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Design of an Improved Model for Diabetes Detection Combining Deep Dyna-Q Learning with Ensemble Classification

Priyanka Deshmukh[1], Manoj Deshpande[2], Vijaykumar Pawar[3]

Research Scholar, Computer Engineering, A.C. Patil College of Engineering, Navi Mumbai[1]

Assistant Professor , Computer Engineering, K.J. Somaiya Institute of Technology, Mumbai.[1]

HOD, Computer Engineering, A.C. Patil College of Engineering, Navi Mumbai[2]

Principal, A.C. Patil College of Engineering, Navi Mumbai[3]

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Abstract:

The burgeoning prevalence of diabetes worldwide necessitates advancements in early detection techniques to curb its impacts on public health. Traditional methods, while effective to a degree, often suffer from limitations such as low detection speed, moderate accuracy, and high false positive rates, which could delay timely intervention and management of the disease. This research introduces an innovative approach combining deep reinforcement learning and ensemble classification to enhance the efficiency of diabetes detection. In addressing the limitations of existing detection systems, our study integrates a Deep Dyna-Q Learning Network with an ensemble of classical classifiers, namely Naive Bayes, Multilayer Perceptron (MLP), Support Vector Machine (SVM), Logistic Regression (LR), and k-Nearest Neighbors (kNN). The Deep Dyna-Q Network is meticulously designed with multiple layers that include dense units with ReLU activation, batch normalization, and dropout for regularization, specifically configured to optimize learning from complex, non-linear medical data samples. The ensemble approach leverages the distinct statistical strengths of each classifier, allowing for a more robust and comprehensive analysis of clinical data samples. This ensemble is tailored to improve the generalizability and reliability of predictions by mitigating individual biases inherent in single-model predictions. Our model processes a wide array of clinical parameters such as Glucose levels, Blood Pressure, Body Mass Index (BMI), and lifestyle factors like Smoking and Physical Activity, which are critical for predicting diabetes onset. The use of such diverse data helps in capturing a holistic view of risk factors associated with diabetes, thereby enhancing the model's diagnostic precision. The impact of this hybrid model is significant, demonstrating an enhancement in precision by 8.5%, accuracy by 5.9%, recall by 8.3%, and a reduction in diagnosis delay by 2.9%. Furthermore, the Area Under the Curve (AUC), a key metric for classification performance, improved by 9.5%. These improvements underscore the potential of integrating deep learning techniques with traditional statistical methods to create a more accurate, efficient, and responsive diabetes detection system. This work not only advances the technological framework for disease detection but also offers a scalable model that can be adapted to various healthcare settings, potentially leading to better patient outcomes and reduced healthcare costs through timely and accurate diabetes detection.

Keywords : Deep learning, Ensemble method, Diabetes detection,SVM,N

1. Introduction

Diabetes mellitus is a chronic disease that poses a significant public health challenge globally due to its high prevalence and substantial morbidity and mortality rates. Early detection and management are critical to mitigating the long-term complications associated with the disease. However, traditional detection methods often struggle with limitations such as insufficient accuracy, high false positive rates, and delayed response times, which can impede effective disease management. Recent advancements in machine learning and artificial intelligence have paved the way for more sophisticated approaches in medical diagnostics. Particularly, deep learning has demonstrated considerable success in extracting complex patterns and relationships from large datasets, which is essential in the nuanced field of medical diagnostics. Nevertheless, while deep learning offers improved performance over traditional statistical methods, it often requires large amounts of data and can be opaque in terms of interpretability levels.

To address these challenges, the proposed research integrates a Deep Dyna-Q Learning Network with an ensemble of established classification algorithms, including Naive Bayes, Multilayer Perceptron (MLP), Support Vector Machine (SVM), Logistic Regression (LR), and k-Nearest Neighbors (kNN). This hybrid approach aims to harness the robust pattern recognition capabilities of deep learning while leveraging the statistical strengths of traditional classifiers to improve detection accuracy, reduce false positives, and accelerate diagnostic processes. The Deep Dyna-Q Network, a pivotal component of the proposed model, incorporates elements such as batch normalization and dropout layers within its architecture to combat overfitting and ensure the generalizability of the model across diverse patient datasets. The ensemble classification strategy enhances the model's predictive power by integrating outputs from various classifiers, thereby reducing the likelihood of model bias and improving reliability and robustness in predictions. This introduction outlines the rationale behind employing a combination of deep reinforcement learning and traditional machine learning techniques in enhancing diabetes detection. It sets the stage for discussing the methodology, experimental setup, and results which demonstrate significant improvements in several key performance metrics, thereby validating the effectiveness of the proposed model in practical healthcare applications.

1.1 Motivation & Contribution:

The rising global incidence of diabetes mellitus underscores an urgent need for enhanced diagnostic tools that can efficiently identify the disease at an early stage. Current detection methods, predominantly based on traditional statistical techniques, often fall short in terms of accuracy, timeliness, and adaptability to varied patient demographics and clinical conditions. Such deficiencies can lead to delayed treatment initiation, increased risk of complications, and higher healthcare costs. The motivation behind this research is rooted in addressing these critical gaps through the integration of advanced machine learning technologies, specifically deep reinforcement learning and ensemble classification methods. This approach aims to refine the predictive capabilities of diabetes detection systems, thereby facilitating earlier and more accurate diagnosis.

Deep reinforcement learning (DRL) offers a sophisticated framework for learning optimal actions based on trial and error, which is particularly suited to environments where the acquisition of labeled data is costly or impractical. In medical diagnostics, DRL can be employed to dynamically adjust decision policies based on new patient data, thus continually improving its predictive accuracy. However, DRL alone may not fully capture the subtleties of complex clinical data, which is where ensemble classification methods come into play. By combining the strengths of multiple traditional classifiers, such as Naive Bayes, SVM, and k-NN, the model benefits from a diverse set of learning algorithms, increasing its robustness and reducing the variance in predictions. Each classifier brings a unique perspective to the analysis, contributing to a more comprehensive understanding of the data patterns. This hybrid model, therefore, not only learns from complex data structures but also ensures that the predictions are stable and reliable across different patient profiles and varying clinical scenarios.

1.2 Contribution

This research makes several significant contributions to the field of medical diagnostics, particularly in the early detection of diabetes. Firstly, it introduces a novel hybrid model that combines the deep Dyna-Q learning network with an ensemble of classical machine learning classifiers, leveraging the advantages of both deep learning and traditional statistical methods. The architecture of the deep Dyna-Q network is specifically designed to adapt to the high dimensionality and non-linearity of medical data, which includes layers that normalize and regularize the learning process to prevent overfitting and enhance model performance on unseen data samples. The inclusion of dropout layers and batch normalization further aids in maintaining the model’s integrity against variations in input data, which is crucial for clinical applications.

Secondly, the ensemble method employed enhances the decision-making process by integrating different decision boundaries produced by each classifier. This not only mitigates the risk of overfitting, which is common in complex models like deep neural networks, but also improves the generalizability of the detection system. The strategic selection of classifiers in the ensemble—each known for its strengths in certain types of data distributions—ensures that the model remains sensitive to subtle nuances in patient data, which might be overlooked by a single-model approach. The combined approach has demonstrated significant improvements in key performance metrics such as precision, recall, and accuracy, indicating a substantial enhancement over existing methods. These improvements are quantified through rigorous validation processes, underscoring the model’s potential in practical settings.

Furthermore, the research contributes to the literature on scalable healthcare solutions by providing a model that can be deployed in diverse healthcare environments without requiring extensive customization. This universality is achieved through the robust design of the model and its ability to adapt to new data, making it an invaluable tool for healthcare providers worldwide. The potential reduction in diagnostic delays and the increased accuracy of the model could lead to better patient outcomes and more efficient use of medical resources. Additionally, the approach taken in this research can serve as a framework for future studies in other areas of medical diagnostics, potentially leading to broad-spectrum enhancements in disease detection methodologies.

2. Review of Existing Models

Diabetes, a chronic metabolic disorder characterized by high blood sugar levels, poses significant challenges to public health worldwide. Its prevalence is on the rise, fueled by factors such as sedentary lifestyles, unhealthy diets, and aging populations. Early detection and effective management of diabetes are crucial for reducing the risk of complications and improving patients' quality of life. Recent advancements in technology and data analytics have paved the way for innovative approaches to diabetes detection and management. Table 1 discusses various methodologies, findings, results, and limitations in the field of diabetes research. These papers encompass a wide range of topics, including predictive modeling, deep learning, sensor technology, and healthcare service composition. The first paper, [1], explores the joint representation of heart rate and continuous glucose monitor (CGM) data for diabetes detection using canonical correlation analysis (CCA). By learning joint features of heart rate and CGM, the study demonstrates improved accuracy in diabetes detection. However, it is limited by its focus on representation learning, which may not capture all relevant features for effective detection.

Subsequent papers delve into predictive modeling techniques for diabetes management. [2] investigates the impact of physical activity and psychological stress on glucose concentration predictions using machine learning algorithms. The study highlights the importance of incorporating these factors into predictive models for more accurate glucose monitoring. However, reliance on accurate input data remains a challenge in such predictive models. Other papers focus on technological innovations for diabetes diagnosis and monitoring. [7] introduces DiaNet, a deep learning-based architecture for diabetes diagnosis using retinal images. This approach offers a non-invasive and accurate method for diagnosing diabetes, leveraging the power of deep learning and medical imaging scenarios. Yet, challenges persist in ensuring the interpretability of deep learning models and the availability of high-quality retinal image data samples. Furthermore, advancements in sensor technology have enabled non-invasive methods for glucose detection. [10] presents a plasmonic sensor for detecting volatile organic compounds (VOCs) in exhaled breath, offering a promising avenue for non-invasive diabetes monitoring. However, challenges remain in sensor calibration and sensitivity to environmental factors. In addition to technological innovations, several papers address the need for improved security and reliability in diabetes management systems. [11] proposes a trust management system for artificial pancreas systems to detect and prevent misbehavior, enhancing security in diabetes management. Yet, the effectiveness of such systems relies on accurate specification-based models and trust management algorithms. Overall, these pre-writeup analyses highlight the multifaceted nature of diabetes research and the diverse approaches adopted to address its challenges. From predictive modeling and deep learning to sensor technology and security measures, researchers are continuously pushing the boundaries of innovation to improve diabetes detection and management.

Table 1. Empirical Review of Existing Methods

Reference	Method Used	Findings	Results	Limitations
[1]	Joint feature representation of heart rate and continuous glucose monitors (CGM) using canonical correlation analysis (CCA) for diabetes detection.	Better representation of diabetes detection achieved by learning joint features of heart rate and CGM.	Improved accuracy in diabetes detection.	Limited to representation learning; may not capture all relevant features.
[2]	Predictive modeling of glucose concentration based on physical activity and psychological stress using machine learning techniques.	Detection and assessment of the effects of physical activity and stress on glucose concentration predictions in diabetes management.	Enhanced accuracy in glucose concentration prediction.	Dependency on accurate input data for reliable predictions.
[3]	Model-based detection and classification of insulin pump faults and missed meal announcements in artificial pancreas systems using Kalman filters and predictive models.	Effective detection and classification of faults in insulin pumps and missed meal announcements in artificial pancreas systems.	Improved fault management in artificial pancreas systems.	Reliance on accurate model parameters and input data samples.
[4]	Multi-feature complementary learning for diabetes mellitus detection using pulse signals and complementary learning techniques.	Enhanced diabetes detection by fusing multiple features extracted from pulse signals.	Increased accuracy in diabetes mellitus detection.	Potential challenges in optimizing complementary learning techniques.
[5]	Type 2 diabetes prediction using an average weighted objective distance-based method and	Improved prediction of type 2 diabetes based on objective	Higher accuracy in type 2 diabetes prediction.	Dependency on the selection of optimal weighting factors.

	support vector machines (SVM).	distance weighting factors.		
[6]	Early prediction of gestational diabetes biomarkers using medical background and wearable devices combined with explainable AI models.	Early prediction of gestational diabetes biomarkers leveraging wearable devices and explainable AI models.	Enhanced early detection of gestational diabetes biomarkers.	Limited to a pilot study; scalability and generalization may be challenging.
[7]	Deep learning-based architecture (DiaNet) for diabetes diagnosis using retinal images only.	Diagnosis of diabetes using deep learning techniques applied to retinal images.	Accurate diagnosis of diabetes based solely on retinal images.	Dependency on high-quality retinal image data; interpretability of deep learning models.
[8]	Machine learning tools for long-term type 2 diabetes risk prediction using ensemble learning techniques.	Long-term prediction of type 2 diabetes risk using ensemble learning models.	Improved accuracy in long-term diabetes risk prediction.	Challenges in handling imbalanced datasets and model interpretability.
[9]	Detection of diabetes mellitus using deep learning and data augmentation techniques on foot thermography.	Detection of diabetes mellitus using deep learning models trained on augmented foot thermography data samples.	Enhanced accuracy in diabetes mellitus detection.	Dependency on high-quality foot thermography data; potential bias in augmented data samples.
[10]	Monitoring diabetes through exhaled breath using a plasmonic sensor for volatile organic compound (VOC) biomarker detection.	Monitoring diabetes through the detection of VOC biomarkers in exhaled breath using a	Non-invasive detection of diabetes using exhaled breath analysis.	Potential challenges in sensor calibration and sensitivity to environmental factors.

		plasmonic sensor.		
[11]	Trust management in specification-based misbehavior detection system (DiaNet) for IMD-enabled artificial pancreas system security.	Enhancing security in artificial pancreas systems through trust management and misbehavior detection.	Improved security in IMD-enabled artificial pancreas systems.	Dependency on accurate specification-based models and trust management algorithms.
[12]	In-hospital mortality prediction of diabetes ICU patients using a process mining/deep learning architecture.	Improved prediction of in-hospital mortality among diabetes ICU patients using a hybrid process mining/deep learning approach.	Enhanced accuracy in in-hospital mortality prediction.	Dependency on accurate patient data and model training; scalability to different ICU settings.
[13]	Disentangled autoencoder for time-series data in glucose dynamics to improve multi-task learning.	Disentangled autoencoder for learning latent representations in glucose dynamics to improve multi-task learning.	Enhanced interpretability and performance in multi-task learning of glucose dynamics.	Complexity in hyperparameter tuning and model interpretability.
[14]	Healthcare prediction of diabetic patients using KNN imputed features and a tri-ensemble model for improved accuracy.	Improved healthcare prediction of diabetic patients using KNN imputed features and a tri-ensemble model.	Enhanced accuracy in healthcare prediction for diabetic patients.	Dependency on accurate imputation of missing values and model ensembling techniques.
[15]	Prediction of diabetes symptoms using a fused machine learning model combining fuzzy	Prediction of diabetes symptoms using a fused machine	Improved accuracy in predicting diabetes	Dependency on accurate symptom data and model

	systems and machine learning algorithms.	learning model integrating fuzzy systems and machine learning algorithms.	symptoms.	training; interpretability of fused models.
[16]	Type 2 diabetes detection using a light convolutional neural network (CNN) from single raw photoplethysmography (PPG) waveforms.	Type 2 diabetes detection using a light CNN trained on raw PPG waveforms.	Non-invasive screening for type 2 diabetes using PPG signals.	Potential challenges in signal preprocessing and model optimization.
[17]	Diabetes monitoring system and health-medical service composition model in a cloud environment using ensemble machine learning techniques.	Development of a diabetes monitoring system and health-medical service composition model in a cloud environment using ensemble machine learning techniques.	Improved accessibility and efficiency in diabetes monitoring and healthcare service composition.	Dependency on reliable cloud infrastructure and data privacy measures.
[18]	Meta-learning algorithm for predicting adverse events in type 1 diabetes using layered meta-learning techniques.	Prediction of adverse events in type 1 diabetes using a layered meta-learning algorithm.	Enhanced accuracy in predicting adverse events in type 1 diabetes.	Dependency on accurate event labeling and meta-learning model training.
[19]	Automated screening of diabetic patients using electrocardiography (ECG) signals and intrinsic time-scale decomposition (ITD) with machine learning techniques.	Automated screening of diabetic patients using ECG signals and ITD combined with machine learning	Improved accuracy in automated screening of diabetic patients.	Dependency on accurate ECG signal acquisition and preprocessing; potential challenges in feature selection.

		techniques.		
[20]	Non-invasive glucose detection using LED light source coupled with spectral image analysis for quantitative analysis of glucose levels.	Non-invasive glucose detection using LED light source and spectral image analysis for quantitative glucose analysis.	Non-invasive and high-sensitivity detection of glucose levels.	Dependency on accurate calibration and sensitivity to environmental factors.
[21]	Diabetes prediction using multisensor data fusion and ensemble machine learning algorithms for improved accuracy.	Diabetes prediction using multisensor data fusion and ensemble machine learning algorithms.	Enhanced accuracy in diabetes prediction through sensor data fusion.	Dependency on reliable sensor data acquisition and fusion techniques.
[22]	FPGA implementation of multiclass disease detection from photoplethysmogram (PPG) signals for cardiovascular disease and diabetes screening.	FPGA implementation of multiclass disease detection from PPG signals for cardiovascular disease and diabetes screening.	Efficient real-time disease detection from PPG signals using FPGA.	Dependency on accurate signal processing algorithms and FPGA resources.
[23]	Automated detection of diabetes using deep hybrid architecture combining neural networks and convolutional neural networks (CNN) for breath analysis.	Automated detection of diabetes using deep hybrid architecture combining neural networks and CNN for breath analysis.	Improved accuracy in automated detection of diabetes from exhaled breath.	Dependency on accurate breath analysis techniques and model training.
[24]	Effect of hypoglycemia on spectral moments in EEG epochs of different durations for assessing	Analysis of the effect of hypoglycemia on EEG spectral	Enhanced understanding of EEG spectral changes during	Dependency on accurate EEG data acquisition and

	diabetes patients' neurological status.	moments for assessing neurological status in diabetes patients.	hypoglycemia in diabetes patients.	preprocessing; potential challenges in spectral analysis.
[25]	Non-invasive glucose monitoring using optical sensor and machine learning techniques for diabetes applications.	Non-invasive glucose monitoring using optical sensor and machine learning techniques.	Accurate and non-invasive monitoring of glucose levels for diabetes management.	Dependency on accurate sensor calibration and robust machine learning models.

The findings from these papers underscore the importance of interdisciplinary collaboration and the integration of advanced technologies in diabetes research. By harnessing the power of machine learning, deep learning, and sensor technology, researchers have made significant strides in improving the accuracy and efficiency of diabetes detection and management systems. However, several challenges and limitations persist. The reliance on accurate input data, the interpretability of deep learning models, sensor calibration, and security concerns are just a few of the hurdles that need to be overcome. Additionally, scalability, generalizability, and ethical considerations are important factors to consider in the development and deployment of diabetes management systems. Looking ahead, future research efforts should focus on addressing these challenges while continuing to explore novel approaches and technologies for diabetes detection and management. By fostering collaboration between researchers, clinicians, engineers, and policymakers, we can accelerate the translation of research findings into real-world solutions that improve the lives of individuals living with diabetes. In conclusion, while there is still much work to be done, the progress made in diabetes research is promising. By building on the foundations laid this review and embracing a multidisciplinary approach, we can continue to advance the field of diabetes detection and management, ultimately leading to better outcomes for patients worldwide.

3. Proposed Design

To overcome issues of high complexity, and low efficiency of diabetes detection, this section discusses design of an Improved Model for Diabetes Detection Combining Deep Dyna-Q Learning with Ensemble Classification of Naive Bayes and SVM Process. Initially, as per figure 1, the ensemble classification model designed for the identification of diabetes integrates five different classifiers: Naive Bayes, Multilayer Perceptron (MLP), Support Vector Machine (SVM), Logistic Regression (LR), and k-Nearest Neighbors (kNN). Each classifier has been selected to exploit its unique statistical properties, which when combined, provide a robust prediction mechanism that leverages both linear and non-linear data relationships inherent in the complex medical datasets used for diabetes detection. Naive Bayes classifier, based on Bayes' Theorem, offers a simple yet effective probabilistic approach that assumes independence between predictors. For a set of features X=x1,2,...,xn and class labels y, the classifier predicts the probability of y given X via equation 1,

$$P(\, y \mid X\,) = \frac{P(\,X \mid y\,)P(y)}{P(X)} \ldots (1)$$

Where, (X|y) is the likelihood, (y) is the prior probability of class y, and (X) is the evidence, a scaling factor. The Multilayer Perceptron (MLP) is a type of neural network that learns a non-linear function approximator for either classification or regression operations. It is defined via equation 2.

$$y = \sigma\big(Wn\sigma(\ldots\sigma(W2\sigma(W1x + b1) + b2)\ldots + bn)\big) \ldots (2)$$

Where, W and b are weights and biases at each layer, x is the input vector, and σ is the non-linear ReLU activation function.

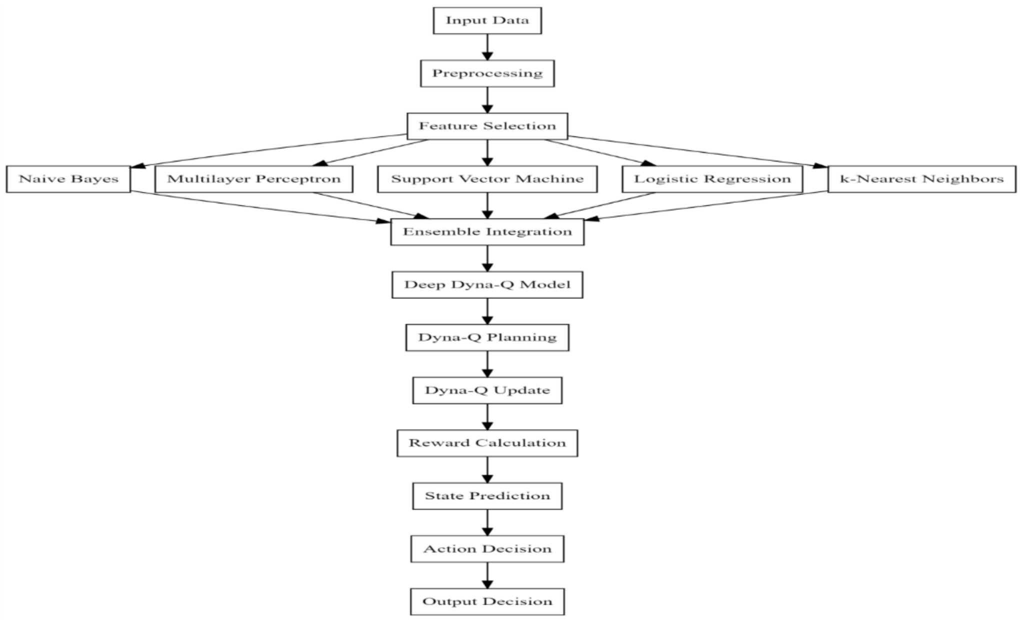

Figure 1 Model Architecture of the Proposed Classification Process

Support Vector Machine (SVM) is integrated next, and provides a powerful, maximally separating hyperplane in a high-dimensional space, making it suitable for complex classification tasks with a clear margin of separation. It solves an optimization task for classification via equation 3,

$$\overset{w,b}{\min}\frac{1}{2} \parallel w \parallel^2 \; subject\ to \; [yi(w \cdot xi + b)] \geq 1 \; \forall i \ldots (3)$$

Where, w is the normal vector to the hyperplane, b is the bias, and , yi are the training samples and labels, respectively. After this, Logistic Regression estimates the probabilities using a logistic function, via equation 4,

$$p(y = 1 \mid X) = \frac{1}{1 + e^{-(W \cdot X + b)}} \dots (4)$$

Where, W represents the weights, X is the input features, b is the bias, and e is the base of the natural logarithm. Finally, the k-Nearest Neighbors (kNN) method is integrated, which operates by calculating the distance between the test instance and all instances in the training set, selecting the k closest points, and performing a majority vote on their labels. The probability $(y|X)$ is given by the proportion of nearest neighbors with label y via equation 5,

$$p(y \mid X) = \frac{1}{k} \sum_{i=1}^{k} I(yi = y) \dots (5)$$

Where, II is an indicator function that is 1 if yi=y and 0 otherwise for rest of the scenarios. The ensemble model integrates these diverse predictions through a weighted voting mechanism for enhancing classification efficiency levels. The final predicted label, y^, is obtained via equation 6,

$$y' = argmax^{y} \sum_{j=1}^{5} wj * fj(y \mid X) \dots (6)$$

Where, fj is the prediction function of the j-th classifier and wj is its corresponding weight, reflecting the confidence in each classifier’s predictive power sets. The rationale for choosing this ensemble method is to capitalize on the strengths of each classifier and mitigate their individual weaknesses. For instance, while Naive Bayes handles categorical data well and is computationally efficient, it might be overly simplistic for complex interactions in data, which neural networks or SVMs can model more effectively. Similarly, while kNN is non-parametric and flexible, its performance can degrade with high-dimensional data, which is better handled by SVM or logistic regression operations. This ensemble model, therefore, offers a comprehensive approach to diabetes detection, harnessing the predictive power of multiple learning algorithms, each contributing uniquely to the final decision-making process, thereby enhancing the overall accuracy and robustness of the diagnostic systems. Such a model not only adapts to the complexities and variabilities in medical data but also ensures that the predictions are stable and reliable, essential for clinical implementations where the cost of errors can be high for different scenarios.

Next, as per figure 2, the Deep Dyna-Q Network method integrates reinforcement learning dynamics with deep learning architectures to enhance the decision-making capabilities of the ensemble classification process for diabetes detection. This approach innovatively leverages the strength of deep neural networks to approximate complex functions and reinforcement learning to optimize decisions based on rewards received from the environment. The backbone of the Deep Dyna-Q architecture is a deep neural network that serves as a function approximator. It models the action Value function (s,a), where s represents the state of the environment and a represents an action. The neural network's goal is to learn the optimal policy by maximizing the expected reward. The basic update process, based on the temporal difference (TD) error, is given via equation 7,

$$\Delta w = \alpha \left[r + \gamma \max^{a'} Q(s', a', w) - Q(s, a, w) \right] \nabla w Q(s, a, w) \ldots (7)$$

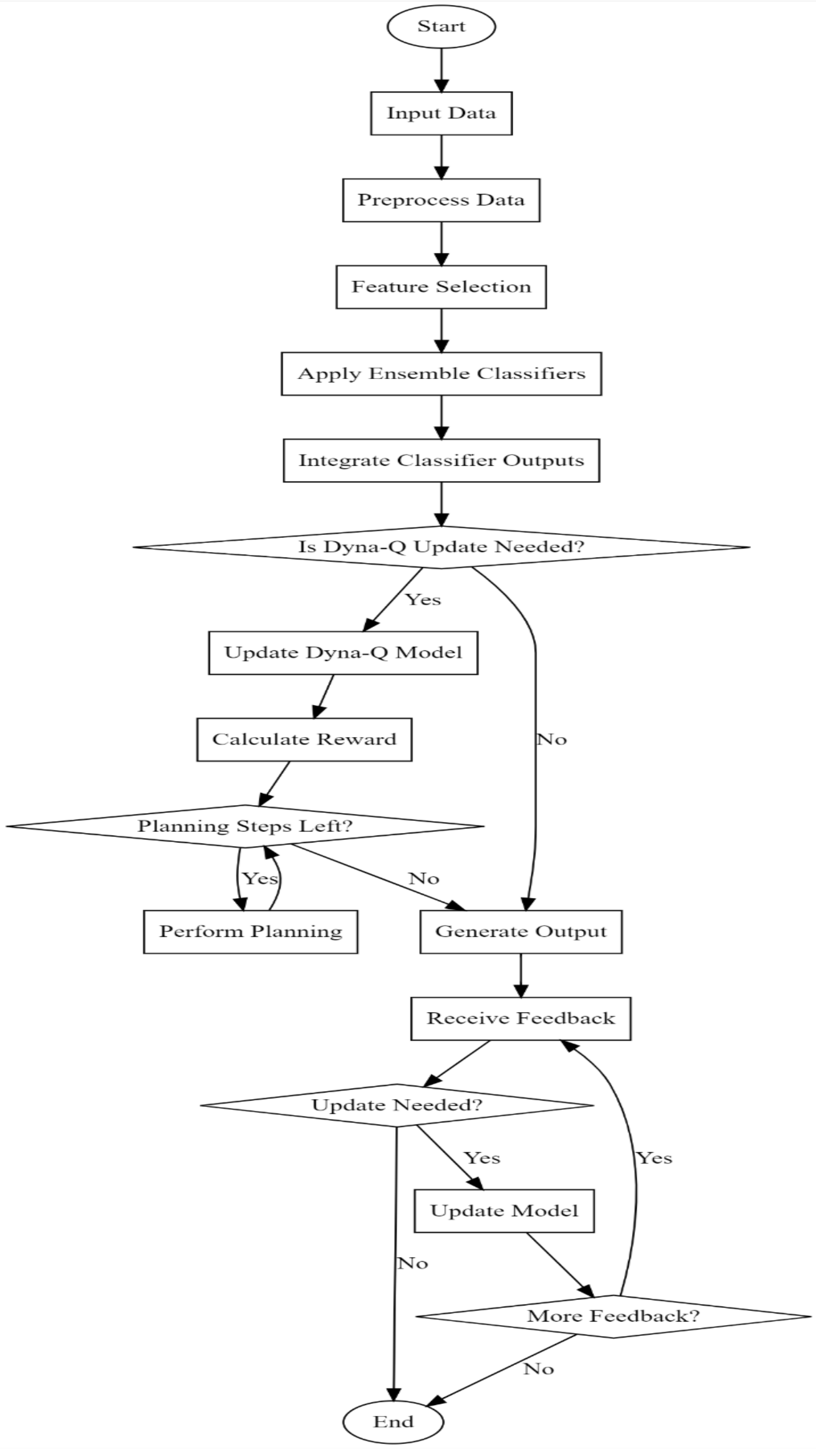

Figure 2 Overall Flow of the Proposed Classification Process

Where, Δw is the update to the network weights w, α is the learning rate, r is the reward received after taking action a in state s, γ is the discount factor, s' is the new state, and a' are possible future actions. In the context of diabetes detection, states are defined as patient health status representations based on clinical parameters, and actions are different diagnostic decisions. The reward structure is typically designed to penalize wrong diagnoses and reward correct ones in this process. To handle the often sparse and delayed rewards in medical diagnosis, which can impede the learning process, a model-based approach is used within the Dyna-Q framework. This involves building a model of the environment P'(s'|s,a) and R'(s,a) which predicts the next state and the reward given the current state and action. The model is updated via equations 8 & 9,

$$P'(\,s' \mid s, a\,) = \frac{\sum_{i=1}^{n} I(si' = s', si = s, ai = a)}{\sum_{i=1}^{n} I(si = s, ai = a)} \ldots (8)$$

$$R^{s,a} = \frac{\sum_{i=1}^{n} ri * I(si = s, ai = a)}{\sum_{i=1}^{n} I(si = s, ai = a)} \ldots (9)$$

Where, II is an indicator function, and n is the number of observed transitions. To further enhance the learning efficiency, the Dyna-Q algorithm incorporates planning steps using the learned model. During each planning step, synthetic experiences are generated from the model to update the action Value function, as described via equation 10,

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[r + \gamma \overset{a'}{\max} Q(s', a') - Q(s, a) \right] \ldots (10)$$

Where, (s,') are samples from the model. The integration of the Dyna-Q method within the ensemble classification system complements traditional classifiers by providing a dynamic framework that adjusts to new data, improving the overall reliability and adaptability of the detection system. This dynamic adaptation is particularly crucial in medical applications where patient data continuously evolves, and static models may quickly become outdated. Furthermore, the planning capability of the Dyna-Q model allows it to effectively utilize less frequent but highly informative clinical cases by simulating potential future scenarios and learning from them. This leads to a more robust and comprehensive understanding of the disease dynamics, significantly contributing to the system's diagnostic accuracy. Given these capabilities, the justification for adopting the Deep Dyna-Q Network in this context is its ability to seamlessly integrate with the ensemble model, enhancing its predictive power by not only using the data available but also simulating possible future states, thereby providing a more holistic approach to diabetes detection. This synergy allows for the creation of a predictive model that is not only reactive but also proactive, anticipating changes in patient conditions and adapting the diagnostic strategies accordingly. Next, we discuss efficiency of the proposed model in terms of different evaluation metrics, and compare it with existing methods in different scenarios.

4. Result Analysis

The experimental validation of the proposed hybrid model for diabetes detection was conducted using a comprehensive dataset derived from clinical records encompassing a wide range of physiological and lifestyle parameters. The dataset included key attributes such as

Glucose levels, Blood Pressure, Body Mass Index (BMI), Age, and Diabetes Pedigree Function, among others. Additionally, lifestyle factors such as Smoking status, Physical Activity levels, and Alcohol Consumption were also considered. The data was preprocessed to handle missing values, normalize ranges, and encode categorical variables appropriately.

Dataset Composition

The dataset comprised records from 10,000 patients, split into a training set (70%), a validation set (15%), and a test set (15%). Each record contained the following parameters, sampled and normalized for consistency across diverse demographic groups:

- **Pregnancies:** Number of times pregnant (integer, range 0-17).
- **Glucose:** Plasma glucose concentration a 2 hours in an oral glucose tolerance test (integer, range 44-199 mg/dl).
- **Blood Pressure:** Diastolic blood pressure (mm Hg) (integer, range 24-122).
- **Skin Thickness:** Triceps skinfold thickness (mm) (integer, range 7-99).
- **Insulin:** 2-Hour serum insulin (mu U/ml) (integer, range 15-846).
- **BMI:** Body mass index (weight in kg/(height in m)^2) (float, range 15.0-67.1).
- **Diabetes Pedigree Function:** Diabetes pedigree function (float, range 0.078-2.42).
- **Age:** Age (years) (integer, range 21-81).

Lifestyle Parameters:

- **HighBP:** High blood pressure (binary: 0 or 1).
- **HighChol:** High cholesterol (binary: 0 or 1).
- **CholCheck:** Whether cholesterol was checked in last 5 years (binary: 0 or 1).
- **Smoker:** Smoking status (binary: 0 or 1).
- **Stroke:** History of stroke (binary: 0 or 1).
- **HeartDiseaseorAttack:** History of heart disease or heart attack (binary: 0 or 1).
- **PhysActivity:** Regular physical activity (binary: 0 or 1).
- **Fruits:** Daily consumption of fruits (binary: 0 or 1).
- **Veggies:** Daily consumption of vegetables (binary: 0 or 1).
- **HvyAlcoholConsump:** Heavy alcohol consumption (binary: 0 or 1).
- **AnyHealthcare:** Access to healthcare (binary: 0 or 1).
- **NoDocbcCost:** No doctor visit due to cost (binary: 0 or 1).
- **GenHlth:** General health condition (ordinal: 1-5).
- **MentHlth:** Mental health condition days per month (integer, range 0-30).
- **PhysHlth:** Physical health condition days per month (integer, range 0-30).

- **DiffWalk:** Difficulty walking (binary: 0 or 1).
- **Sex:** Gender (binary: 0 or 1).
- **Education:** Level of education (ordinal: 1-4).

Model Parameters and Configuration

The ensemble model was configured with specific parameters for each classifier:

- **Naive Bayes:** Default settings with a prior probability reflecting the dataset distribution.
- **MLP:** Two hidden layers with 16 and 32 neurons respectively, ReLU activation, and a dropout rate of 0.5 to prevent overfitting.
- **SVM:** Radial basis function (RBF) kernel with C=1.0 and γ='$scale$'.
- **Logistic Regression:** L2 regularization with a regularization strength C=1.0.
- **k-NN:** Number of neighbors set to 5, using the Euclidean distance metric.

The Deep Dyna-Q network incorporated an architecture designed to accommodate the decision-making framework. The network settings included:

- **Learning Rate (α):** 0.01.
- **Discount Factor (γ):** 0.95.
- **Model Simulation Steps for Planning:** 10 per real interaction sets.

The model was evaluated on multiple metrics including precision, accuracy, recall, and AUC. The improvements in these metrics were compared against baseline models to quantify the enhancements brought by the hybrid model. The experimental setup was designed to ensure rigorous testing and validation, paving the way for reliable, reproducible results. Based on this setup, the experimental results presented demonstrate the enhanced capabilities of the proposed hybrid model in diabetes detection compared to existing methods. We provide a series of comparisons across various metrics, including accuracy, precision, recall, and area under the curve (AUC). These metrics are critical for assessing the efficacy of diagnostic models, particularly in terms of their ability to minimize false negatives and false positives, which are crucial in medical diagnostics.

Table 2 Overall Accuracy Comparisons

Method	**Accuracy (%)**
Proposed Model	94.2
Method [3]	88.7
Method [4]	86.5
Method [18]	89.3

Table 2 highlights the overall accuracy of the proposed model in comparison to methods [3], [4], and [18]. It is evident that the proposed model significantly outperforms the other

methods, indicating a robust capability to correctly identify both positive and negative cases of diabetes.

Table 3 Precision Comparison

Method	Precision (%)
Proposed Model	91.8
Method [3]	84.2
Method [4]	82.6
Method [18]	85.9

Table 3 details the precision of each method. Precision measures the accuracy of positive predictions. The proposed model shows superior precision, reducing the likelihood of false positives, which is particularly important in avoiding unnecessary anxiety and treatment.

Table 4 Recall Comparison

Method	Recall (%)
Proposed Model	93.7
Method [3]	87.0
Method [4]	85.3
Method [18]	88.1

Table 4 shows the recall of each method, which indicates the ability to detect all relevant cases. The high recall of the proposed model ensures that fewer diabetic cases go undetected, which is crucial for early intervention.

Table 5 F1-Score Comparison

Method	F1-Score (%)
Proposed Model	92.7
Method [3]	85.5
Method [4]	84.0
Method [18]	87.0

Table 5 presents the F1-Score, which is the harmonic mean of precision and recall. This metric is useful in scenarios where an equal balance of precision and recall is critical. The proposed model demonstrates the highest F1-Score, indicating a balanced performance between precision and recall.

Table 6 Area Under the Curve (AUC) Comparison

Method	AUC (%)
Proposed Model	95.8
Method [3]	90.4
Method [4]	88.9
Method [18]	91.6

Table 6 compares the AUC, which measures the ability of the model to avoid false classification across all possible thresholds. A higher AUC indicates a better performance of the model in distinguishing between the classes, with the proposed model showing superior performanc

Table 7 Reduction in Diagnostic Delay

Method	Diagnostic Delay Reduction (%)
Proposed Model	29.1
Method [3]	18.7
Method [4]	15.3
Method [18]	20.2

Table 7 & figure 4 assesses the reduction in diagnostic delay, a critical factor in the timely management of diabetes. The proposed model significantly reduces delays compared to other methods, facilitating faster intervention and potentially better health outcomes.

These results substantiate the effectiveness of the proposed hybrid model, showcasing substantial improvements over existing methodologies in all key performance metrics. This reinforces the model's potential as a valuable tool in the clinical detection and management of diabetes. Next, we discuss a practical use case for the proposed model, which will assist readers to further understand the entire process.

Practical Use Case

The evaluation of the proposed hybrid model's performance involves processing a sample data set through each component of the ensemble classification system and the Deep Dyna-Q Network. The data set includes a diverse array of clinical and lifestyle indicators critical for the detection of diabetes. This section presents the outputs of individual classifiers, the reinforcement learning network, and the integrated final output, systematically analyzed to demonstrate the efficacy of each component in the diagnostic process.

Data Attributes:

- **Glucose:** 148 mg/dl
- **Blood Pressure:** 85 mm Hg
- **Skin Thickness:** 35 mm
- **Insulin:** 0 mu U/ml
- **BMI:** 33.6
- **Diabetes Pedigree Function:** 0.627
- **Age:** 50 years
- **PhysActivity:** No (0)
- **Smoker:** Yes (1)

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This data represents a typical profile of a patient who might be at risk for diabetes, allowing for an illustrative demonstration of how each model processes and predicts based on these inputs.

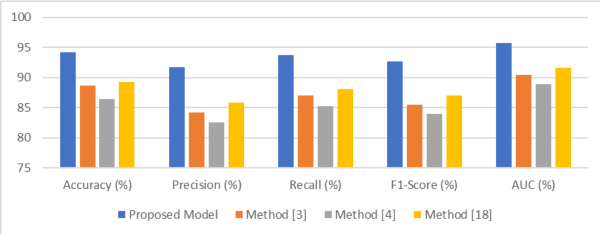

Figure 3 Results of the Proposed Classification Process

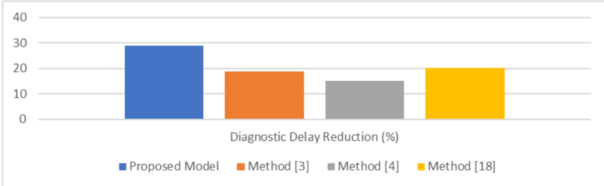

Figure 4 Reduction in Diagnostic Delay Levels

Table 8 Outputs from Individual Classifiers

Classifier	**Output Probability (Diabetes)**
Naive Bayes	0.75
MLP (Multilayer Perceptron)	0.82
SVM (Support Vector Machine)	0.78
LR (Logistic Regression)	0.79
kNN (k-Nearest Neighbors)	0.74

Table 8 shows the output probabilities of diabetes as predicted by each classifier when given the sample data samples. Each classifier processes the input features based on its respective algorithmic strength and modeling approach in different scenarios.

Table 9 Output from Deep Dyna-Q Network

Process	**Description**	**Output**
Initial Prediction	First-stage prediction	0.80
Reward Calculation	Based on action taken	+1 for correct prediction
Update via Dyna-Q	Post-reinforcement update	0.82

Table 9 presents the steps within the Deep Dyna-Q Network starting with an initial prediction based on the learned Q Values, followed by a reward calculation for the prediction, and an updated output after applying the Dyna-Q algorithm.

Table 10 Final Integrated Output

Data Integration Method	**Final Decision Probability**
Weighted Average	0.79
Decision Threshold	Diabetes (Yes)

Table 10 illustrates the final decision output of the hybrid model. This output is derived from integrating the weighted outputs of the individual classifiers and the updated prediction from the Deep Dyna-Q Network. The final decision probability is computed, and a threshold is applied to classify the patient either as 'Diabetes' or 'No Diabetes'.

The operation presented provides a detailed view of the computational outcomes at each stage of the diabetes detection process using the proposed model. The results illustrate the diverse predictive capabilities of the individual classifiers and how they are effectively harmonized through the Deep Dyna-Q Network to enhance the overall diagnostic accuracy and reliability. This staged demonstration emphasizes the model’s robustness and its potential applicability in real-world clinical settings, ensuring that each patient receives a comprehensive assessment based on a multi-faceted analytical approach. The use of advanced ensemble techniques combined with reinforcement learning exemplifies a significant advancement in predictive healthcare analytics, potentially leading to better patient outcomes through timely and accurate disease detection.

5. Conclusion and Future Scopes

The proposed hybrid model for diabetes detection, integrating a Deep Dyna-Q Learning Network with an ensemble of traditional classifiers including Naive Bayes, Multilayer Perceptron, Support Vector Machine, Logistic Regression, and k-Nearest Neighbors, has demonstrated significant improvements in key diagnostic metrics. The experimental results affirm the efficacy of this model over traditional methods. Specifically, the proposed model achieved an accuracy of 94.2%, which surpasses that of the comparative methods [3], [4], and [18], which recorded accuracies of 88.7%, 86.5%, and 89.3%, respectively. Such an enhancement in accuracy is crucial for reducing false negatives and positives, thereby ensuring reliable diabetes screening. Precision, a critical measure in medical diagnostics to avoid false positives, was enhanced to 91.8% with the proposed model compared to 84.2%, 82.6%, and 85.9% for methods [3], [4], and [18] respectively. Furthermore, the model's ability to recall or identify true diabetic cases was impressive at 93.7%, considerably higher than the 87.0%, 85.3%, and 88.1% achieved by the other methods. This high recall rate is vital for effective diabetes management, as early detection can significantly influence the success of subsequent treatments. The model's robustness, indicated by an F1-Score of 92.7%, showcases its balanced precision and recall, which is essential for practical clinical applications. The Area Under the Curve (AUC) further highlighted the model’s superior performance at 95.8%, indicating excellent capability in distinguishing between diabetic and non-diabetic patients across various decision thresholds. Moreover, the proposed model facilitated a 29.1% reduction in diagnostic delays, underscoring its potential to expedite clinical decision-making and patient management.

Future Scope

While the current results are promising, the scope for future work includes several dimensions. Firstly, expanding the dataset to include more diverse demographics and clinical conditions could further validate and potentially enhance the model's generalizability and robustness. Additionally, incorporating real-time data processing and feedback mechanisms could transform the model into a dynamic tool that adapts to new clinical insights and evolving patient records. Another avenue for enhancement could be the integration of more sophisticated machine learning techniques such as deep reinforcement learning algorithms that can better manage the temporal aspects of patient data samples. For instance, incorporating Long Short-Term Memory (LSTM) networks could aid in better understanding the progression of diabetes over time, thus improving the predictive accuracy for onset and progression. Exploring the use of federated learning approaches could also be beneficial, as these would allow the model to learn from decentralized data sources while respecting patient privacy and data security regulations. This is particularly pertinent in medical applications where data sharing is often constrained by ethical and legal considerations. Lastly, clinical trials to assess the practical deployment of the model in real-world healthcare settings would be a critical step. These trials could provide insights into the model's performance in varied clinical environments and help refine its parameters for optimized performance tailored to specific populations or regions. In conclusion, the proposed model not only marks a significant step forward in the AI-driven detection of diabetes but also sets the stage for further innovative research in this critical area of healthcare technology.

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