Literature Review

In this section, we review key studies that have shaped the modeling and prediction of glucose dynamics and diabetes risk using both mathematical and machine learning approaches. The selected works span explicit ODE-based models, broad modeling overviews, and modern machine learning implementations for glucose tolerance test (GTT) data.

## **Mathematical Analysis of a Model for Glucose Regulation (Fessel et al., 2016)**

This paper presents an explicit solution to the classic minimal model of glucose-insulin interaction, a system of coupled ordinary differential equations (ODEs) widely used for interpreting intravenous glucose tolerance test (IVGTT) data. The authors’ approach allows for separate analysis of glucose and insulin dynamics and enables direct estimation of patient-specific parameters from IVGTT data. Their method improves practical parameter identification and facilitates the calculation of clinically significant indices such as insulin sensitivity and glucose effectiveness, which are critical for diabetes diagnostics. The explicit solution and its clinical application make this work a cornerstone for both theoretical understanding and practical assessment of glucose regulation.

## **Mathematical Models and Software Tools for the Glucose-Insulin Regulatory System and Diabetes: An Overview (Makroglou et al., 2006)**

Makroglou et al. offer a comprehensive overview of mathematical models for the glucose-insulin system, covering ODEs, delay differential equations, partial differential equations, and integro-differential equations. The review discusses the physiological basis of each model type, their mathematical structure, and their relevance to different aspects of diabetes (e.g., Type 1 vs. Type 2, oscillatory behavior, response to meals). The paper also surveys available software tools for simulation and analysis, highlighting the importance of computational approaches in both research and clinical settings. This work is valuable for understanding the landscape of glucose-insulin modeling and for selecting appropriate numerical tools for simulation and parameter estimation.

## **Predicting Long-Term Type 2 Diabetes with Support Vector Machine Using Oral Glucose Tolerance Test (Abbas et al., 2019)**

Abbas et al. propose a machine learning framework using support vector machines (SVMs) to predict the long-term risk of developing Type 2 diabetes based on oral glucose tolerance test (OGTT) and demographic data. Using a large cohort from the San Antonio Heart Study, the authors extract and rank features from OGTT measurements, identifying plasma glucose-derived features as the strongest predictors of future diabetes. Their SVM model achieves high accuracy and sensitivity, demonstrating the clinical utility of targeted feature selection and machine learning for early diabetes risk stratification.

## **Artificial Intelligence‑based Learning Techniques for Diabetes Prediction: Challenges and Systematic Review (Kaul & Kumar, 2020)**

Kaul and Kumar present a systematic review of AI-based learning techniques for diabetes prediction, focusing on machine learning classification algorithms such as genetic algorithms, decision trees, random forests, logistic regression, SVM, and Naive Bayes. Using the Pima Indians Diabetes Database (PIDD), the authors compare the performance of these algorithms based on metrics like precision, accuracy, F-measure, and recall. The review finds that genetic algorithms yield the best classification performance. The paper also discusses challenges in diabetes prediction, including data quality, feature selection, and model robustness, and highlights the importance of dataset choice for model accuracy. This work provides a broad perspective on the strengths and limitations of various AI approaches in diabetes risk prediction.

**A comprehensive comparison**

| **Paper (Authors, Year)** | **Modeling Approach** | **Methodology / Algorithms** | **Data Used** | **Key Findings / Contribution** |
| --- | --- | --- | --- | --- |
| **Fessel et al., 2016** | **Mathematical** | **Explicit solution to minimal model ODEs; parameter estimation for glucose-insulin dynamics** | **Clinical IVGTT data (glucose, insulin)** | **Enables separate analysis of glucose and insulin, improves parameter identification, supports calculation of insulin sensitivity and glucose effectiveness** |
| **Makroglou et al., 2006** | **Mathematical (Survey)** | **Comprehensive review of ODE, DDE, PDE, and computational models; overview of software tools** | **Literature survey** | **Summarizes the landscape of glucose-insulin models, discusses physiological basis, and reviews available simulation tools** |
| **Abbas et al., 2019** | **Machine Learning (Applied)** | **Support Vector Machine (SVM) with feature selection (mRMR); model validation** | **OGTT and demographic data from 1,492 individuals (San Antonio Heart Study)** | **Plasma glucose-derived features are strongest T2DM predictors; SVM model achieves 96.8% accuracy and 80.1% sensitivity; demographic/insulin features less predictive** |
| **Kaul & Kumar, 2020** | **Machine Learning (Systematic Review)** | **Comparative analysis of ML classifiers: genetic algorithm, decision tree, random forest, logistic regression, SVM, Naive Bayes** | **Pima Indians Diabetes Database (PIDD) and other datasets** | **Genetic algorithm achieved best accuracy for diabetes prediction; highlights challenges in data quality, feature selection, and model robustness** |