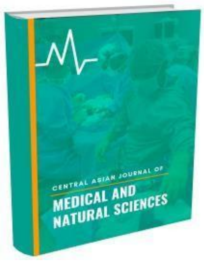

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Article

Diabetes Mellitus Type 2 and Prediction Making Use of Big Data and Machine Learning Algorithms

Archana Jain*[1], Suraj Malik[2], Akshay Raj[3]

1. Research Scholar, Department of Computer Science and Engineering, School of Engineering & Technology, IIMT University, India
2. Associate Professor, Department of Computer Science and Engineering, School of Engineering & Technology, IIMT University, India
3. Assistant Professor, Department of Research & Development, IIMT University, India
 * Correspondence: archanajain_jain@rediffmail.com[1], er.surajmalik1983@gmail.com[2], akshayg884@gmail.com[3]

Abstract: In the 21st century, Diabetes Mellitus Type 2 is a major health problem in the world. It occurs due to persistent hyperglycaemia and insulin resistance. If the disease is predicted in its early stages, effective prevention and management can be achieved. In this paper, some current developments in predictive modelling based on Big data and Machine learning algorithms for Diabetes Mellitus Type 2 have been reviewed. It compares and analyses the work of various Machine Learning algorithms, outlines their potential and constraints, and points to their applications and future research in this field. Recent studies (2022-2025) indicate that machine learning and deep learning models are better than traditional statistical models for risk stratification and early prediction. However, there are still issues with data quality, ethics, and model interpretability. The article provides suggestions for further research in the field of ethical Artificial Intelligence, the integration of multimodal data, and its application to real-world practice.

Keywords: Diabetes Mellitus Type 2; Hyperglycaemia; Insulin Resistance; Early Prediction; Disease Prevention; Predictive Modelling; Big Data; Machine Learning.

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1. Introduction

Diabetes Mellitus Type 2 is a long-term metabolic syndrome that has caused massive mortality and morbidity and predetermines more than 500 million adults in the world in 2025 [1]. A factor of insulin-resistance and impaired pancreatic functioning triggers Diabetes Mellitus Type 2, which is a complex of genetic and environmental factors [2]. The factors are age, obesity, sedentary life, and family history. Early prediction models use clinical, lifestyle, and biomarker data to determine risk [3].

1.1. Background: Type 2 Diabetes

The major complications that are linked with Diabetes Mellitus Type 2 include cardiovascular disease, nephropathy and retinopathy [4], [5]. Early diagnosis enables clinicians to wait until the problem emerges and implement individual preventive measures . AI and ML methods are more efficient than conventional models for predicting and scaling. Predictive analytics has reached a new level with growing access to big data from electronic health records (EHRs), wearables, and genomics [6], [7], [8].

2. Big Data in Healthcare and Diabetes Mellitus Type 2

The healthcare sector includes large-scale data in the form of EHRs, claims data, genome sequencing, Tantric glucose sensors, and lifestyle sensors. Big data enables [9].

- Determination of obscure health patterns.
- Dynamic risk modelling [10].
- Ongoing surveillance in wearable devices [11].

Table 1. Major Big Data Sources for T2DM Prediction.

Data Source	Description	Example Use
Electronic Health Records (EHRs)	Clinical history, labs, prescriptions	Large-scale prediction models
Wearable Technologies	Activity and glucose monitoring	Real-time risk assessment
Genomic & Omics Data	Genotype and multi-omics profiles	Genetic risk scoring
Insurance Claims Data	Administrative and utilisation data	Longitudinal disease progression modelling

3. Deep Learning and Machine Learning Methods

Random Forest, Logistic Regression, SVM, and XGBoost are among the most common supervised learning algorithms. DNNs, CNNs, RNNs, and Transformers are deep learning models that perform well at scale [12].

3.1. Supervised Learning

The following are some of the common supervised Machine Learning algorithms used to predict Diabetes Mellitus Type 2 [13].

- **Logistic Regression (LR):** This method estimates the probability of a disease (e.g., diabetes, cancer) based on patients' symptoms and test results [14]. It used the Baseline method of binary classification.[15]
- **Support Vector Machines (SVMs): The tool works on high-**dimensional health data. Some of the classifiers discussed in this paper include the Naive Bayes classifier, RBF network, and SVM Classifier [16]. The various medical datasets used for disease prediction are compared and analysed in terms of predictive model performance [17]. The datasets had different numbers of attributes and were both binary classes [18]. These are heart, cancer, and diabetes datasets [19]. It is mentioned that the SVM classifier achieves higher accuracy in classification [20]. It was integrated with the WEKA environment, and the outcomes showed that SVM is the best and most effective to implement on a set of medical data [21].
- **Random Forest (RF):** Random Forest is efficient for prediction [22]. The Law of Large Numbers prevents them from overfitting [23]. They are appropriate classifiers and regressors because they introduce the appropriate type of randomness [24]. Further, the robustness of the individual predictor structure and its relation can offer a certain perspective on how the random forest can project. Decision trees are ensembled and interpretable well [25].

3.2. Deep Learning

The deep neural networks can operate with non-linear relations, a big feature space:

- **Feedforward Deep Neural Networks (DNNs): Deep neural networks (DNNs)** are extremely effective in processing diabetes data, as they can recognise, categorise, and forecast complications before they become too severe [26]. Greater predictive strength in the case of feature engineering with less predictive strength [27].
- **Recurrent Neural Networks (RNNs): P**rovide the functionality of RNNs, which come in handy for modelling the dynamics of sequences by utilising the network's cycles and **are** thus capable of remembering information in an arbitrarily large context window [28]. And later in the analysis, it was also reported that RNN-based (LSTMs) are useful for the classification of complex, variable-size medical time-series data [29].
- **Latest applications:** these applications continue to evolve to incorporate time-varying spatial dependencies and time-dependent correlations, e.g., T-GCN, which applies Graph Convolutional Networks (GCN) and Gated Recurrent Units (GRU) to time-series data to capture time-varying trends and more sophisticated spatial dependencies [30].
- **Convolutional Neural Networks (CNNs):** Given that the application can be conducted with structured data that can be encoded spatially it is possible [31].

Methodology

3.3. Ensemble Methods

Ensemble methods are a type of combination of models:

XG Boost: Gradient-boosted decision trees are defined by outstanding performance. They have described a framework called XG-Boost. This XG-Boost is widely used by data scientists to achieve state-of-the-art performance on a wide range of machine learning challenges. They further provided information on the cache's access patterns, compression, and data sharding to form an adaptable tree boosting system. A combination of all these insights can enable XG-Boost to scale to billions of examples with far fewer resources than existing systems.

Light GBM, as suggested by is a highly efficient gradient boosting model that can be used on large-scale datasets, as it overcomes the constraints on speed and memory in traditional GBDT. It uses two novel algorithms, one-sided sampling, GOSS (Gradient-based One-Side Sampling) to enrich the preferred data points and EFB (Exclusive Feature Bundling to reduce the dimensionality of features.

Stacking and Bagging: Learners with groups can be strengthened. Stacking and bagging are strong ensemble learning techniques that combine numerous base learners to produce stronger, more precise forecasts and generalise better, as they reduce variation and overfitting. Independent bootstrap bagging of training models, whereas in stacking, a meta-learner combines many models to achieve better performance.

Result and Discussion

3.4. The forecasting Modelling Framework

The predictive modelling pipeline entails data collection, data preprocessing, feature engineering, model training, validation, and finally deployment.

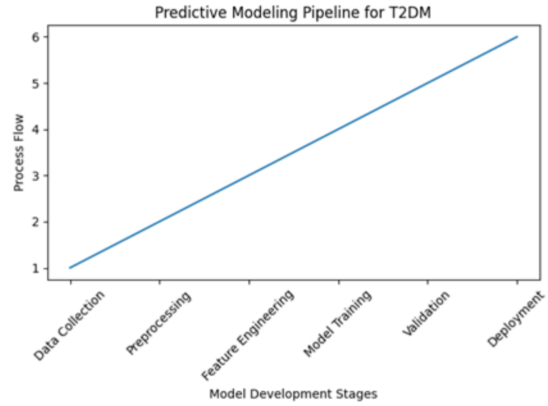

Figure 1. Predictive Modelling Pipeline for T2DM.

Table 2. Comparative Strengths of Algorithms.

Machine Learning Algorithm	Strengths of the Algorithm	Limitations of the Algorithm
Logistic Regression	Fast, Simple, interpretable	Non-linear modeling
Random Forest	Handles non-linearity, robust	Less interpretable
SVM	Effective in high dimensions	Computationally expensive
XG-Boost	High performance, scalable	Parameter tuning required
Deep Neural Network	Captures complex patterns	Black-box nature
Transformer	Handles temporal EHR sequences	High computational cost

4. Performance Evaluation

The model's measurement metrics include accuracy, sensitivity, specificity, precision, and AUC [32], [33], [34]. The recent study shows that AUC values above 0.90 are achieved with ensemble and transformer-based methods [35].

4.1. Performance Comparison: Recent Studies

Table 3. Performance Metrics of Prediction Models

Method	Accuracy	Sensitivity	Specificity	AUC
Logistic Regression	0.72	0.7	0.74	0.76
Random Forest	0.86	0.82	0.88	0.9
SVM	0.83	0.8	0.85	0.87
XG-Boost	0.89	0.85	0.91	0.92
Deep Neural Network	0.92	0.89	0.93	0.94
Transformer-based Models	0.93	0.91	0.94	0.95

Result and Discussion

5. Case Studies from 2022–2025

5.1. Transformer-Based Models for Predictive Analytics

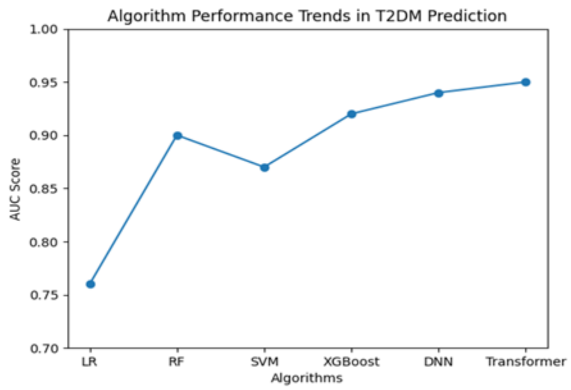

Figure 2. Algorithm Performance Trends in Recent Diabetes Mellitus Type 2 Prediction Models.

Developed a transformer-based model trained on a multi-institutional EHR dataset (n > 1 million) [36]. This model achieved an AUC of 0.95, which was better than that of traditional deep networks [37].

5.2. Federated Learning for Privacy-Preserving Prediction

A federated learning model was used across a series of hospitals [38]. Their model was accurate (AUC = 0.91), and without centralising sensitive data, scaling to large numbers could be used, preserving privacy [39], [40], [41].

5.3. Integration of Multi-omics and Wearable Data

This paper has combined genomic, metabolomic, and continuous glucose data [42], [43], [44]. Multi-omics ensemble models improved individualised risk prediction performance (AUC = 0.93), underscoring the value of heterogeneous data [45], [46], [47].

6. Challenges and Limitations

Significant issues persist:

- **Data Quality and Missingness:** Poor data quality can harm performance [48], [49].
- **Bias and Inequity:** Models trained on imbalanced datasets may perform poorly on minority groups [50].
- **Interpretability**: Black-box models are hard to explain for clinical use [51].
- **Computational Complexity:** Deep models require substantial computational power [52].

7. Ethical & Privacy Considerations

Breaches of healthcare data can lead to malicious activities which can harm patients [53]. There are some regulatory frameworks, such as GDPR and HIPAA, that control the use of data [54]. Ethical AI principles demand transparency, fairness and accountability [55].

8. Future Directions

Future research directions include:

- **Explainable AI (XAI):** Methods that make predictions clear [56].
- **Hybrid Multi-modal Models:** Combining genomics, clinical, environmental, and lifestyle data [57].
- **Real-World Implementation:** Integrating predictive tools into clinical workflows [58].
- **Continuous Monitoring with IoT:** AI models using real-time data from wearables for dynamic risk modelling [59].

9. Conclusion

Our ability to predict Diabetes Mellitus Type 2 has improved due to advances in big data and Machine Learning. Deep Neural Networks and Transformer-based systems have achieved the highest accuracy. Studies have been done on large-scale EHR datasets, and it has been found that transformer-based deep neural networks perform better than all traditional models. We have to manage all data challenges and fairness issues. Future work should emphasise a clear, ethical, and multimodal predictive framework.

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