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Diabetes Risk Prediction Models: A Comparative Review of Traditional Machine Learning, and Agentic AI Approaches

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Abstract: Chronic illness, particularly, Type 2 Diabetes Mellitus (T2DM), is a critical health issue in Sri Lanka with the prevalence being attributed to lifestyle and dietary choices and socioeconomic aspects. Although the global research has already applied Artificial Intelligence in predicting diabetes, no research has been conducted in Sri Lanka since no country-relevant datasets or culturally sensitive preventive interventions reflecting unique dietary and behavioral patterns have yet been available. To overcome this, the proposed study comes up with an Agentic Artificial Intelligence model that automatically interprets medical history, lifestyle, and self-reported health data to grade an individual into low, moderate, and high as regards hyperglycemia risks. Based on the data of a health survey in Sri Lanka, the model will use Machine Learning to make prediction and issue Personalized Recommendations for preventive healthcare in cooperation with licensed physicians in Sri Lanka. The Agentic AI will be able to adjust to new data all the time, becoming more accurate in predicting. The strategy would plug this Sri Lankan research gap, integrating AI based analytics with patient-focused care to provide a preventive care solution to underserved areas at scale.

Index Terms: Agentic Artificial Intelligence, Hyperglycemia, Machine Learning, Personalized Recommendations, Preventive Healthcare, Sri Lanka, Type 2 Diabetes Mellitus

1 INTRODUCTION

Chronic diseases like type 2 diabetes mellitus (T2DM) are becoming a serious health issue not only in the world but also in Sri Lanka. Diabetes in the country has spiked in the last 30 years and studies have found out that over 12% of the countries are diabetic and close to 15% is prediabetic and some surveys put the figure at 23% in some areas [1],[2],[3]. This epidemic is mainly caused by sedentary living conditions, poor diet, fast rate of urbanization, and dissimilarity among people with distinct socio-economic gaps [1],[2]. Effects of uncontrolled diabetes are far reaching and include cardiovascular disease, renal failure, blindness and quality of life reduction. Access to limited healthcare resources, particularly in the rural settings has necessitated the importance of early detection and preventive measures that can limit the amount of disease burden.

Chronic diseases such as diabetes demand a mix of complex data such as medical record, lifestyle, diet, and psychology. Conventional systems, statistical models and physical health evaluations have always been utilized but they are reactive, time-consuming and cumbersome to adjust [4],[5]. Artificial intelligence (AI) has the ability to change this situation as it allows us to analyze health data continuously, automatically, and while taking it into account. The most promising advance is that of agentic AI, which is not only able to observe but rationalize, adjust, and act very minimally under human supervision [6],[7].

In the medical field, agentic AI may also serve as an interaction mediator among patients and providers, identifying risks at early stages, personalizing responses, and improving proposals as new data is acquired. This is particularly useful in the management of chronic diseases, where progress may occur over time, and which preventive interventions may help before the situation worsens. Autonomous, flexible, and learning AI helps to close the gap existing between the high volume of information and personalized healthcare delivery [6].

Although these perks of using AI in the sphere of health should be noted, Sri Lanka has not witnessed the application of AI in health systems on a large scale, and models suggested are usually based on foreign data which is not potent in terms of culture and context. This localization would be extremely essential since the cultural and classic stages of Sri Lankan food lifestyles such as the majority consumption of white rice, coconut recipes, and low density of proteins cause glycemic fluctuation in dimensions which cannot be represented by western based models [8],[9]. Also, the patterns of behavior as well as inequality in access to healthcare and socio-economic status vary greatly with the rest of the countries, and culturally specific datasets may enhance predictive quality and clinical confidence [10],[11].

This study expects to fill that gap by developing an agentic AI framework that fits Sri Lanka's cultural and lifestyle realities. In the proposed model, a rich dataset will be used and will contain both medical-related (e.g. diabetes, blood pressure, cholesterol, BMI, smoking, heart disease, stroke) and lifestyle characteristics (e.g. alcohol use, mobility, healthcare access). The recommendations of the predictions will be categorized into three, that is, low, moderate, and high risk of diabetes and the prevention strategies will be prepared in consultation with the certified Sri Lankan doctors so as to be medically as well culturally appropriate.

This review is conducted to investigate existing gaps in current prediction models of diabetes in technology and in contexts in order to justify the need of a localized, independently operating, and explainable framework of AI. Section 2 gives an elevator pitch of what Agentic AI and autonomous systems are and how they have evolved, architectures of multi-agents and the role of these systems in healthcare applications. Section 3 is devoted to the data analysis in chronic disease monitoring where the importance of clinical, behavioral, and environmental data in diabetes management and the development of machine learning as a predictive tool are provided. In Section 4, the article is an overview of diabetes risk prediction models and compares conventional statistical tools, machine learning tools, and other emerging hybrid or agentic AI systems, the applicability, limitations, and reflections of these models in the localized healthcare context of Sri Lanka.

The anticipated result is to create a plain roadmap that can achieve an authentic agentic AI architecture that would incorporate data-rich multi-modal Sri Lankan health data, will improve overtime and will provide actionable credible insight to close the gap that exists between AI analytics and clinical utility.

2 Overview of Agentic AI and Autonomous Systems

2.1 Defining Agentic AI

Artificial intelligence has evolved beyond human-controlled or preprogrammed systems to embodied AI agents capable of perceiving, reasoning, learning, and acting autonomously, with goal-directedness and limited supervision. This represents a shift between decision support and decision making. Within the socio-technical systems framework, embodied AI should perform well based on its technical capabilities in a way that is aligned with its human stakeholders, the healthcare organization, and the wider community. The ethical principles proposed by Floridi, transparency, accountability, and benefits, help ensure that AI used in healthcare does not undermine clinical safety or equity [12], [13].

2.2 Multi-Agent Architectures and Industry Adoption

Multi-agent systems (MAS), also known as agent-based AI, are collections of multiple autonomous agents

that collaborate to achieve high-level goals [14]. This modular design aligns with socio-technical systems theory and achieves excellent performance when technical subsystems interact with social processes. It shows tangible benefits in industrial applications: Siemens' predictive maintenance reduces downtime [15], and JPMorgan's LOXM trading agent can adapt to volatile markets. Gartner's projections highlight the growing prominence of agentic AI in industry, predicting that by 2028 one in three enterprise software suites will shift toward closed-loop orchestration driven by autonomous decision-making and agentic AI.

2.3 Relevance in Healthcare and Data Analysis

AI has the potential to have a transformative impact on healthcare, from administrative efficiency to patient flow, resource optimization, and clinical decision support. In some cases, systems like Doctoronic have demonstrated diagnostic agreement with human physicians exceeding 90% (Fig. 1), demonstrating that automated medical reasoning is indeed possible. [16].

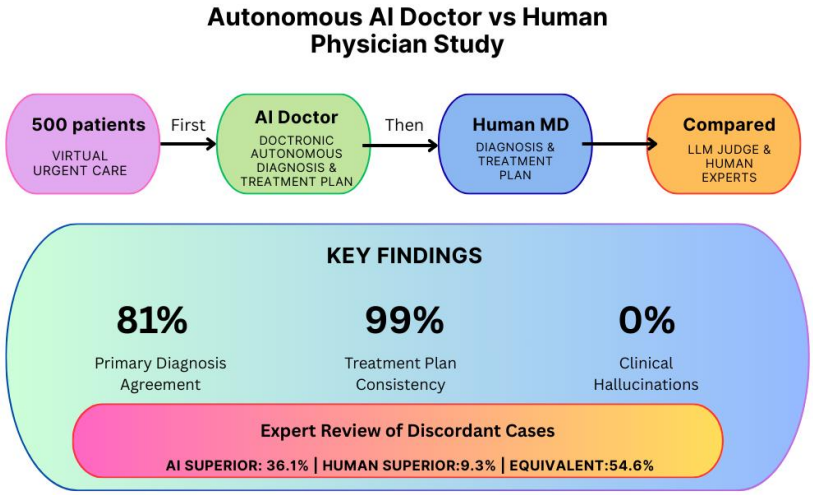

Fig. 1. Agreement rate (%) between Doctronic vs human clinicians.

Additional oversight frameworks, such as Tiered Agentic Oversight (TAO), can help safely integrate AI into clinical workflows by intelligently distributing tasks and responsibilities between agents and human supervisors, supporting accountability and patient safety. Regulatory standards such as HIPAA are important, and security-sensitive system design should utilize role-based access controls, data integrity safeguards, and limited audit practices [17],[18].

The implementation of agent-based AI in medicine can be understood in three ways:

• AI ethics: The 2025 Bioethics Artificial Intelligence Advisory (BAIA) proposal addresses fairness, accountability, transparency, and informed consent for the use of AI in clinical settings [19].

• Healthcare informatics: Agent-based AI complements electronic health records (EHRs) and clinical workflows to support data-driven decision-making.

• Socio-technical systems: Healthcare is understood as a self-sustaining ecosystem, in which technology is a complement to, rather than a substitute for, human activity [20].

Current trends show increasing maturity of agentic AI in clinical settings. According to the 2025 Stanford AI Index, performance in multimodal disease diagnosis has improved, and open-source solutions like mAIstro and SuperAGI are lowering barriers to technical adoption. Modular agent-based AI, for example, has been demonstrated in a 2025 report in the Journal of Clinical Oncology to accelerate breast cancer trials through

automated patient stratification and data matching [21].

Overall, distributed, collaborative agent-based AI systems can provide context-aware and patient-centric care by providing adaptive, real-time recommendations. However, issues of transparency, governance, and ethical alignment remain. To ensure sustainable deployment, human-in-the-loop control is essential to ensure adherence to regulatory standards and adherence to social values [4].

While agent-based AI can support automated decision-making, its effectiveness in healthcare depends on the standard and disparate of data. Conditions like type 2 diabetes are chronic and complex, producing continuous streams of data, and robust data analysis is essential for developing reliable predictive models.

3 Data Analysis in Chronic Disease Monitoring

3.1 Importance of Data in Chronic Disease Management

Type 2 diabetes mellitus (T2DM) has a long preclinical phase where early intervention is critical. Effective monitoring requires not only biomarkers but also psychosocial factors such as lifestyle, correlation and glucose levels, body mass index, blood pressure, diet and physical activity. As shown in Fig. 2, features such as age, gender, having diabetes in family and daily consumption of medicine demonstrate higher significance in diabetes prediction models.

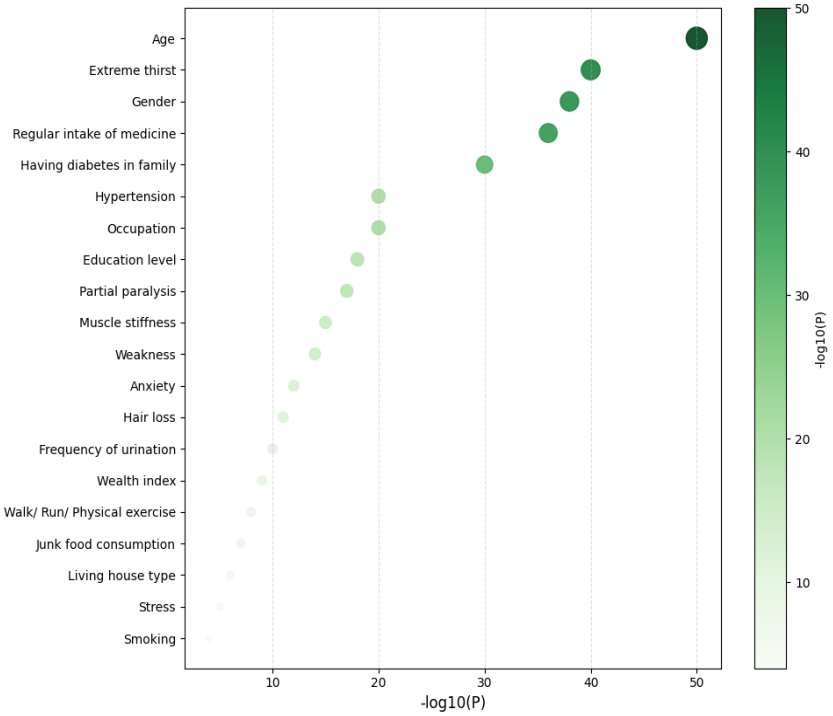

Fig. 2. Significance of the features, p values with negative 10 base logarithm, the darker and larger bubbles represent more significance.

The amount, rate, and variety of health data have already increased dramatically with the introduction of population surveys, wearables, electronic medical records (EHRs), and mobile health (mHealth) applications. [22]. This has its advantages and pressures. On one hand, such information can be used by agentic AI to make predictions and offer personalized care, but on the other, agentic AI is particularly sensitive to heterogeneity, missing data, and privacy concerns [23]. Any future implementation should consider proper data collection, data cleansing, data validation and privacy intrusion protection [24].

3.2 Traditional Statistical Models

Conventional statistical techniques, including regression, survival analysis, and time series methods, have in

the past yielded interpretable information about the causes of risk and the effects of interventions. They are useful because they are simple and easy to understand, but they are linear and independent between variables and do not lend themselves to modeling complex, dynamic interactions such as those seen in the progression of chronic disease [25]. This means that these approaches are restricted in practical clinical scenarios, where patient data are high-dimensional and many dimensional.

3.3 Machine Learning Models for Diabetes Prediction

Machine learning (ML)-based methods such as decision trees, support vector machines (SVM), random forests, sequence boosters, and neural networks can capture and incrementally learn nonlinear relationships when presented with different types of data. Their ability to integrate high-dimensional clinical, lifestyle, and demographic data makes them particularly useful for chronic disease models [26].

Recent works show that when compared to traditional statistical methods, machine learning (ML) models are more effective in predicting diabetes. As an example, Sneha and Gangil trained SVM, random forest, Naive Bayes, Decision tree and k-NN models on a South Asian dataset on diabetes with the highest accuracy of 0.78 [27]. Equally, Zhang found that XGBoost and neural networks in the form of ensembles offered a better and noise-resistant forecast when using a multi-regional dataset [28].

Regardless of their advantages, ML models are often lacking in transparency, limiting clinical use. The proposed agent AI framework addresses this by incorporating interpretable AI techniques such as SHAP values, attention maps, and rule-based overlays to provide clinicians with clear, interpretable predictions for informed decision making [29],[30].

3.4 Integration of multi-model data

Multi-modal data, including clinical, behavioral, socio-demographic and environmental variables, can increase the predictive capabilities of agent AI systems [31]. As illustrated in Fig. 3, the multimodal precision health framework demonstrates how such diverse data streams can be effectively integrated to enhance real-time monitoring, detection of anomalies, as well as context-based recommendations especially within culturally specific groups such as those in Sri Lanka [32].

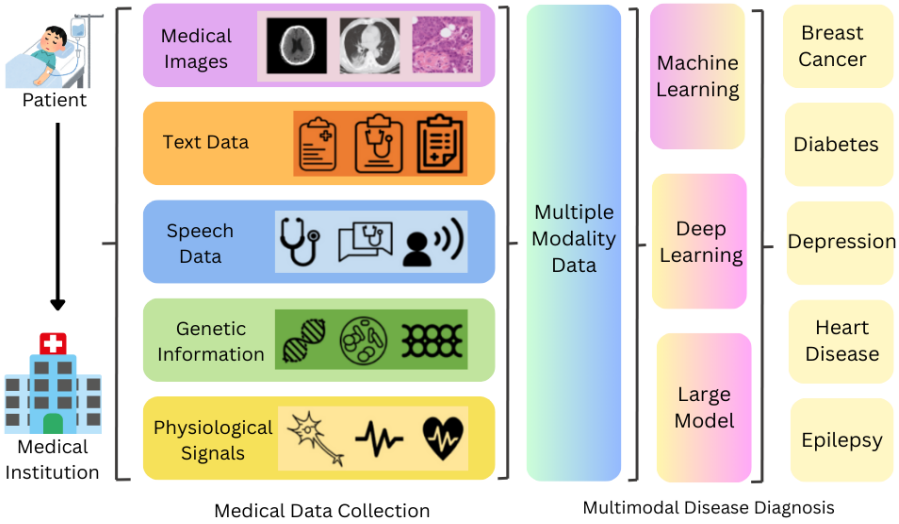

Fig. 3. Multimodal Precision Health Framework.

Henceforward, AI-based systems will be used to continuously analyze patient data, identify local anomalies, and keep risk profiles updated. But still, it is crucial to make sure that the systems are robust, privacy-

respecting, user-friendly, and trustworthy [32].

3.5 Proposed Data Pipeline for Sri Lankan Diabetes Dataset

Table 1 summarizes the proposed data pipeline, showing each stage from data acquisition to learning from survey data and their respective roles in preparing high-quality inputs to the prediction model.

Table 1. Proposed Data Pipeline Description

Stage	Brief Description
Data Acquisition	Collection of Sri Lankan T2DM patient data (glucose, blood pressure, cholesterol, BMI, lifestyle factors) with real-time survey inputs to ensure cultural relevance and dynamic learning.
Preprocessing and Cleaning	Handling missing values using median or mode imputation, correcting outliers, normalizing continuous data, and encoding categorical variables.
Data Validation	Comparing feature distributions with population norms and applying correlation analysis to remove redundant features.
Integration and Feature Engineering	Transforming key risk factors into model-ready inputs and preparing the pipeline for future multimodal data (e.g., wearable sensors and surveys).
Privacy-Preserving Measures	Ensuring anonymized data usage and exploring federated learning and differential privacy for secure model training.
Learning from Survey Data	Incorporating patient-reported survey data into the agentic AI framework to enhance personalization, prediction accuracy, and proactive disease management.

Fig. 4 below shows the conceptual framework of the proposed AI-based diabetes risk prediction system, highlighting the data flow, model training, evaluation, and feedback loop for continuous improvement.

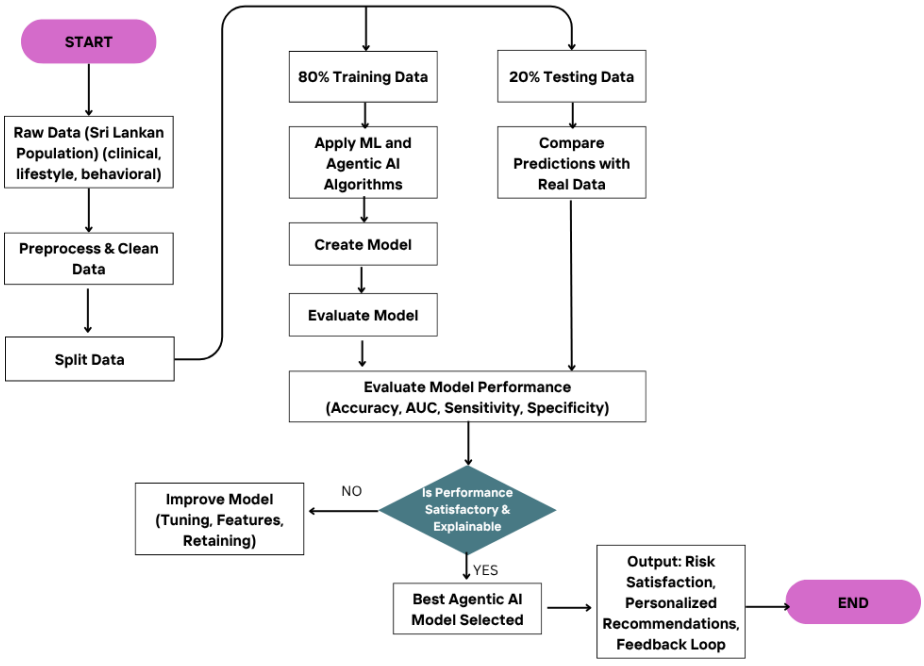

Fig. 4. Proposed Conceptual Framework for Agentic AI–Based Diabetes Risk Prediction.

4 Diabetes Risk Prediction Models

With the latest advances in Machine Learning and AI, the models used to predict diabetes risk are becoming much more accurate [33]. Access points, data needs, and insights can differ, making them unique, and they bring challenges when used in a clinical setting.

4.1 Traditional Statistical Models

Traditional risk prediction models are shown by logistic regression, Cox proportional hazards models, and discriminant analysis. Several established diabetes screening tools assess risk by combining demographic features, lifestyle patterns, and clinical measurements; the FINDRISC [34] and ADA risk tests [35] are among the most commonly used approaches.

However, such models are largely linear in nature and therefore have limited ability to represent the complex, nonlinear interplay of biological, behavioral, and environmental factors. In addition, their generalizability to non-homogeneous population groups such as South Asia is limited due to their limited validation with region-specific datasets. Indian and Bangladesh comparative studies have found that most predictive accuracy is likely to be lower when using European or North American models on South Asian cohorts, and there is a significant need to adapt such models locally [36],[37].

4.2 Machine Learning models

Machine learning (ML) models such as decision trees, random forests, support vector machines, neural networks, and gradient boosting work together to address some of the shortcomings of classical statistical models. By modeling complex associations between high-dimensional, heterogeneous, and non-linear data, these models are shown to be effective in classification (when such data are targeted) [15],[38]. As illustrated in Fig. 5, a comparative analysis of ML techniques applied to diabetes detection in Bangladesh demonstrates the relative performance of these models.

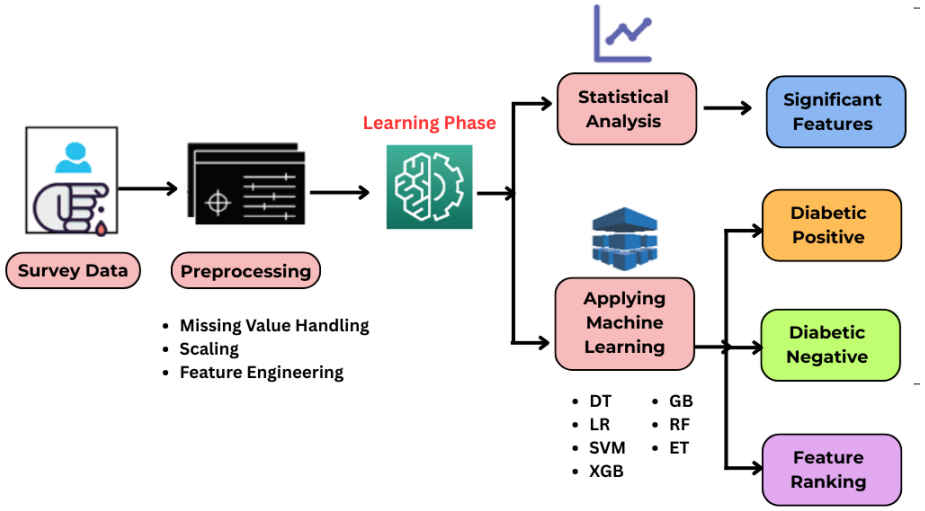

Fig. 5. Comparative analysis of various machine learning techniques applied to diabetes detection in Bangladesh.

Random forests and gradient boosting are always reliable in terms of their performance in both training and testing. Neural networks allow the use of multimodal features such as clinical, genetic, and lifestyle variables [39]. These observations are further affirmed by the evidence in India that predictive accuracy of the ML models to predict diabetes risks was about 77-88% and was better than the traditional logistic regression predictive accuracy [27],[40]. Despite these advances, ML approaches face significant challenges. Stock market datasets are large in volume and high in quality, and when not all of the usual requirements are met, they tend to be over-fitted [41]. Due to their black-box nature, these systems often lack trust among healthcare

professionals and are rarely used in clinical practice. In addition, studies from India report low external validity for South Asian populations, as cultural and context-specific variables are not adequately represented.

4.3 Hybrid and Agentic AI Systems

More recent developments emphasize hybrid and agential AI systems that combine predictive modeling with adaptive and real-time decision making [42]. Unlike traditional ML, agent-based AI has the ability to dynamically update risk priorities, integrate local clinical experience, and provide culturally sensitive advice. This is particularly important in Sri Lanka, where proper risk measurement tools and behavioral change-based interventions are yet to be established [32],[43]. However, issues of data quality, transparency, interoperability, fairness, and privacy still remain. It is important to note that Sri Lanka does not have any representative AI systems relevant to environmental risk prediction of diabetes, although advances in culturally relevant ML pipelines have been made in neighboring countries such as India and Bangladesh [44].

4.4 Evaluation Metrics

The evaluation of diabetes risk prediction models usually relies on accuracy, sensitivity, specificity, area under the receiver operating characteristic curve (AUC-ROC), and F1-score. Among these, sensitivity and specificity are particularly critical in clinical applications, as they directly affect the identification of individuals at risk [43],[45]. A comparative summary of diabetes risk prediction models and frameworks across different regions is presented in Table 2.

While maintaining strong predictive performance, agent-based AI can provide context-specific, actionable insights. Future research should focus on explainable, adaptive, and ethically designed models validated using culturally relevant data for Sri Lanka and the broader South Asian region.

Table 2. Comprehensive Comparison of Diabetes Risk Prediction Studies

Study	Country / Region	Methodology / Model	Sample Size	Performance (Accuracy / AUC)
[27]	India	Optimal Feature Selection (NB, RF)	768	0.82
[28]	Saudi Arabia / Egypt	Optimized ML (Resampling/Imbalance)	2,000+	0.88 – 0.94
[32]	Bangladesh	Feature Selection + ML Algorithms	2,000	0.81
[33]	China (Fujian)	Retrospective Cohort (RF, XGBoost)	15,469	0.83
[34]	China (Shanghai)	FINDRISC vs. Metabolic Syndrome	713	0.70
[36]	India	European Models vs. Indian IDRS	1,811	0.72
[37]	South Asia	Polygenic & Clinical Risk Scores	5,500+	0.78
[38]	Sri Lanka	SLDRISK Score Development	4,532	0.71
[39]	India (Kolkata)	Bayesian vs. Frequentist ML	1,200	0.84
[44]	Bangladesh / India	Cross-Dataset ML Analysis	1,500	0.79 – 0.83

[45]	USA (CDC BRFSS)	Neural Network & Random Forest	51,280	0.79

Although existing models are useful, the need for a Sri Lanka-specific representative AI framework becomes clear due to limitations in decentralization, data integration, real-time monitoring, and clinical interpretations, which could amplify risks and lead to misleading narratives.

5 Gaps in Existing Literature

Even though significant advances have been made in the prediction of diabetes risk, a series of limitations were identified that reduce the applicability and sensitivity of existing methods in the Sri Lankan context. The most significant gaps are outlined in Table 3 below:

Table 3. Existing Research Gaps Identified

Gap Area	Description	Implication for Sri Lanka
Population-Specific Calibration	Most models are developed on European, North American, or East Asian cohorts [1], [36], [37].	Limited accuracy and relevance for Sri Lankan population due to different diet, socio-economic factors, and genetic predispositions.
Limited Data Integration	Heavy reliance on clinical markers (BMI, blood glucose), minimal inclusion of behavioral, environmental, and healthcare access factors [2], [4].	Reduces predictive power and comprehensiveness for local context.
Cross-Sectional Frameworks	Existing models are often cross-sectional [22].	Cannot support real-time or longitudinal monitoring, unlike wearable and IoT-enabled systems.
Minimal Clinical Knowledge Embedding	Clinical expertise is rarely incorporated [4], [6].	Reduces interpretability, trust, and adoption by healthcare professionals.
Privacy, Equity, and Authentication Challenges	Lack of robust privacy protection and equity considerations [13], [17].	Limits safe and ethical deployment of agentic AI in healthcare

Existing models lack localization, multimedia data integration, and ethical safeguards. Therefore, this study proposes a Sri Lanka-specific agent AI framework that combines clinical, behavioral, and lifestyle data with clinical expertise to provide accurate, fair, and context-aware diabetes risk management insights.

6 Conclusion

While developed countries have a serious health and socio-economic management of chronic diseases such as type 2 diabetes (T2DM) and most importantly prevention through early interventions to reduce complications, this is not the case in developing countries like Sri Lanka. Traditional statistical models have

trouble capturing these complex nonlinear relationships in health data, but they can be interpreted. In developed countries, machine learning algorithms such as decision trees, random forests, and neural networks of the second type improve the level of accuracy of predictions, but they have the drawbacks of lacking transparency and having limited cross-world and cross-society applicability. As an alternative to this practice, my research presents the concept of agent AI as a solution, as it can automatically process health-related data, constantly retrain to update risk assessments, and send contextually aware and personalized suggestions. Unlike existing models that underrepresent Sri Lankan data and multi-modal health factors, this approach incorporates local data and clinical expertise to ensure cultural relevance, accuracy, and reliability.

The expected outcome is a framework that can close the gap between data analytics in health services and real-world responses by providing clear, transparent, and fair diabetes risk predictions. By doing so, it would not only help prevent individual cases of diabetes but also strengthen national health system capacity, support healthy communities, and contribute to broader development in Sri Lanka.

Future research should focus on expanding data sources, adopting federated learning for privacy, and applying fairness audits to ensure equity. Integrating Sri Lanka's national EHR with wearable devices and IoT could enable real-time monitoring, while clinical-in-the-loop designs would support trust and interpretability. Rigorous validation studies and strong regulatory and ethical frameworks are essential before large-scale deployment.

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