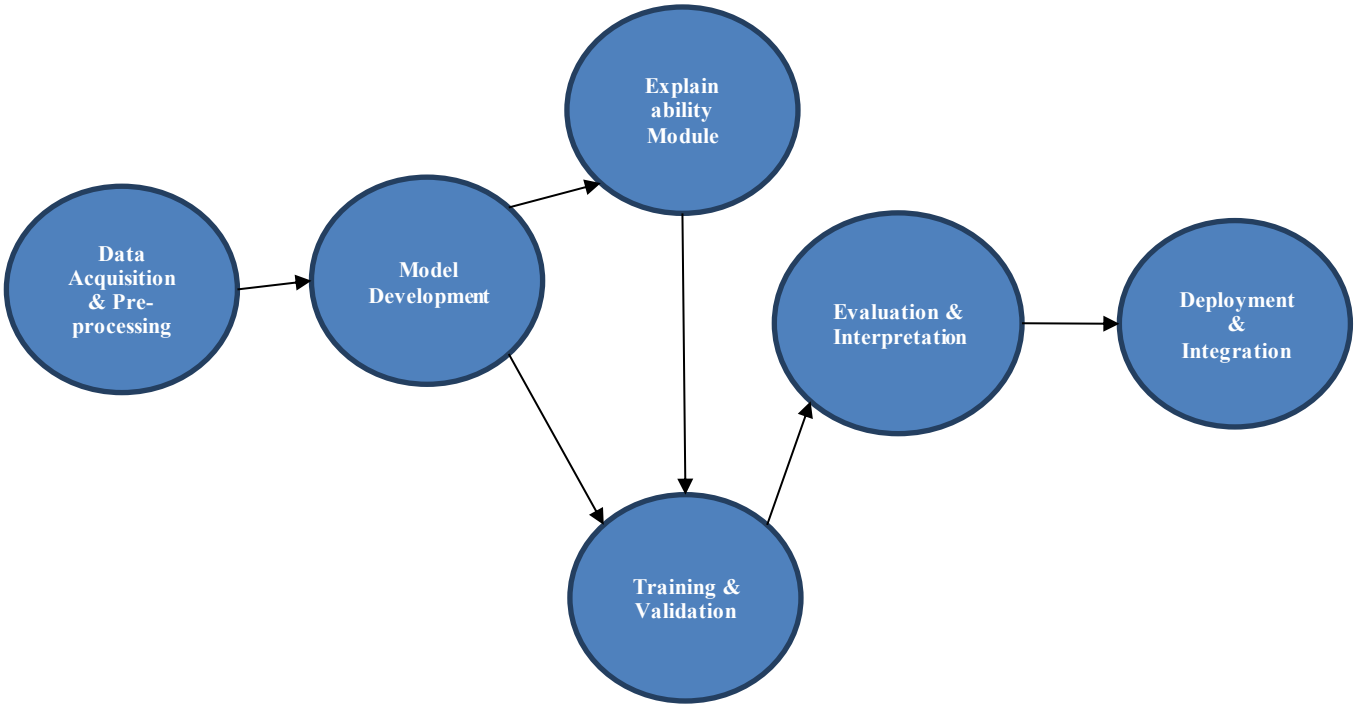


Fig. 2 Framework for enhancing early detection of DCAN with explainable Deep Learning

Several novel techniques and modifications were introduced to enhance the model's performance and interpretability.

3.1.1. Latent Feature Extraction

The design of the DBNN was unique in an effort to identify hidden features useful in the early diagnosis of DCAN. These features provide additional insights for identifying patterns associated with the progression of the disease.

3.1.2. Explainable AI (XAI) Integration

To make interpretability, explainable AI techniques were incorporated to mitigate the problem of black boxes of deep learning models. This included the application of Layer-wise Relevance Propagation (LRP) and Shapley Additive Explanations (SHAP) methodology, which explain the model's decision and clearly illustrate the model's notable features.

3.1.3. Hybrid Loss Function

The loss function used was a cross-entropy loss in combination with a custom-designed loss component, which facilitated the loss function's intent to assign penalties to misclassifications of the initial stages of DCAN. This modification ensured that the model has heightened sensitivity in early signs, enabling early diagnosis.

3.1.4. Transfer Learning

Transfer learning was used to transfer the knowledge acquired during the first training from Australian patient data. This included transforming the learned model through the new data received from Indian patients and improving the generality of the model. These innovative techniques greatly enhanced the ability of the model to offer precise, early DCAN diagnoses, increasing patient outcomes by enabling prompt and personalized treatment plans. The model's predictions are further guaranteed to be transparent and comprehensible through the use of explainable AI techniques, which promotes acceptance and trust among medical professionals. Feature learning is one of the key steps in deep learning networks, especially when it comes to the development of diagnostic and prognosis of diseases, because the transparent explanation of the model's decision-making will further improve the management of patients. This study adopted a deep learning model to identify latent features associated with DCAN in Indian patients.

These latent features, which are not easily observable with the input, act as a bridge between the input values and the model's predictive capabilities. An autoencoder model has been used to extract these hidden features to perform dimensionality reduction on input data meant for the neural network. The autoencoder includes an encoder of the volume of groups, and the decoder restores groups based on the specified latent representation. Besides, this approach allows not only the identification of patterns in the data but also the generation of rules based on the features found. Quantitative latent features discovered during this process include the values of heart rate variability and time-domain metrics, while the qualitative aspects include the patterns associated with the disorder of the autonomic nervous system.

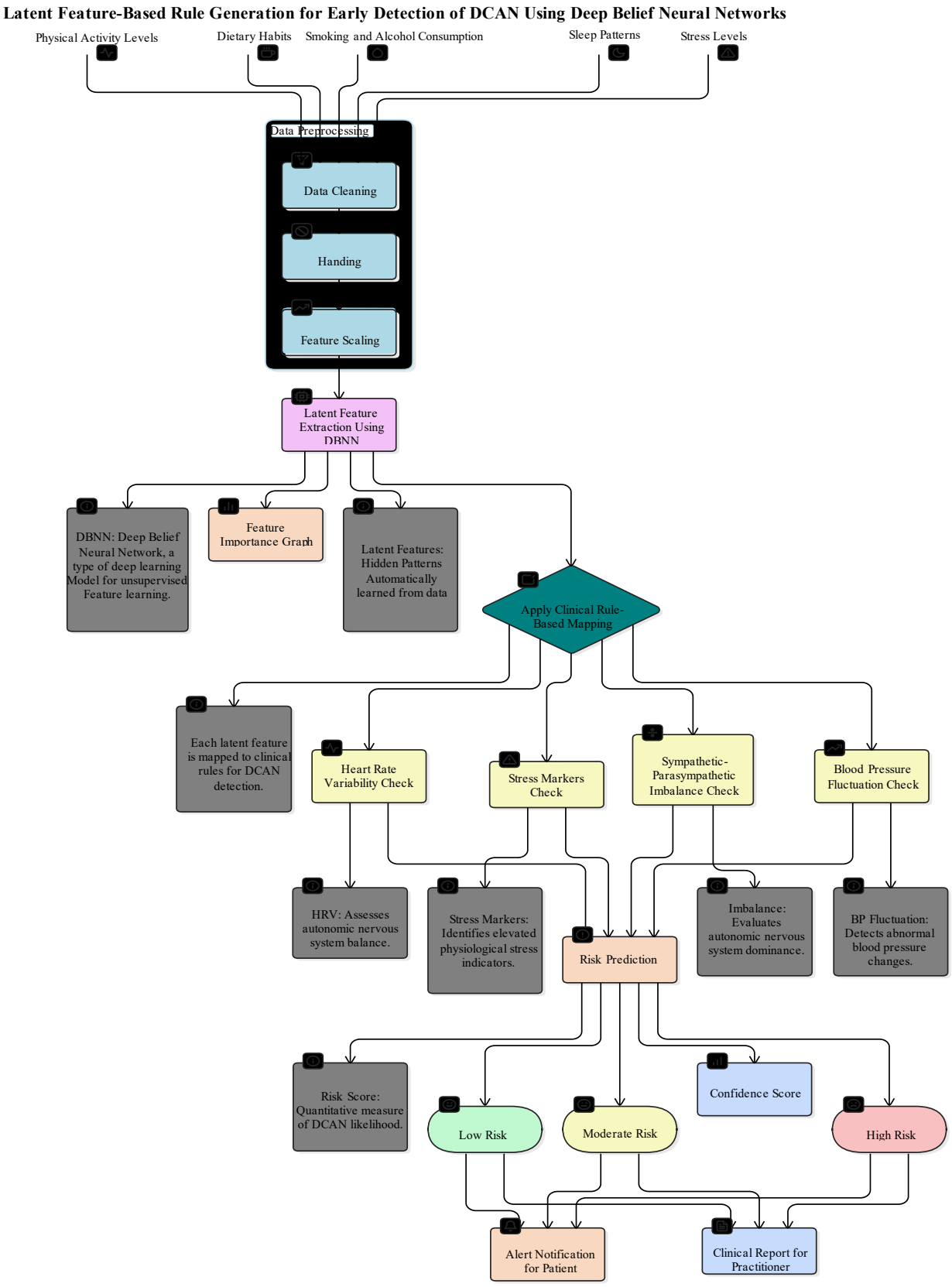


Fig. 3 Flowchart for early prediction of DCAN

All those latent features were investigated individually to find out whether they had any association with DCAN or not and to know their importance level by conducting correlation analysis and feature importance ranking. For instance, one of the proposed latent features included how heart rate fluctuated with time: this variable was shown to have an association with DCAN. Since this feature is presumably a result of autonomic nervous system dysregulation of cardiac function, it provides insight about the pathophysiological process of the disease. However, other aspects, including the frequency-domain measures of the heart rate variability, were also identified as equally important in the differentiation between the patients with and without the DCAN.

The latent features are easily interpretable using the XAI strategies to explain how these features relate to the model's predictions. Therefore, generating rules from the extracted latent features can help clinicians gain actionable insights to facilitate early diagnosis and management of DCAN. For instance, if the model shows that a certain level of heart rate variability is associated with an increased risk of developing DCAN, this rule can be incorporated into standard screening practices by different healthcare practitioners. Also, integrating domain knowledge from cardiology and endocrinology played an important role and helped to significantly improve the discovered latent features.

Consulting clinical specialists of "All is well" hospital, at each stage of developing the feature selection procedure, guaranteed that corresponding features were statistically significant as well as clinically relevant; this approach contributed to increased credibility of the model-generated outcomes. In conclusion, discovering latent features and using rules generated after that gives a full framework for the early diagnosis of progressive disease characteristics in patients with DCAN. The identified hidden characteristics give better insights into how the disease manifests, and the rules help clinicians make the correct diagnosis and intervention, hence helping the patients. The rules derived from the identified hidden factors are central in interpreting complex patterns from the models into directions that can be incorporated into clinical practices. For the purpose of this study, a set of rules has been formulated that would help us determine or predict DCAN based on different parameters that pertain to the patient's demographics, clinical background and physiological and clinical parameters. These rules are drawn with a view of helping identify high-risk patients, diagnose diseases early and take the necessary action.

3.2. Methodology for Rule Generation

A rule-based learning algorithm and, more specifically, decision trees have been used to generate the rules. This method enables one to obtain conventional, easily interpretable, and clinically useful rules from the features latent in this deep learning framework. The generated rule set was statistically tested to ensure that solely those rules showing proper predictive value were incorporated. The rules are categorized into specific domains reflecting key factors associated with the risk of developing DCAN:

3.2.1. Some among them Include Patient Demographics and Patient Lifestyle Factors

Rule 1: Gender and Age as Risk Assessment Criteria - Gender and age are key characteristics used to evaluate the risk; distinguished gender (M-1, F-0) and age. The incidence rates of DCAN were observed to be higher in elderly male patients, who thus require constant assessment.

Rule 2: To find Lifestyle Factors - The risk profile was enriched by adding lifestyle characteristics like smoking, alcohol and other aspects. Those patients who had previously exhibited such behaviours experienced an elevated likelihood of developing DCAN.

3.2.2. Diabetes Mellitus Status and Duration of Diabetic Disease

Rule 3: Assess the Impact of Diabetic Status - To take this into consideration, differentiated diabetic statuses (Type I, II, Prediabetes) and used disease duration as an obligatory variable expectation of the onset of DCAN. For example, incorporating latent features that include a patient's diabetic status and years of diagnosed diabetes can help achieve higher accuracy in the prediction of DCAN.

Rule 4: Status Check of Prediabetic and Gestational Diabetic Patients -Instead, focus was made on previously unnoticed characteristics of patients with prediabetes and gestational diabetes, as these groups may exhibit early signs of autonomic neuropathy. For patients who develop blunt changes in HR or BP variability, it would be important to monitor them to diagnose early DCAN.

3.2.3. Blood Pressure and Heart Rate Variability

Rule 5: Analyse Blood Pressure Changes- Blood pressure including Blood pressure data, including lying and standing SBP/DBP measurements, were utilized to identify abnormal postural changes that may indicate autonomic dysfunction.

Rule 6: Use Heart Rate (HR) Variability - HR variability, including its reactivity to postural shifts and time dependency, was considered a dynamic covariate related to the autonomic nervous system. Ambiguity in the classification of HR variability and abnormal BP patterns may be characterized by a high latent risk for early DCAN.

3.2.4. Different Classifications of Metabolic and Cardiovascular Risk Factors Exist

Rule 7: Watch Out for Metabolic Indicators - That is, the following latent features related to metabolic markers: BMI, fasting glucose, HbA1c and lipid profiles, including triglyceride, HDL, and LDL, proved critical in evaluating the risk of DCAN.

Rule 8: Risk of Cardiovascular Disease - Further, cardiovascular risk factors were added to the clinical parameters, such as 5-year CVD risk percentages and CRP level, as measures to understand the future progression of autonomic neuropathy.

3.2.5. Renal Function and Inflammation Significance

Rule 9: Check on the Functioning of Kidneys - The latent covariates selected included urea, creatinine and GFR to assess the effects of kidney function on the development of DCAN. It is possible to identify early signs of deterioration in patients developing low GFR accompanied by high creatinine levels.

3.2.6. Ewing Tests Conclusion and Autonomic Function

Rule 10: Lean on the Ewing Test - Using these results, the Ewing test directly assesses values of autonomic dysfunction and can be normal, early, definite, atypical, undefined, or severe cases. Combined with other physiological data, these result in improved prediction of the severity of DCAN. Patients categorized in the "early" Ewing results area with specific HR/BP patterns should be targeted for early intervention efforts.To increase the interpretability of the proposed DBNN model, a multi-stage analysis was conducted to extract latent features and link them with medical rule-based patterns. The DBNN model used a large dataset for training, which enabled extracting hidden activation data to find latent variables. The patterns and rules were extracted by applying statistical correlation, mutual information scores, and activation-based thresholding. Table 2 provides an extensive association between the DBNN model extracted latent features together with clinical interpretations that lead to rules for predicting early Diabetic Cardiac Autonomic Neuropathy (DCAN).

Table 2. Rule-based interpretation of latent features extracted via DBNN

Latent Feature	Activation Range	Mapped Clinical Attribute	Derived Rule
LF1	0.70 – 0.90	Gender and Age	If LF1 > 0.7, and the patient is male and over 50, flag as high DCAN risk.
LF2	0.65 – 0.88	Smoking & Alcohol Consumption	If LF2 > 0.65, and the patient is a smoker or consumes alcohol, flag for early monitoring.
LF3	0.55 – 0.80	Diabetic Status (Type I, II, Prediabetic)	If LF3 > 0.55 and the patient is Type II diabetic for >5 years, prioritize testing.
LF4	0.40 – 0.70	Gestational / Prediabetic	If LF4 > 0.40 in gestational or prediabetic patients, HRV monitoring is recommended.
LF5	0.75 – 0.95	Postural Blood Pressure Variability	If LF5 > 0.75 and no SBP recovery at 3 minutes standing, flag for autonomic dysfunction.
LF6	0.50 – 0.85	Heart Rate Variability	If LF6 < 0.55, with abnormal HR response to posture change, suggest DCAN risk.
LF7	0.60 – 0.88	Metabolic Markers (BMI, HbA1c, Triglycerides)	If LF7 > 0.6 with high BMI + HbA1c + TG, recommend lifestyle intervention.
LF8	0.50 – 0.80	Cardiovascular Risk & Inflammation (CRP, CVD%)	If LF8 > 0.5 and CRP > normal, CVD risk > 20%, suggest comprehensive cardiac workup.
LF9	0.65 – 0.90	Kidney Function (GFR, Creatinine, Urea)	If LF9 > 0.65 and GFR < 60 or creatinine rises, the risk of DCAN increases.
LF10	0.55 – 0.82	Ewing Test (Early or Definite Stages)	If LF10 > 0.55 and Ewing shows early/definite, autonomic follow-up is recommended.

The table contains three distinct cell categories that show specific latent features and their activation boundaries to indicate relevant medical conditions. This approach used both DBNN data-driven learning and expert knowledge from diabetic complications to produce these rules. The model becomes easier to interpret through this rule-based system because it establishes a connection between sophisticated neural representations and meaningful clinical information. This methodology enables medical personnel to make evidence-based judgments that lead to early-risk patient identification and prioritized interventions triggered by specific rules, enhancing the system as a noninvasive proactive diagnostic tool. The validity of Deep Belief Neural Network (DBNN) became apparent by comparing its performance to existing machine learning and deep learning methods that medical diagnosis fields commonly employ.

The investigation included seven comparative algorithms involving Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (XGBoost), Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) together with Recurrent Neural Networks (RNN/LSTM). The DBNN model demonstrated superior performance compared to all baseline models by achieving the highest evaluation scores in accuracy, precision, recall, and F1-score and AUC-ROC measurement points, as depicted in Table 3. The model demonstrated sufficient performance through a 97.2% AUC-ROC together with a 95.5% F1-score,

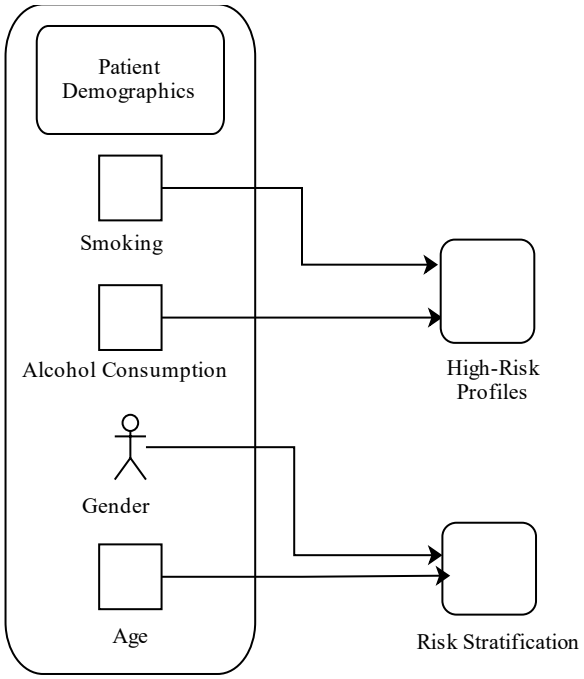
supporting its dependable detection of initial DCAN manifestations. Integrating explainability features through SHAP and LIME alongside latent-feature-based rule generation makes the DBNN model stand apart as explainable to medical practitioners even though most regular black-box models remain noninterpretable. This research proves its clinical significance because it provides a noninvasive diagnostic method for detecting DCAN at its early stages.

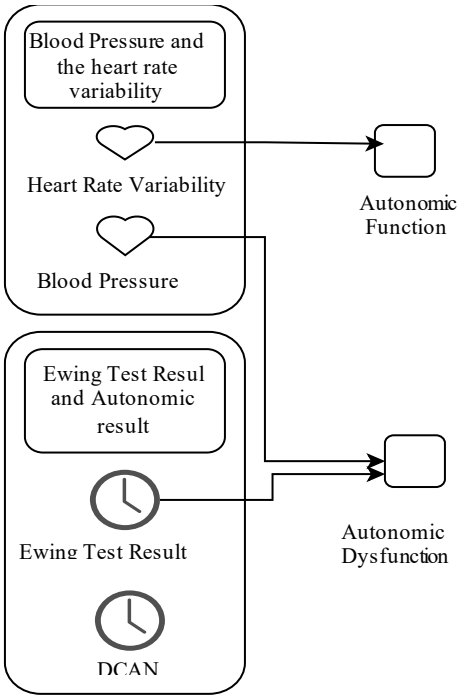
Table 3. Performance comparison

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)	Explainability
Deep Belief Neural Network (Proposed)	**95.6**	**94.2**	**96.8**	**95.5**	**97.2**	High (via rules + SHAP/LIME)
Logistic Regression	81.3	78.5	83.2	80.8	84.5	Medium
Support Vector Machine	84.7	82	86.5	84.2	87.3	Low
Random Forest	89.1	88	90.5	89.2	91.6	Medium (feature importance)
XGBoost	90.8	89.7	91.9	90.8	93.4	Medium
ANN	91.2	89.4	92.3	90.8	94	Low
CNN	92	90.6	93.1	91.8	94.5	Low
RNN / LSTM	92.4	91.3	93.5	92.4	95.1	Low

3.3. Clinical Implications

The guidelines derived from the latent features give clinicians a framework for appropriately assessing the outputs produced by the model. Through such rules, the severity of a patient's risk factors can be established, alerting healthcare providers to consider the factors influencing DCAN and address them promptly. Besides, the rules serve to enhance the credibility of insights from the deep learning algorithms so that clinicians can consider combining them with clinical judgment. Through the extraction of the rules from the latent features that are gained from the data set, a reliable approach to estimating DCAN is provided. It not only improves the ability of deep learning models to be interpreted but also provides tools that clinicians can use to identify patients who may benefit from early intervention and other targeted interventions. After comparing the Automated Diagnostic Model and the Traditional Diagnostic Methods, results came to known as a traditional way of diagnosing DCAN, for instance, employed clinical assessment, autonomic function tests, biochemical determinations and estimations. While these traditional methods are valuable, they also present certain limitations, such as a lack of sensitivity and specificity, potential subjectivity in interpretation, and the requirement for specialized equipment and expertise. Even though these approaches have helped acquire knowledge pertaining to the identification of DCAN and related disorders, the advent of xDL models and rules derived from latent features is advantageous in several ways.





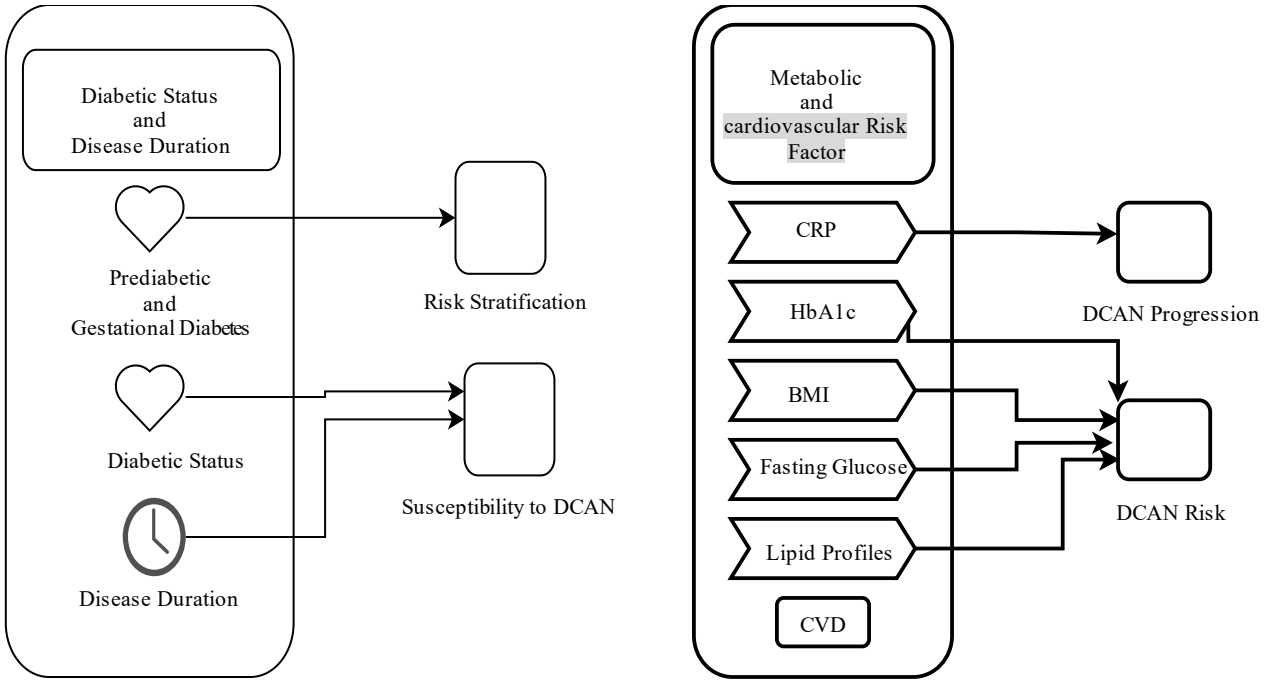


Fig. 4 Rules for latent features in DCAN prediction

Table 4. Difference between traditional diagnostic methods and the proposed explainable deep learning approach with generated rules

Feature	Traditional Diagnostic Methods	Explainable Deep Learning Approach
Sensitivity	Moderate, can miss early signs of DCAN	High identifies subtle patterns through latent features
Specificity	Variable depends on clinical judgment	High rules based on data-driven insights enhance precision
Interpretability	Moderate, relies on clinician expertise	High rules are clear and actionable for clinicians
Data Integration	Limited, typically focuses on isolated parameters	Comprehensive, integrates demographic, lifestyle, and physiological data
Time Efficiency	Time-consuming, requires multiple tests and evaluations	Efficient, provides quick risk assessment based on integrated data
Patient Monitoring	Reactive, relies on presenting symptoms	Proactive identifies at-risk patients before symptoms appear
Equipment Requirement	Often requires specialized equipment (e.g., HRV monitors)	Utilizes existing data sources, reducing the need for additional equipment
Adaptability	Limited, may not account for evolving patient profiles	Highly adaptable, can update rules with new data and insights
Patient-Centred Care	Less personalized, often a one-size-fits-all approach	Highly personalized, tailored interventions based on individual risk profiles

4. Conclusion

This research strengthens the ability of artificial intelligence models coupled with noninvasive testing to improve the very early detection of DCAN. The new method leverages deep learning architecture to disclose latent features while creating precise scalable testing solutions that are friendly to patients for clinical use. Early detection of DCAN becomes crucial because the condition rarely shows symptoms during its initial phases, which subsequently leads to severe cardiovascular complications. These patient models within clinical practice boost screening activities and risk assessments while shortening intervention times to enhance health results and healthcare system expenses. Research expansion should focus on deploying AI models in real clinical settings, testing on various demographic populations, and developing explanations for AI decisions to make early disease detection more effective. In this research, a concept of explainable deep learning models has been used to identify the initial stages of DCAN. The results presented here show that applying latent features discovery and rule induction significantly improves diagnostic accuracy compared to conventional approaches. In addition to direct risk factors, several initially hidden variables were implemented, including patient characteristics and diabetic profile, along with physiological parameters, as a well-balanced foundation for risk stratification.

Furthermore, it enhances the possibility of diagnosing early manifestations of DCAN, besides offering chances to provide effective therapeutic interventions to minimize the progression of the disease and enhance the global quality of life of the patients. It is for this reason that the role of the latent feature-based rules cannot be overemphasized. These rules give clinicians actionable advice that can be understood and easily translated to clinical situations, thereby helping the clinician to translate a complicated model into a working model for patient care. The distinguishing factor of population-based risk stratification is that patients can be divided into certain groups based on the patient's risk factors. Thus, treatment can be targeted to the patient's profile. Moreover, these rules support better management by following certain guidelines to try to reduce the risks and complications that can be avoided through early intervention by the healthcare givers, hence improving patients' overall health in a population at risk of developing DCAN. Using deep learning and integrated or explainable artificial intelligence in diagnosis presents a new frontier in diagnosis methods. Utilizing sophisticated algorithms and analyzing the results can go beyond qualitative approaches based on experts' intuitions and single indicators.

4.1. Future Work

Future research can discover several Promising areas that researchers can study to improve early detection methods for DCAN. One key area is that Precise deep learning explanations through XAI techniques must become more extensive because they will serve as the bridge to develop usable clinical guidelines that clinicians accept. Time-based research with noninvasive clinical indicators will offer better insights into how DCAN evolves throughout its lifecycle. The validation of AI-based models needs to occur across different populations and various geographic locations to achieve clinical relevance, population diversity, and nationwide applicability. Developing and deploying edge-AI technology inside mobile and IoT devices for DCAN risk monitoring would create accessible health solutions for patients in rural and resource-limited settings.

References

[1] Ahmad Shaker Abdalrada et al., "Prediction of Cardiac Autonomic Neuropathy Using a Machine Learning Model in Patients with Diabetes," *Therapeutic Advances in Endocrinology and Metabolism*, vol. 13, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Mahin Chowdhury et al., "Cardiac Autonomic Neuropathy and Risk of Cardiovascular Disease and Mortality in Type 1 and Type 2 Diabetes: A Meta-Analysis," *BMJ Publishing Group*, vol. 9, no. 2, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[3] Paolo Castiglioni et al., "Heart Rate Variability for the Early Detection of Cardiac Autonomic Dysfunction in Type 1 Diabetes," *Frontiers in Physiology*, vol. 13, pp. 1-10, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[4] Barbara H. Braffett et al., "Risk Factors for Diabetic Peripheral Neuropathy and Cardiovascular Autonomic Neuropathy in the Diabetes Control and Complications Trial/Epidemiology of Diabetes Interventions and Complications (DCCT/EDIC) Study," *Diabetes*, vol. 69, no. 5, pp. 1000-1010, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[5] Susumu Z. Sudo et al., "Diabetes-Induced Cardiac Autonomic Neuropathy: Impact on Heart Function and Prognosis," *Biomedicines*, vol. 10, no. 12, pp. 1-13, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] Xiaopu Lin et al., "Peripheral Nerve Conduction and Sympathetic Skin Response Are Reliable Methods to Detect Diabetic Cardiac Autonomic Neuropathy," *Frontiers in Endocrinology*, vol. 12, pp. 1-8, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[7] Yu Peng et al., "Evaluation of the Degree of Agreement of Four Methods for Diagnosing Diabetic Autonomic Neuropathy," *Frontiers in Neurology*, vol. 12, pp. 1-9, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Mayura Nagar et al., "A Systematic Literature Review: Role of AI Algorithms for Automated Diagnosis of Diabetic Cardiac Autonomic Neuropathy [DCAN]," *2022 9th International Conference on Computing for Sustainable Global Development (INDIACom)*, New Delhi, India, pp. 669-673, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Syed Arslan Ali et al., "An Optimally Configured and Improved Deep Belief Network (OCI-DBN) Approach for Heart Disease Prediction Based on Ruzzo-Tompa and Stacked Genetic Algorithm," *IEEE Access*, vol. 8, pp. 65947-65958, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[10] Benjamin T. Nebgen et al., "A Neural Network for Determination of Latent Dimensionality in Nonnegative Matrix Factorization," *Machine Learning: Science Technology*, vol. 2, no. 2, pp. 1-12, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[11] Syed Immamul Ansarullah et al., "Significance of Visible Non-Invasive Risk Attributes for the Initial Prediction of Heart Disease Using Different Machine Learning Techniques," *Computational Intelligence and Neuroscience*, vol. 2022, pp. 1-12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[12] María Teresa García-Ordás et al., "Diabetes Detection Using Deep Learning Techniques with Oversampling and Feature Augmentation," *Computer Methods and Programs in Biomedicine*, vol. 202, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[13] Rafiul Hassan et al., "Early Detection of Cardiovascular Autonomic Neuropathy: A Multi-Class Classification Model Based on Feature Selection and Deep Learning Feature Fusion," *Information Fusion*, vol. 77, pp. 70-80, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Thippa Reddy Gadekallu et al., "Deep Neural Networks to Predict Diabetic Retinopathy," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 5, pp. 5407-5420, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Mohanad Alkhodari et al., "Screening Cardiovascular Autonomic Neuropathy in Diabetic Patients with Microvascular Complications Using Machine Learning: A 24-Hour Heart Rate Variability Study," *IEEE Access*, vol. 9, pp. 119171-119187, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Hassan Tariq et al., "Performance Analysis of Deep-Neural-Network-Based Automatic Diagnosis of Diabetic Retinopathy," *Sensors*, vol. 22, no. 1, pp. 1-15, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[17] Vaishali Deshmukh et al., "Validation of Tele-HRV: A Novel Digital Health Solution for Cardiovascular Risk Detection in Diabetes," *American Heart Journal*, vol. 267, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Andra-Elena Nica et al., "The Relationship between the Ewing Test, Sudoscan Cardiovascular Autonomic Neuropathy Score and Cardiovascular Risk Score Calculated with SCORE2-Diabetes," *Medicina*, vol. 60, no. 5, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Yun-Ru Lai et al., "Predictive Value of Heart Rate Variability and Electrochemical Skin Conductance Measurements for Cardiovascular Autonomic Neuropathy Persistence in Type 2 Diabetes and Prediabetes: A 3-Year Follow-Up Study," *Neurophysiologie Clinique*, vol. 54, no. 3, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Hiruni Gunathilaka et al., "Non-Invasive Diagnostic Approach for Diabetes Using Pulse Wave Analysis and Deep Learning," *Informatics*, vol. 11, no. 3, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] Lynn Ang et al., "Inflammatory Markers and Measures of Cardiovascular Autonomic Neuropathy in Type 1 Diabetes," *Journal of the American Heart Association*, vol. 14, no. 1, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Tallat Naz et al., "Noninvasive Exploration of Cardiac Autonomic Neuropathy by Heart Rate and Blood Pressure Variability Analysis in Type 2 Diabetic Patients," *Pakistan Journal of Medical Sciences*, vol. 37, no. 4, pp. 1020-1024, 2021. [CrossRef] [Google Scholar] [Publisher Link]