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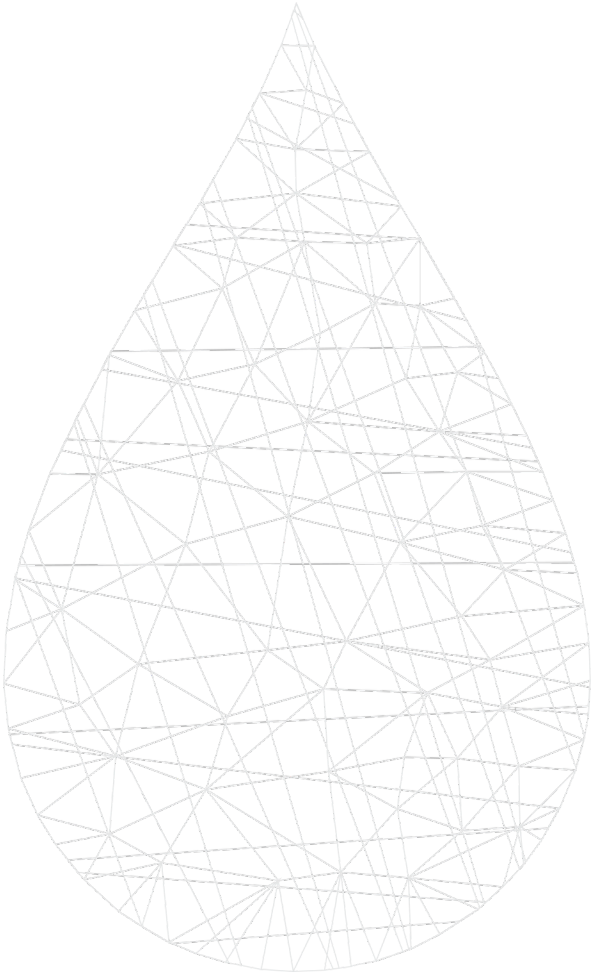

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AI FOR PREDICTIVE ANALYSIS IN HEALTH

AyurVAID D-RISK: AI-Powered, Predictive Framework for Detection of Undiagnosed Diabetics

Rajiv Vasudevan*

Abstract

Undiagnosed diabetesremains a significant public health concern globally and in many low- and middle-income settings. Conventional laboratory-based glucometric diagnostics typically identify diabetes after sustained metabolic dysregulation is established. Population-level risk scores based on limited variables may have constrained sensitivity and specificity across diverse populations.

AyurVAID D-RISK is an AI-assisted, non-invasive diabetes risk screening framework designed to support early identification of individuals who may have undiagnosed diabetes or elevated metabolic risk. The model integrates demographic, anthropometric, lifestyle, and symptom-based indicators, including features derived from classical Ayurveda (traditional medicine) descriptions of early metabolic imbalance, together with machine learning methods. In model-development, datasets of approximately 12,000 individuals, the AutoML-based framework demonstrated moderate-to-high discrimination metrics under cross-validation conditions.

D-RISK is intended as a screening and triage support tool to help prioritise individuals for confirmatory laboratory testing. Reported metrics reflect model-development validation results and should not be interpreted as definitive clinical diagnostic performance. The framework illustrates how culturally contextualised, non-invasive risk indicators combined with AI methods may support earlier risk stratification when implemented with clinical oversight and governance safeguards.

Background

A.Problem Overview

Diabetes is a chronic metabolic disorder marked by persistently elevated blood glucose due to inadequate insulin production or reduced insulin effectiveness. Its progression from normal glucose levels to overt disease is gradual and strongly shaped by lifestyle factors such as obesity, physical inactivity, and poor diet. Insulin resistance typically

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appears first, prompting compensatory overactivity of pancreatic beta cells; over time this compensation fails, leading to sustained hyperglycaemia often after significant physiological decline has already occurred.

In Ayurveda, the diabetes spectrum (Prameha) describes 22 prodromal features that may appear 2–5 years before measurable hyperglycaemia, including metabolic, digestive, and systemic symptoms. A retrospective cohort study of 141 newly diagnosed patients found that 11 of these prodromal features were significantly more prevalent than in healthy controls ($p < .001$)[1]. Incorporating such indicators into the D-RISK model is intended to support earlier risk stratification, complementing conventional biomarker-based screening approaches.

B. Clinical Relevance

Early Risk Identification

Evidence indicates that insulin resistance and metabolic imbalance precede elevated/abnormal glucose biomarkers by several years. This asymptomatic phase remains undetected by conventional screening, delaying intervention and increasing healthcare burden. Proactive, non-invasive, population-level screening tools are therefore of significant clinical and public health importance.

Limitations of Current Diagnostics

Definitive diagnosis of diabetes relies on laboratory measures such as HbA1c, fasting plasma glucose, and oral glucose tolerance testing. These tests are clinically established but require infrastructure, logistics, and cost. They are generally applied after risk suspicion arises. Risk scores such as IDRS support pre-screening but may show variable performance across populations and contexts.

Role of AI/ML in Addressing the Gap

The D-RISK approach applies machine learning to combine more than 40 non-invasive features to estimate the probability that an individual may have undiagnosed diabetes or elevated metabolic risk. Many of these features have weak predictive value individually but may contribute useful signal when analysed jointly through multivariable models. Machine learning methods support modelling of non-linear feature interactions and subgroup variation across demographic and regional strata. They also enable post hoc interpretability analyses to estimate relative feature contributions at the model level. This approach aligns with broader WHO priorities encouraging responsible use of AI-enabled digital tools, including in traditional, complementary, and integrative medicine contexts, provided that safety, transparency, and validation requirements are met. AI outputs in this framework are intended to support screening decisions, not to replace diagnostic testing.

Development Process

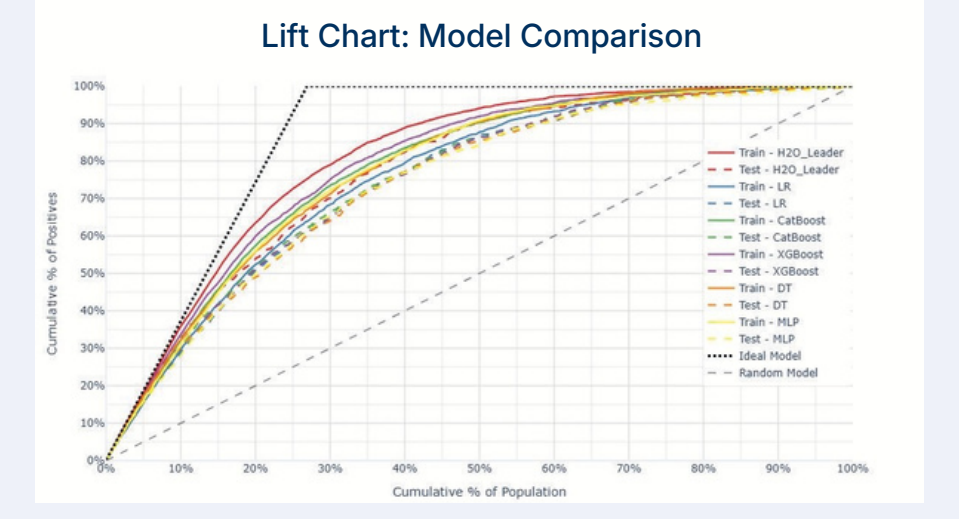
Scope

The project defines a structured, self-reported questionnaire designed to support a prediction model for identifying undiagnosed diabetes risk. Gestational diabetes is excluded because it is a pregnancy-specific, short-term condition. Data governance relies on patient self-reported questionnaires covering demographics, symptoms, lifestyle factors, and medication use, with audit and provenance controls to record who entered the data, when it was entered, and whether inputs were lab-verified or self-reported. Data cleaning and standardization procedures include validation of externally captured inputs to detect and flag incorrect values for clinician review or exclusion, normalization of free-text responses into predefined categories, and a minimal, clinically conservative imputation strategy that prioritizes clinically verified replacements wherever possible.

Model Development and Validation

Modeldevelopmentand validation combined culturally contextualized feature engineering with automated ensemble learning. The model incorporates Ayurveda diagnostic indicators alongside conventional clinical and lifestyle variables to better reflect India's pluralistic healthcare ecosystem and capture early metabolic imbalances not typically included in standard Western screening tools. Feature sets include demographics (age, gender, family history), anthropometric measures (waist and hip circumference), lifestyle factors (physical activity, diet patterns, sleep quality), and Ayurveda clinical indicators such as Agni Vaishamyam and Saamatva lakshanas, which correspond to metabolic dysregulation and inflammatory states associated with insulin resistance. Model training used the H2O AutoML framework to train and cross-validate multiple candidate algorithms and automatically select the top-performing ensemble (H2O Leader) based on validation results. Comparative evaluation showed the ensemble consistently outperformed individual models such as Logistic Regression, CatBoost, XGBoost, and deep learning approaches, capturing approximately 95–98% of positive cases within the top 30% of predicted risk scores—supporting efficient prioritization for confirmatory testing in resource-constrained settings. The model was trained on a dataset of about 12,000 individuals using five-fold cross-validation, with stratified sampling and threshold tuning to address class imbalance. Performance metrics include 78% accuracy, 75% sensitivity, 86% specificity, and an AUC–ROC of 0.87, indicating moderate-to-high discrimination under cross-validation conditions. SHAP (SHapley Additive exPlanations) values provide feature importance rankings and individual prediction explanations, enabling clinicians to understand and validate model decisions. These artefacts are intended to support clinical review and governance requirements.

Figure 01: Lift Chart: Comparison of H2O AutoML Ensemble and Individual Algorithms

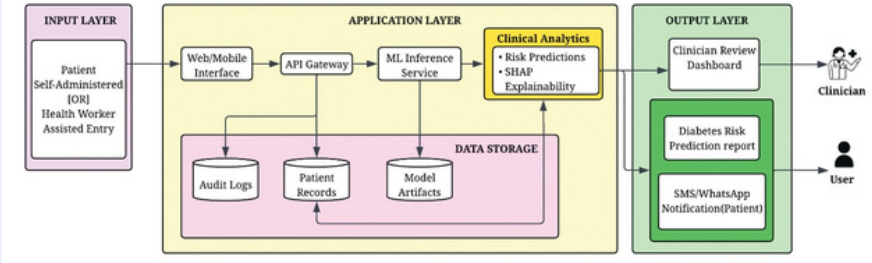


These metrics are derived from internal cross-validation and indicate discrimination performance under model-development conditions. They should be interpreted as illustrative performance indicators, not guaranteed field performance.

Clinical Integration and Deployment

A. Clinical Workflow and System Integration

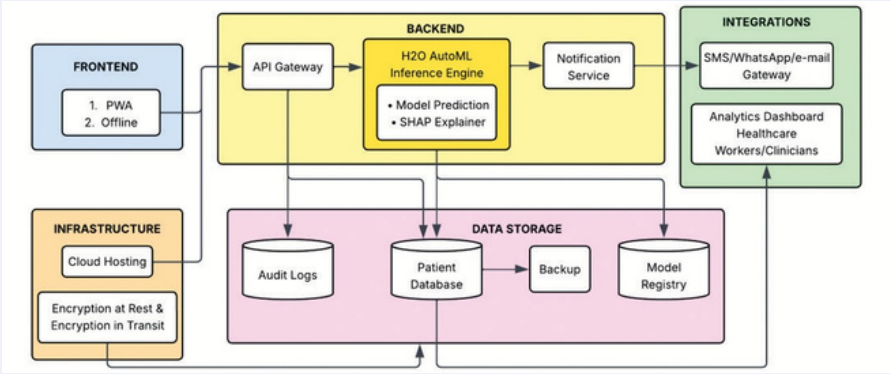
Figure 02: D-RISK Clinical Workflow and System Integration



The workflow (Figure 2) illustrates end-to-end patient flow and clinical decision support integration. Users access the platform through web/mobile interfaces with role-specific functionalities: patients complete self-assessments, health workers provide assisted data entry, and clinicians review the predictions via dashboard.

B. System Architecture and Infrastructure

Figure 03: D-RISK Multi-Tier System Architecture and Infrastructure



The D-RISK technical architecture (Figure 3) comprises five integrated layers:

- Frontend: Progressive Web App (PWA) with offline capability, supporting patient self-assessment, health worker-assisted entry, and clinician review dashboards
- Backend: RESTful API Gateway orchestrating requests to H2O AutoML inference engine, model result and SHAP explainer (feature importance visualization)
- Data Storage: Encrypted databases for patient records, versioned model registry with rollback capability, immutable audit logs, and automated backup with 30-day retention
- Integrations: Bidirectional EMR connectivity, SMS/WhatsApp notifications, and analytics dashboards for program-level monitoring
- Infrastructure: Cloud hosting, encryption in transit, encryption at rest, DPDP and HIPAA compliant. PII & sensitive data are encrypted both at rest & in transit adhering to Data privacy regulations as per ISO/IEC 27018 – PII Protection Standard

This modular design enables phased deployment from pilot sites to national scale while maintaining security, interoperability, and clinical safety standards.

C. Roles and Responsibilities

- Clinical Lead: Approves thresholds, pathways, and model updates in production
- Data Steward (IT): Enforces validation rules and manages flowchart-based data entry constraints
- ML Engineer: Maintains model services, calibration, and CI/CD pipelines
- Data Scientist: Performance monitoring, drift analysis, retraining, and documentation (model cards)
- Privacy Officer: Compliance audits, consent tracking, and data-sharing controls

Implementation Scale and Geographical Coverage

A. Phased Rollout Plan

Preparation and pilot phases have been completed in selected urban and semi-urban centres, with calibration and user-interface refinement. Regional and multi-centre scale-up phases are planned, subject to governance approvals and operational readiness. Federated learning approaches are under consideration where data-sharing constraints exist.

B. Identified Users

- Primary: Individuals using self-assessment tools for early risk awareness and referrals
- Secondary: Community health workers and clinicians using D-RISK to triage a group and prioritize confirmatory testing
- Tertiary: Program managers and policymakers using aggregate outputs (prevalence estimates, NNS) to plan screening and resource allocation

Impact and Value

Note: The models compared in Table 1 were developed using different populations, feature sets, data sources, and validation methodologies. These differences may substantially influence performance metrics

Table 01: Performance metrics for the US AutoML model and IDRS for diabetes detection are reported as published in the respective studies[6][7] and are presented for comparative, benchmarking purposes

Model	Sensitivity (Recall)	Specificity	PPV(Positive Predictive Value)	NPV(Negative Predictive Value)	AUC	Accuracy
US AutoML Model (JMIR AI, 2023)	70.26%	90.46%	64.10%	92.61%	90.90%	-
Indian Diabetes Risk Score – IDRS (MDRF)	72.50%	60.10%	17.00%	95.10%	-	61.30%
Apollo AyurVAID - D-RISK	75.00%	86.00%	62.00%	94.00%	87.00%	78.00%

such as sensitivity, specificity, AUC, and predictive values. Therefore, the results should not be interpreted as direct head-to-head evaluations, and caution should be exercised when comparing performance across models.

Compared to IDRS, the D-RISK model shows higher specificity, PPV, and accuracy values in development validation, though direct comparison is limited by differences in study populations and methods. When compared with a published US AutoML model trained on an older population (average age 59 years, with multimorbidity), D-RISK shows a different sensitivity–specificity balance appropriate to its target context. These cross-study comparisons are illustrative and should be interpreted with caution given differences in populations, feature sets, and validation approaches. D-RISK's metrics reflect internal cross-validation in an Indian general population (average age 45 years) and have not yet been validated prospectively or in external datasets.

If validated prospectively, a non-invasive, low-cost screening tool of this kind could support more efficient use of confirmatory testing and help prioritise clinical follow-up in resource-constrained settings.

Ethics, Governance, and Responsible Deployment

Privacy-by-design aligned with DPDP and HIPAA principles including consent, data minimisation, pseudonymisation, and role-based access controls, aligned with applicable data protection laws. Consent for use of patient data on redacted/anonymised basis was obtained from each individual at the time of registration. Human oversight is required, and the model is deployed as a clinician-reviewed triage support tool. Explainability artefacts (model cards, SHAP summaries) document intended use, limitations, and performance. Subgroup monitoring by age and gender is planned to identify disparities and support recalibration. Responsible use depends on continuous monitoring and governance.

Discussion: Successes and Challenges

Successes

The framework demonstrates feasibility of combining culturally contextualised indicators (Ayurveda descriptors), with AutoML methods for non-invasive diabetes risk screening. Ensemble modelling showed stable discrimination in development datasets, and explainability tools supported clinician review.

Challenges

Self-reported data introduce measurement error and label noise. Missing data handling and workflow redesign were required. Class imbalance and subgroup disparities required threshold tuning and monitoring. External generalisability remains to be established.

Lessons Learned and Future Enhancements

Key lessons include the importance of domain knowledge integration, explainability for clinician acceptance, and strong data governance. Planned enhancements include prospective blinded validation against gold-standard biomarkers, subgroup-aware recalibration, improved data capture quality, and multi-region pilots to assess operational effectiveness beyond initial settings.

Conclusion

AyurVAID D-RISKillustrates that a culturally contextualised, non-invasive, AutoML-based risk model can function as a screening and triage support tool for identifying individuals who may have undiagnosed diabetes and should receive confirmatory testing. Development-phase validation indicates useful discrimination under internal evaluation conditions. Responsible scale-up will require prospective external validation, fairness assessment, input standardisation, and operational pilots assessing clinical and economic value.

References

Sanjeev Rastogi, Neelendra Singh, Manish Gutch,

Arindam Bhattacharya,Prameha purvaroopa as diabetes risk predictor - trends from a retrospective cohort study of newly diagnosed type 2 diabetes patients, Journal of Ayurveda and Integrative Medicine, Volume 14, Issue 1, 2023, 100671, ISSN 0975-9476, https://doi.org/10.1016/j.jaim.2022.100671. (https://www.sciencedirect.com/science/ar ticle/pii/S0975947622001309)

International Diabetes Federation. (2024). IDF diabetes atlas (11th ed.). https://diabetesatlas.org/data-by-location/country/india/

Kurian, J., Bilagi, A., & Deo, G. (2024). Etiopathogenesis and management of Prameha Poorvaroopa (prediabetes), Prameha and Madhumeha (diabetes mellitus): An ancient perspective. Advances in Mind-Body Medicine, 38(3), 47–51. https://pubmed.ncbi.nlm.nih.gov/39213491 (pubmed.ncbi.nlm.nih.gov in Bing)

Rastogi, S., Chaudhari, P., & Singh, R. H. (2018). Linking Prameha etiology with diabetes mellitus: Inferences from a matched case-control study. AYU, 39(3), 139–145.

American Diabetes Association. (2025). Classification and diagnosis of diabetes. Diabetes Care, 48(Suppl. 1), S20–S42. https://doi.org/10.2337/dc25-S002

World Health Organization. (2025). Global traditional medicine strategy 2025–2034 (Health Systems Performance Assessment toolkit for universal health coverage). Geneva: World Health Organization.

Mohan, V., & Anbalagan, V. (2013). Expanding role of the Madras Diabetes Research Foundation–Indian Diabetes Risk Score in clinical practice. Indian Journal of Endocrinology and Metabolism, 17(1), 31–36. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3659903/

Liu, J., Ssewamala, F., An, R., & Ji, M. (2025). Use of automated machine learning to detect undiagnosed diabetes in US adults: Development and validation study. JMIR AI, 4, e68260. https://ai.jmir.org/2025/1/e68260/

Government of India. (2023). Digital Personal Data Protection Act.

U.S. Department of Health & Human Services. (n.d.). HIPAA security rule.