Literature Survey: AI and Machine Learning for Diabetes Prediction

1. Abstract

Diabetes mellitus is a critical global health issue requiring timely and accurate diagnosis to reduce long-term complications. Machine Learning (ML) and Artificial Intelligence (AI) techniques have shown promising potential in predicting and managing diabetes. This literature survey analysis 22 recent research papers focused exclusively on diabetes prediction using various datasets and models. It highlights the methodologies, accuracies, and limitations of each study, followed by a synthesis of common research gaps. A proposed solution using an improved and interpretable model is also discussed.

2. Introduction

Diabetes is a chronic disease affecting over 400 million people globally, with increasing prevalence. Early detection and intervention are crucial to managing its progression. Traditional diagnostic methods are often time-consuming or reactive. Hence, the application of AI and ML in healthcare, especially for diabetes prediction, has gained momentum. Numerous algorithms, including XGBoost, SVM, Decision Trees, and Neural Networks, have been employed using datasets like PIMA, NHANES, and EHR. However, gaps remain in terms of interpretability, generalizability, and robustness across populations. This review critically examines the recent literature to identify key methodologies and limitations, culminating in a roadmap for an enhanced predictive model.

3. Literature Review

3.1 Overview of Methodologies and Datasets

A variety of studies have leveraged classical machine learning and deep learning approaches for diabetes prediction. Common datasets include PIMA Indians Diabetes, NHANES, and hospital-specific electronic health records (EHRs). Popular algorithms include Decision Trees, SVM, Logistic Regression, Random Forest, XGBoost, and hybrid deep learning models. While many achieve accuracies ranging from 75% to 95%, challenges persist in areas such as feature interpretability, handling of imbalanced data, transparency in predictions, and applicability to real-world clinical settings. Few studies incorporate explainable AI (XAI) techniques, and generalizability across diverse populations remains limited.

3.2 Summary of Selected Literature

The following tables summarize 22 selected studies, including dataset usage, methods applied, performance, and noted limitations.

Ref	Title of Paper	Journal / Publisher / Year	Dataset Used	Methodology with Accuracy	Limitations
1	Artificial Intelligence in Current Diabetes Management and Prediction	Healthcare Technology Letters, IET, 2022	EHRs, Literature Review	General AI techniques overview	Lacks experimental validation
2	Diabetes Prediction using ML and Explainable AI	North South University, 2022	PIMA	XGBoost, SHAP, LIME — 85.3%	Lacks real-time deployment
3	A Comprehensive Review of ML Techniques on Diabetes Detection	Visual Computing for Industry, Biomedicine, and Art, 2021	Multiple (review)	Survey paper	No experimentation or benchmark
4	Diabetes Detection using ML and DL	Multimedia Tools and Applications, Springer, 2023	PIMA, Kaggle datasets	CNN, Random Forest — up to 93.2%	High data imbalance
5	Quantum ML vs DL for Diabetes	Complex & Intelligent Systems, 2021	PIMA	Quantum SVM vs DL — 91%	Quantum model lacks scalability
6	ML and DL Predictive Models for Type 2 Diabetes	Diabetology & Metabolic Syndrome, 2021	Multiple clinical datasets	Ensemble, LSTM, Logistic — 82–92%	Complex models, hard to interpret
7	Transparent Diabetes Prediction: AutoML + Explainable AI	MDPI, 2023	PIMA	AutoML, SHAP — 88.4%	Lacks personalization
8	Hybrid ML Framework using Electrogastrograms	Springer Nature, 2024	Hospital ECG-based data	RF + KNN Hybrid — 87%	Niche dataset, less generalizable
9	Attention-based Deep Belief Networks	IEEE, 2025	PIMA (imbalanced)	ADBN — 90.1%	Needs more explainability
10	Transparent & Accurate ML + Explainable AI	University of Salerno, 2023	PIMA	SHAP + Logistic Regression — 86%	Only tested on one dataset
11	Prediction Model for Diabetic Nephropathy	Tianjin Medical University, 2022	Clinical diabetic nephropathy data	Logistic + XGBoost — 82%	Focused only on complications

Ref	Title of Paper	Journal / Publisher / Year	Dataset Used	Methodology with Accuracy	Limitations
12	Comparison of ML Algorithms for Diabetes	Elsevier, 2021	PIMA	RF, SVM, KNN — 79%–88%	Feature redundancy
13	Diabetes Prediction Using Hybrid ML	SCPE Journal, 2024	PIMA + custom data	NB + RF hybrid — 89.6%	Overfitting suspected
14	AI/ML in Diabetes Care	Indian Journal of Endocrinology, 2022	Clinical experience	Review of ML-based interventions	No quantitative analysis
15	Comparative Study of ML Techniques	Jadara University, 2023	PIMA	Logistic, SVM, DT — 87%	Dataset imbalance
16	Diabetes Prediction Using ML Analytics	IEEE Conference, 2022	UCI, PIMA	XGBoost, LR — 86%	Simple preprocessing
17	Diabetes Classification Using ML	Silpakorn University, 2023	PIMA	SVM, RF — 89%	Model not deployed/tested in clinics
18	AI-Based Diabetes Care in India & USA	Health Services Research, Sage, 2024	Literature + Hospital data	Policy + AI survey	Lacks algorithm-level detail
19	Type 2 Diabetes with ML: Methods & Eval	Archives of Computational Methods in Eng., 2021	PIMA, NHANES	XGBoost, SVM, LSTM — 88%	Imbalanced data, no personalization
20	Explainable ML for Early Diabetes	Nirma University, 2024	PIMA	SHAP, LIME, SVM — 87.6%	Limited patient context
21	Early Detection via ML (PIMA-focused)	Arxiv Preprint, 2024	PIMA	Logistic Regression — 84%	Poor interpretability
22	Deep Neural Models in Diabetes Prediction	IEEE, 2023	Kaggle data	DNN + PCA — 91.5%	Overfitting concerns

Research Gaps identified across 22 papers:

Ref(s)	Research Gap
1, 3, 14, 18	Many are literature-only reviews, lacking hands-on implementation or validation
4, 5, 6, 13, 22	Deep/Quantum models are accurate but lack interpretability and clinical explainability
2, 7, 10, 20	Explainable AI is explored but limited to SHAP/LIME only — no counterfactuals or patient-specific feedback
4, 6, 15, 19	Imbalanced data handling is insufficient or missing
8, 11	Models trained on narrow or niche datasets don't generalize
12, 17, 21	No clinical deployment or testing beyond benchmark datasets
9	Attention-based models are promising but underexplored
13, 16	Feature engineering and preprocessing often shallow or static
5, 6, 22	Personalization (age, gender, lifestyle) missing from prediction models

4. Comparative Analysis

This section compares model performance, dataset usage, interpretability, and deployability across reviewed studies.

4.1 Accuracy vs. Interpretability Trade-off

While models like Deep Neural Networks and Quantum SVM offer high accuracy (>90%), they lack the transparency needed for clinical use. Interpretable models such as Logistic Regression, when combined with SHAP, strike a balance between performance and explainability.

4.2 Dataset Diversity and Generalization

Most models heavily depend on PIMA, a relatively small and homogeneous dataset. Broader datasets like NHANES or EHRs are less commonly used but provide more diverse training contexts for generalization.

4.3 Real-world Deployability

Few studies validate their models in live clinical environments. Real-time applicability, noise tolerance, and integration with EHR systems are often ignored in model development.

5. Conclusion

This literature survey presents an overview of approaches applied using Artificial Intelligence (AI) and Machine Learning (ML) algorithms in the detection of diabetes. However, these techniques show limitations in interpretability, personalization, and clinical applicability which continue to hinder their widespread adoption in real-world healthcare. The insights gathered through this review can serve as a foundation for fine-tuning the existing models that seamlessly integrate with healthcare infrastructure.