

Diabetes Prediction Based on Ensemble Methods: A Review

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Abstract

Diabetes is a global health crisis, and early prediction is critical to preventing serious complications. Recent research shows that ensemble machine learning methods and deep learning architectures significantly improve diabetes prediction accuracy. Ensemble methods such as random forest, XGBoost, bagging, boosting, and stacking utilize multiple algorithms to capture diverse data patterns and consistently outperform traditional single classifiers. In parallel, deep learning models, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and hybrid CNN-LSTM architectures, excel at identifying complex temporal and spatial relationships. These techniques are widely applied to benchmark datasets, such as the Pima Indian diabetes data and other repositories at the University of California, Irvine, and are evaluated through metrics including area under the curve (AUC-ROC), precision, and recall. Challenges remain—particularly computational cost and model interpretability—but both approaches deliver superior accuracy and reliability. By integrating current evidence, this overview highlights the potential of ensemble learning and deep learning methods to enable earlier and more accurate detection of diabetes and enhance personalized healthcare solutions.

A. Introduction

Diabetes mellitus is a set of metabolic disorders characterized via extended blood sugar stages introduced on by using deficiencies in both the movement or secretion of insulin, or each [1]. When frame is not able to properly produce or use its insulin, it seems as this circumstance [2]. The Prevalence of diabetes in each adult and kids has made it one of the most important public health issues of our day [3]. A chronic metabolic condition called diabetes mellitus is brought on by a problem with the metabolism of glucose, which results in abnormal blood glucose levels. Insulin deficiency, the body's ineffective use of insulin, or, in certain situations, pregnancy may be the cause. About 9.3% of adults worldwide are thought to have diabetes, with an estimated 578 million people living with the illness by 2030 and 700 million by 2045 [4]. Currently, it impacts over 415 million individuals, making it a leading cause of mortality in both developed and developing countries [5]. Effective diabetes management aims to maintain normal blood glucose levels, reducing the risk of complications and mitigating the significant mortality associated with the disease [6]. Diabetes is a disease characterized by high blood sugar levels, primarily caused by unhealthy lifestyles and lack of exercise. Type 2 diabetes, which often develops after the age of 40, can affect various organs [7]. About 40 distinct forms of diabetes exist; some of the most prevalent ones are gestational diabetes, pre-diabetes, Type 1 (insulin-dependent), and Type 2 (insulin-independent) [8][9]. Insulin-subordinate diabetes mellitus (ISDM) is a condition where the pancreas produces less insulin than needed, resulting in type 1 diabetes. Type-2 diabetes is insulin resistive, more not unusual in excessive BMI or sedentary individuals. The third shape of diabetes, called gestational diabetes, may additionally seem during pregnancy [10]. The maximum not unusual sort of diabetes, kind 2 diabetes mellitus, is becoming extra not unusual worldwide and putting a heavy pressure on healthcare structures [11].

Ensemble methods, which combine multiple machine mastering algorithms to decorate predictive overall performance [12]. Have emerged as an effective tool in this region. By aggregating the strengths of individual fashions, ensemble techniques together with bagging, boosting, and stacking can drastically beautify accuracy, robustness, and generalization abilities [13]. This is particularly relevant in diabetes prediction, where the relationships between capabilities may be intricate and non-linear. In this overview, we goal to discover the utility of ensemble methods in predicting diabetes, highlighting their effectiveness and evaluating their performance to conventional unmarried-version techniques. We will also discuss the datasets applied, the methodologies adopted in numerous studies, and the demanding situations confronted on this evolving area. Ultimately, this evaluation seeks to provide insights into the cutting-edge nation of diabetes prediction the use of ensemble techniques and become aware of areas for future studies.

The next sections of this paper are organized as follows: Section 2 presents a detailed description of the dataset used in the research. Section 3 explores the theoretical background, supplying an in-depth clarification of the relevant ideas. Section 4 presents a literature review on diabetes prediction, while Section 5 focuses specifically on the prediction of diabetes using deep learning techniques. Section 6 discusses the results and findings from the literature reviews. The

research is finally concluded in Section 7, which also outlines the future and summarizes the main findings. directions for future research.

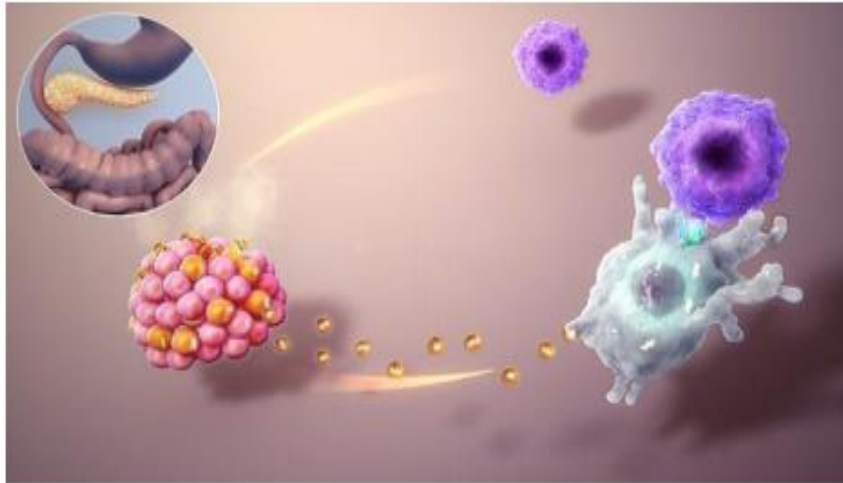


Figure 1. Diabetes mellitus [14]

B. Dataset

The provided datasets highlight the diversity and richness available for diabetes prediction research. Notably, the PIMA Indian dataset, which includes essential health indicators such as BMI, insulin levels, and diabetes pedigree function, is pivotal due to its focus on a high-risk demographic. The variety of attributes (ranging from 8 to 17) across different datasets emphasizes the complexity of diabetes risk factors, while the number of instances ensures sufficient data for model training. The distinction between public and private datasets is significant. Public datasets, such as those from Kaggle and UCI, enhance accessibility and foster collaboration, whereas private datasets may offer unique insights specific to particular populations but are less accessible for broader research.

Table 1. Comparative Analysis of Published Diabetes Datasets

Ref #	Dataset Name	Year	Number of attribute/instances	Access Type	Link & Accessed Date
[14]	PIMA Indian	2024	Pregnancy, BMI, insulin, age, blood pressure, blood glucose, skinfold thickness, and diabetes pedigree function are examples of Pima datasets.	Public	Pima Indians Diabetes Database (kaggle.com) ,10 - 9- 2022
[15]	Early-stage Diabetes risk prediction dataset	2024	Contained 520 instances and 17 attributes	Public	7 - 6 - 2020

Ref #	Dataset Name	Year	Number of attribute/instances	Access Type	Link & Accessed Date
	PIMA Indian		Contained 768 observations with 10 attributes		https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database
[2]	Dataset was collected from ethical guidelines from Pabna Diabetes Hospital.	2024	465 female patients aged 21 and above, including 373 patients with diabetes and 92 patients without it	Public	https://github.com/rul256/Pabna-Diabetes-Dataset-Bangladesh
[16]	Real-world dataset from Care Hospital (Dr. K.D Modi)	2024	contains 13 independent variables	Private	-----
[17]	PIMA Indian	2024	contains 768 observations and consists of 9 variables	Public	Pima Indians Diabetes Database (kaggle.com)
[18]	PIMA Indian	2024	includes 768 records of women who are older than 21.	Public	Pima Indians Diabetes Database (kaggle.com)
[19]	PIMA Indian	2024	The dataset comprises 769 imbalanced data values	Public	Pima Indians Diabetes Database (kaggle.com)
	Germany Diabetes Dataset		-----	Private	-----
[20]	MIMIC-III dataset	2024	A retrospective cohort study involving 1,177 patients divided into two groups: 978 with normal chloride levels (83%), and 199 with hyperchloremia (17%).	Public	MIMIC-III Clinical Database v1.4 (physionet.org) ,2001–2012 at Beth Israel Medical Center
[21]	Diabetes and Digestive and Kidney Diseases National Institute	2023	768 instances make up the dataset.	Public	https://www.kaggle.com/datasets/mathchi/diabetes-data-set
[22]	PIMA Indian	2023	Pima Indian has eight traits and 768 recordings.	Public	https://www.kaggle.com/datasets/uciml/pima-indians-diabetes-database

Ref #	Dataset Name	Year	Number of attribute/instances	Access Type	Link & Accessed Date
[23]	PIMA Indian Patients of Sylhet Diabetes Hospital	2023	768 women from Arizona with and without diabetes made up the dataset. This dataset had 17 attributes, 16 of which were associated with the diagnosis of diabetes and 1 of which was associated with a designated attribute.	Public	https://archive.ics.uci.edu/ml/machine-learning-databases/00529/

C. Background Theoretical

a. Ensemble Methods Overview

Ensemble learning uses trained predictions to improve the performance of individual machine learning models. Decision trees are commonly used for this, generating final classification based on ensembled results [25][26] is a type of ensemble learning method that is also used for classification and regression tasks. It offers a higher level of accuracy than previous models. This approach makes handling large datasets simple [27]. Ensemble approaches can be broadly split into two groups: parallel and sequential. The predictions of many base classifiers that have been trained independently are combined using a combiner in the parallel techniques. Bagging, along with its extension, the random forest algorithm, is a widely used parallel ensemble technique [28].

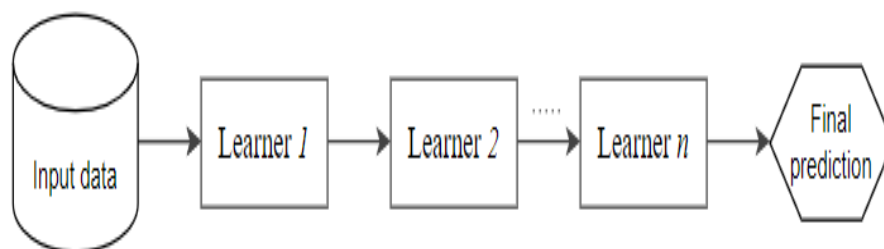


Figure 2. Sequential ensemble learning block diagram [28].

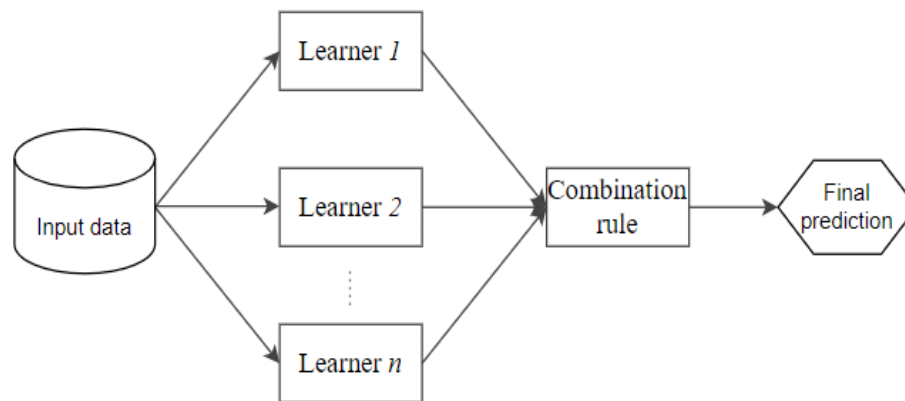


Figure 3. Parallel ensemble learning block diagram [28].

- **Bagging (Bootstrap Aggregating):** Bagging is a technique for creating a varied ensemble for a mix of models [28]. Aggregation and bootstrapping techniques are the foundation of bagging, offering benefits like obtaining irregular instances and replacing them with similar-sized ones [29].
- **Boosting:** Boosting is a technique that works like magic and creates a wide ensemble [28]. An ensemble algorithm is boosting. The primary dataset is divided into several subsets at the main event. The ensembling process then improves their performance by utilizing a cost function to combine the weak models [29]. This incremental approach helps weak learners correctly classify data points, but it can overfit to the training data, leading to incorrect predictions. Multiple boosting algorithms are available for classification and regression purposes [30].
- **Stacking:** One kind of ensemble learning system that combines additional classifiers in a ranked or hierarchical architecture is the stacking algorithm [29]. Stacking is an assembly technique that uses original data as input and stacks base-level classifiers with a metalearner classifier. The metalearner estimates input, output, and weights, and the models with the best performance are selected. Mixing, another name for ensemble stacking, is the process of combining data to create a classification or forecast. Complex methods such as probability distribution stacking and multilinear response are employed. [31].

3.2 Ensemble Methods Applied to Diabetes Prediction

- **Random Forest:** A random forest method for machine learning classification was first presented by Breiman in 2001. Machine learning, artificial intelligence, and computer development are all significantly impacted by random forest theory [32]. Random Forest is a machine learning algorithm that falls under the category of supervised learning. The RF classifier is composed of many decision trees that represent the different subjects from the given data

set. In order to improve prediction accuracy [33]. A random forest is composed of several independent decision trees that cooperate. In a random forest, these individual trees split up class predictions, and the model predicts the class that receives the most votes [25][34][35].

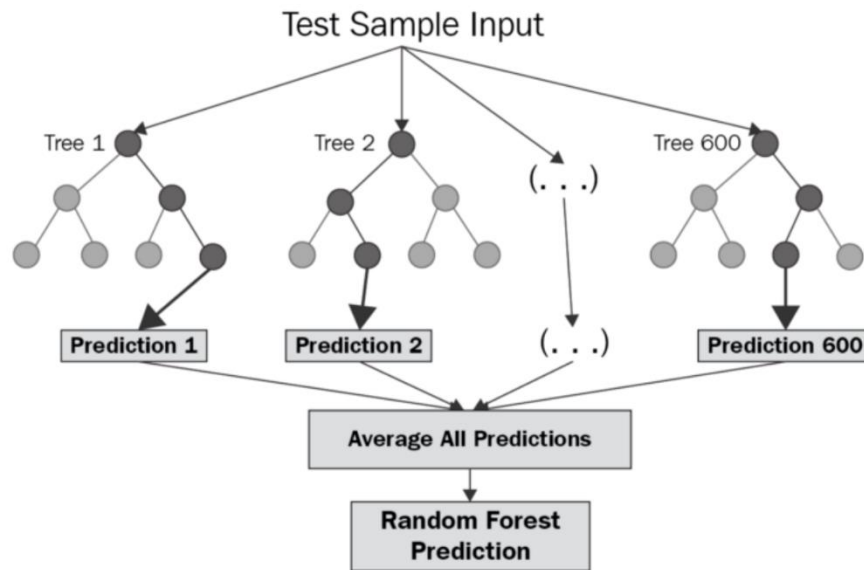


Figure 4. Random Forest [36]

- **AdaBoost:** Freund and Schapire introduced the machine learning meta-algorithm known as Adaptive Boosting, or AdaBoost, in 1995 [37]. The AdaBoost algorithm is an adaptive boosting technique used in machine learning to create strong classifiers from weak ones. It improves the performance of ML algorithms by adding models to rectify errors, primarily for decision trees in binary problem classification [25], [38]. Incorrectly classified instances will be given more weight when the weights of each instance are adjusted, whereas correctly handled cases would receive less weight [39]. The AdaBoost approach commonly uses decision tree stumps to address problems with regression and classification. [8].
- **Gradient Boosting Machines (GBM):** Gradient boosting is a tree-based machine learning technique [40]. The best ensemble strategy for prediction and classification is gradient boosting [27]. The gradient boosting (GB) approach adds estimators one at a time by modifying their weights, training weak learners in a sequential fashion [8]. An increased loss function, a weak learner to produce predictions, and an additive model to combine weak learners to minimize the loss function are the three key components of this technique [41].

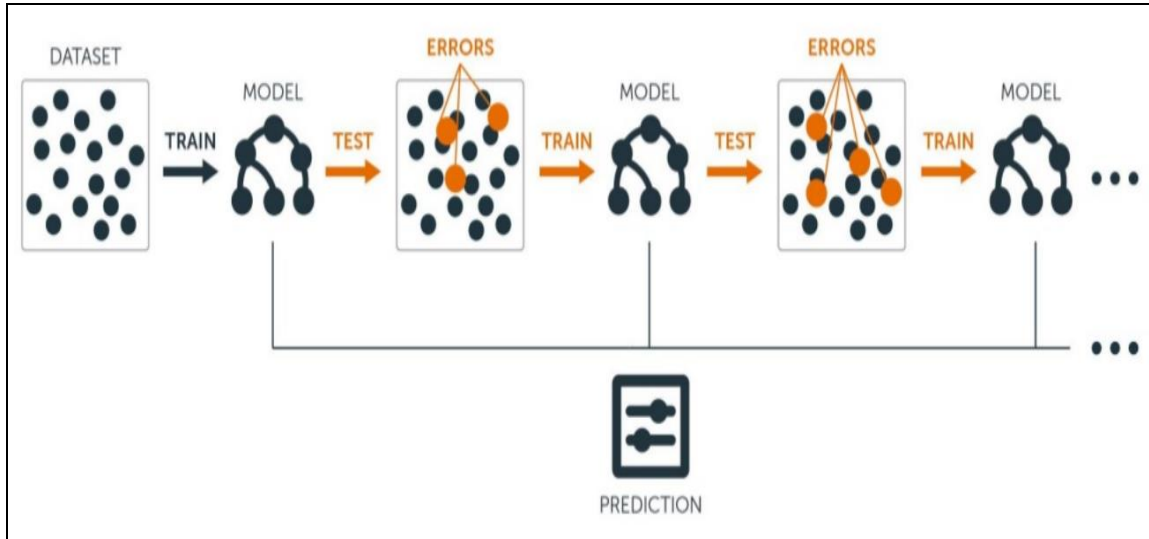


Figure 5.Gradient Boosting Machines (GBM) [42]

- XGBoost:** XGBoost combines different decision tree structures, sometimes known as weak learners, to calculate similarity scores independently. By integrating regularization and gradient descent methods, XGBoost effectively addresses the issue of overfitting that could arise during the training phase. It does this by modifying the gradient descent and regularization procedure, which helps to address the issue of overfitting during the training phase [8]. Fig. 6 shows how to create an ML (Machine Learning) model using the XGBoost approach. The computation's primary steps are as follows [43].

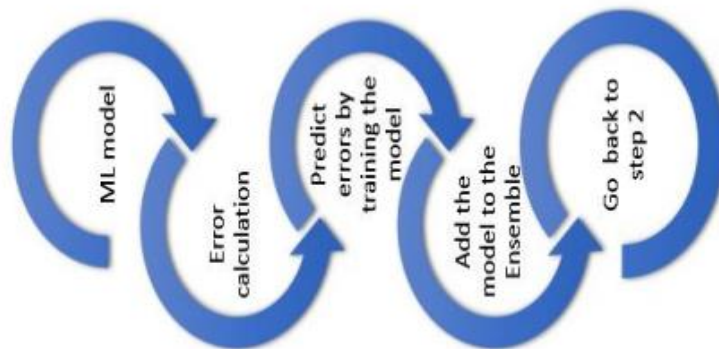


Figure 6.Process of XGBoost[43]

- **LightGBM:** An adaptation of a gradient boosting technique, the Light Gradient Boosting Machine (LightGBM) can process big datasets while using less memory when evaluating the model. During training, a gradient-based one-sided sampling technique is employed to divide data samples and lower the number of features in sparse datasets [8].

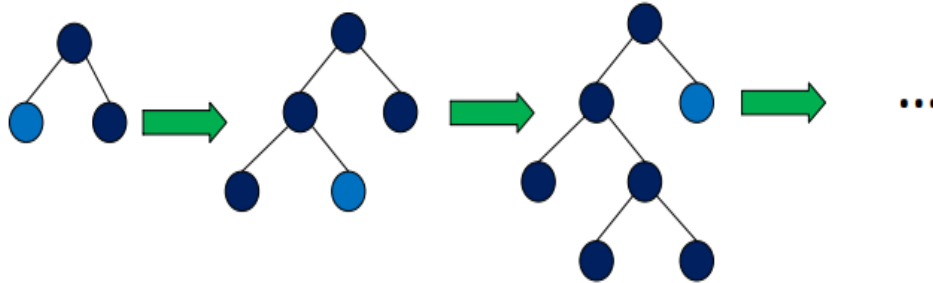


Figure 7. LightGBM [44]

D. Literature Review of Prediction Diabetes

In [45] The study discussed the predictive power of machine learning algorithms for Diabetes Mellitus, with fusion ensemble approaches yielding a maximum accuracy of 86%. It notes limits including dataset privacy, restricted features, and the lack of clinical research, while highlighting strengths like excellent accuracy, a comprehensive approach, and relevance to public health.

In [16] The study developed a diabetes prediction prototype using an Ensemble Model, achieving a high accuracy of 90.87%. The model outperformed individual classifiers and provided users with health predictions and historical data access. Future work aims to enhance model selection, data input flexibility, and additional functionalities for improved user experience.

In [15] discussed a diabetes prediction model that was proposed and achieved 90.62% accuracy utilizing ensemble classifiers and preprocessing approaches. It emphasizes the challenges of limited data availability and outliers in generating precise outcomes for diabetes prediction models. This study focuses on using correlation-based feature selection and classifying diabetes mellitus into subtypes.

In [2] The study implemented stacking ensemble methods to improve diabetes prediction accuracy, achieving a peak accuracy of 96.91% with local healthcare data. Key strengths include advanced techniques and effective data preprocessing, while limitations involve computational costs and potential class imbalance.

In [17] Discussed a study on diabetes prediction using an ensemble model approach, combining Random Forest, Extra Trees, and Multilayer Perceptron algorithms. It evaluates Type-1 and Type-2 error rates for males, revealing low false positive diagnoses but moderate false negatives. The study highlights SMOTE technique's effectiveness.

In [18] The study Discussed the utilizing machine learning techniques on a Kaggle dataset about diabetes. Ensemble techniques like AdasBoost, Bagging, and

RF are used, with the XGBOOST algorithm achieving 90% accuracy. Preprocessing is crucial for data transformation and usability.

In [19] The study Discussed presents Predicting diabetes using an ensemble machine learning approach, utilizing decision trees, logistic regression, KNN, random forest, and XGBoost classifiers. Metrics that show the correctness of the classification, such as sensitivity, specificity, and accuracy, are used to assess the model's efficacy.

In [20] The study used machine learning techniques, specifically ensemble methods, to improve diabetes classification accuracy and resilience in early detection and diagnosis. It uses a voting classifier, Boruta technique, and Random Over Sampling, achieving 93% and 90% accuracy for the PIDD and German datasets.

In [23] The study used advanced machine learning techniques to detect early diabetes in females, achieving a competitive accuracy of 92.91%. The stacked ensemble model, based on random forest classifiers, was interpreted using Shapley additive explanation.

In [24] The study investigated utilizing machine learning methods to predict diabetes on the PIMA Indian diabetes dataset. The model succeeded an accuracy of 98%, with strong performance across precision and F1 score. The system additionally concerned facts preprocessing and feature choice techniques to enhance results.

In [46] This looks at evolved an ensemble methods framework for early Type-II diabetes prediction the use of lifestyle facts. Techniques like Voting, Bagging, and Boosting had been implemented, with the Bagged Decision Tree showing the pleasant overall performance at 99.14% accuracy. The framework is effective for enhancing early detection and may be carried out to comparable datasets for healthcare choice-making.

In [47] This study suggested using weighted machine learning classifiers, which will reach 73.5% accuracy and 83.2% AUC, and presented updated diabetes data from Bangladesh. According to the study, there is a strong model for verifying the early prognosis of diabetes, demonstrating the strength of machine learning.

In [48] The take a look at focused on developing an ensemble mastering approach for correct diabetes prediction using machine gaining knowledge of algorithms, achieving performance between 98.8% and 99.9%. It emphasizes the significance of characteristic choice and the use of Genetic Algorithms to beautify version accuracy.

In[49] The observer Discussed Diabetes is a chronic illness brought on by elevated blood sugar levels that, if unchecked, can result in serious complications. utilized ensemble learning approaches, such as Bagging, Random Forest, and AdaBoost, for early prediction using a dataset with 17 variables from the UCI repository. At 97%, the Random Forest method had the highest accuracy.

In [50] This study proposed an interpretable diabetes detection version using the Pima Indian dataset, making use of six ML algorithms and an ensemble classifier with Shapley additive factors (SHAP) to enhance expertise for physicians. The version carried out ninety% balanced accuracy and an 89% F1 score, improving early diagnosis and medical decision-making.

In [51] This examine evolved a gadget mastering model to predict diabetes the usage of an imbalanced dataset, which become balanced with SMOTE and Tomek strategies. Random Forest completed eighty.7% accuracy, and a voting algorithm combining Gradient Boosting, Random Forest, and Naive Bayes increased accuracy to 81.7% using the balanced dataset and 82.0% using the default dataset.

In[52] This examine identifies key risk factors for gestational diabetes mellitus (GDM) and proposes an incorporated LightGBM-XGBoost-GB version. The model improves prediction accuracy and outperforms conventional device mastering strategies, supplying a bendy technique for early detection and relevant to other studies areas.

In [53] The study discussed the eDiaPredict framework is an advanced diabetes prediction system that makes use of ensemble machine studying techniques, accomplishing high accuracy fees of as much as 95%. It combines multiple algorithms, such as XGBoost and Random Forest, to enhance predictive overall performance and decrease bias. The framework is flexible and can be adapted for numerous healthcare datasets, contributing considerably to diabetes management and studies.

In [54] This study compared decision tree-based classifiers for diabetes prediction, using bagging and boosting methods. The results show that both ensemble techniques improve accuracy has the maximum accuracy of 98.65% when bagging and AdaBoost utilizing Naive Bayes Tree are used.

In[55] This study used rule-based classifiers (Decision Table, OneR, JRIP) with Boosting and Bagging on a diabetes dataset. The Bagging method achieves the highest accuracy of 98%, outperforming individual classifiers and boosting in terms of accuracy, precision, recall, and F1-score. Key features were extracted using Chi-Square, and the dataset was visualized with plots and a correlation matrix.

In[56] This study examined predicting diabetic protein markers using ensemble methods critical for diabetes diagnosis. It utilizes three feature extraction methods: 188D (composition and physicochemical), 400D (adaptive skip-gram), and 670D (g-gap). Results show that ensemble methods surpass single methods, with Random Forest and the combined feature method 588D (188D + 400D) achieving the highest accuracy. Method 1285D (all three combined) follows, while 188D is the best single method, and g-gap is the least effective.

In [57] This study proposes a robust diabetes prediction framework using data preprocessing and various machine learning models, including an ensemble method weighted by AUC. Tested on the Pima Indian Diabetes Dataset, the ensemble achieved the best performance with an AUC of 0.950, surpassing state-of-the-art results by 2%. The framework improves prediction accuracy, and the source code is publicly available.

In [58] This study addresses diabetes prediction Using Random Forest, Bagging, and AdaBoost, three machine learning algorithms. examining 464 cases with 22 risk variables in a dataset, the algorithms achieved accuracies of 97.84% (AdaBoost), 98.28% (Bagging), and 99.35% (Random Forest), with the best accuracy coming from Random Forest.

In[59] This study assesses ensemble approaches for type 1 diabetes glucose prediction, with an emphasis on how well they integrate with compartment

models for the absorption of fast-acting insulin. Three methods (Linear, Bagging, and Boosting metaregressor) were tested on data from six patients for 30, 45, and 60-minute predictions. Bagging outperformed individual algorithms, improving zone A percentages in Clarke's analysis by 4% to 9%. The use of compartment models further enhanced prediction accuracy, highlighting their importance in diabetes management.

In [60] This paper reviewed machine learning techniques for predicting diabetes, such as CNN, ANN, SVM, KNN, Random Forest, LSTM, CNN, and their ensembles, as well as Naive Bayes. The suggested CNN and LSTM combination outperformed all other techniques examined, with 97.14% accuracy, 97.30% precision, 96.30% recall, 96.79% F1-score, and 0.97 AUC.

Table 2. Comparison of Classification Techniques for Diabetes

Ref #	Dataset info	Technique	Performance Metrics	Results	Strengths
Aziz et al .2024[44]	This dataset contains essential health characteristics for predicting diabetes, such as blood pressure, BMI, insulin sensitivity, skin thickness, pregnancy, age, target result, and glucose levels.	Fusion (Ensemble) Method, RF, DT, SVC, KNN	F1 score, Confusion Matrix, Accuracy, Precision, and Recall	Fusion: 86%, RF: 83%	High Accuracy
Hang et al. 2024 [15]	520 instances with 17 attributes, sourced from a diabetes hospital in Bangladesh.	AdaBoost, SVM, AND DT	Accuracy, Precision, Recall, Confusion Matrix, and ROC Curve	Ensemble Model achieved the highest accuracy of 90.87% on the test set.	Outperforms single models
Kawarkhea and Kaur.2024[14]	Pima datasets include skinfold thickness, blood pressure, blood glucose levels, age, BMI, insulin, pregnancies, and diabetes pedigree function.	LR, RF, GBC, Linear Discriminant Analysis, catboost	F1, Kappa, MCC, Accuracy, AUC, Recall, and Precision	The mixed ensemble technique has the highest accuracy of 90.62% when compared to other models.	Outperforms single models

Reza et al. 2024[2]	Pregnancy, blood pressure, skin thickness, insulin, BMI, age, glucose levels, diabetes pedigree function, and 768 observations with 10 features make up PIMA.	machine learning and deep learning models, stacking algorithms	F1-Score, Accuracy, Precision, and Recall	Accuracy: 96.91% (local), 95.50% (simulated), 77.10% (PIMA).	Outperforms single models
Jain et al .2024[16]	dataset related to diabetes was collected from a diabetologist and maintained by Dr. Reddys' lab.	The model integrates the strengths of three different algorithms: Multilayer Perceptron (MLP), Random Forest, and Extra Trees.	Recall, F1 score, accuracy, precision, and curve (AUC-ROC).	The ensemble model classified diabetes with great accuracy.	Outperforms single models
Mazhar et al 2024 [17]	PIMA Indian Diabetes Dataset	Logistic regression, SVM, RF, KNN, decision trees, XGBoost and LightGBM	F1-score, Accuracy, Precision, and Recall	Accuracies. XGBOOST algorithm achieves a maximum accuracy of 90%	High Accuracy, Comprehensive Evaluation, Feature Importance Analysis
Rashid et al.2024[18]	PIMA Indian, consists of 768 records of women over the age of 21	decision trees, logistic regression, KNN, random forests, and XGBoost	Sensitivity Specificity Accuracy	The ensemble approach, which employed soft voting classifiers, achieved an accuracy rate of 81%.	Robust ensemble
ASHISHA et al.2024[19]	PIMA Indian comprises 769 imbalanced data values, Germany Diabetes Dataset	Random Forest, XGB, and Logistic Regression	Accuracy, precision, and recall	PIMA: 93%, Germany: 90%	high accuracy
Oliullah et al.2023[22]	Pima Indian has 768 records with eight characteristics, including pregnancy.	AdaBoost, XGB, NGBost, RF, LGBM	F1 Score, ROC, Accuracy Miss Rate, Precision, and Recall	accuracy: 92.91%	Effective classification

Zhou et al.2023[23]	768 women from Arizona, both with and without diabetes, made up the PIMA Indian dataset.	K-Means++ SVM, KNN, DT (stacking), and DT.	Precision, MCC, F1 Index, Accuracy, Recall, and Kappa	98% accuracy rate on the PIMA Indian diabetes dataset.	High Performance, Use of Ensemble Techniques, and Feature Selection
Ganie and Malik.2022 [45]	The dataset included 11 biological/lifestyle characteristics and 1939 records.	Bagging (BDT, RF, ET), Boosting (AB, SGB), Voting (LR, SVM, DT)	Recall, specificity, accuracy rate, precision, F1-score, MCR, and ROC curve	Bagging DT: 99.41%	Strong prediction
Dutta et al. 2022[46]	The DDC-2011 dataset includes 4,751 diabetes cases and 2,814 non-diabetic cases, while the DDC-2017 dataset contains 3,492 diabetes cases and 4,073 non-diabetic cases	NB, RF, DT, XGB, LGBM	Accuracy, Sensitivity, Area Under Curve (AUC)	Max Accuracy: 0.735, AUC: 83.2%	Strong AUC
Abdollahi and Nouri-Moghaddam.2022 [47]	Pima Indian Diabetes and 130 US hospitals with diabetes between 1999 and 2008	SVM, RF, DT, LR (Voting)	Specifically, specificity, sensitivity, and accuracy	Achieved 98.8% and 99% accuracy in diabetes diagnosis.	High reliability
Laila et al.2022[48]	UCI Machine Learning Repository.17 characteristics, one of which is a class trait for estimating the risk of diabetes	RF, Bagging, AdaBoost	F1-score, Accuracy, Precision, and Recall	RF: 97%	Improved risk prediction
Kibria et al.2022[49]	The Pima Indian diabetes dataset, which included 768 cases with nine characteristics, was used.	ANN, RF, SVM, LR, Adaboost, XGBoost	Precision Accuracy Specificity of Sensitivity AUC of the F1 score	Weighted ensemble: 90%	SHAP, interpretable

Mushtaqet al.2022[50]	PIMA diabetes dataset, which contains 768 samples with attributes	RF, NB, SVM, KNN, GB, LR	Accuracy, ROC	RF: 80.7%, Voting: 81.7%	Improved accuracy
Wang et al.2022[51]	The dataset, which includes 1200 data points and 85 fields overall, comes from the Tianchi Precision Medicine Competition. .	Ensemble LightGBM-XGBoos t-GB Model	F1-score, AUC, Accuracy, Precision, and Recall	The accuracy of the integrated LightGBM-XGBoost-GB ensemble model is 77.92%.	Maternal health impact
SINGH et al.2021[52]	The 768-patient PIMA Indian diabetes dataset includes information from female patients aged 21 to 65.	DT, NN, SVM,RF, XGBoost	Precision, GI, AUC, AUCH, MER, sensitivity, specificity, and minimum weighted coefficient (MWC)	Achieved 95% accuracy	Outperforms individual models.
Taser.2021[53]	Patients at the Sylhet Diabetes Hospital in Sylhet, Bangladesh, comprises 520 occurrences and 17 attributes.	Decision stump, Hoeffding tree, random tree, REPTree, C4.5, and NBTree	Accuracy rate	The best accuracy score of 98.65%	Improved Accuracy, Robustness, Versatility
Yadav and Pal.2021[54]	utilizes 9 characteristics and 768 instances from the diabetes UCI dataset.	Bagging, Boosting + Decision Table, OneR, Jrip)	F1-Score, Accuracy, Precision, and Recall	Highest accuracy achieved: 98% with Bagging method	High Accuracy, Comprehensive Analysis, Robust Methodology
Qu et al. 2021[55]	The dataset is derived from the Protein Family Database (PFAM) and includes sequences extracted from the UniProt Database.	LR, KNN, NB, DT, RF	F-Measure, AUC, accuracy, and the Matthews correlation coefficient (MCC)	The best accuracy (ACC) achieved was 0.8333	Protein marker focus
Hasan et al. 2020[56]	768 female diabetes patients from the PIMA Indians Diabetes (PID) dataset	AdaBoost, RF, KNN, DT, NB, XGBoost, and MLP	AUC, diagnostic odds ratio, false omission rate, sensitivity, and specificity	(AdaBoost + XGBoost) achieved the highest AUC of 0.950	Comprehensive Evaluation, Effective Preprocessing, Robust Ensemble Model

Islam et al.2020[57]	Data collected from diagnostic facilities in Khulna, Bangladesh, involving 237 female and 227 male patients out of 464 instances, each with 23 characteristics.	AdaBoost, Bagging and RF	MCC, specificity, sensitivity, accuracy, and precision The F1 Score False Negative and False Positive Rates	RF: 99.35% accuracy, AdaBoost :97.84% accuracy, and Bagging: 98.28% accuracy.	Reduction of Variance, Robustness, Parallelization
Saiti et al.2020[58]	Data from D1NAMO for four patients and FN Motol University	Linear, Bagging, Boosting	Clarke Error Grid Analysis, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE)	Compared to individual algorithms, ensemble approaches can yield glucose concentrations that are more precise.	Enhanced Accuracy, Clinical Relevance, Comprehensive Data Collection
Mishra and Tiwari.2020[59]	The PIMA Indian diabetes dataset 51, which was obtained from Kaggle, was utilized.	RF, ANN, SVM, KNN, LSTM, Naive Bayes, and CNN-LSTM ensemble	F1 Score, Accuracy, Precision, Recall, and AUC	CNN-LSTM: 97.14%	High Accuracy

E. Literature Review of Prediction Diabetes using deep learning technique

In [61] The study presented Predicting diabetes risk in its early stages using a hybrid deep learning approach, achieving an accuracy of 98.72%. It combines stacked autoencoders and Softmax classifiers, optimized through genetic algorithms, to enhance feature extraction and classification.

In [62] The study proposed two ensemble models, Hi-Le and HiTCLe, for diabetes prediction using an imbalanced dataset. Hi-Le combines Highway and LeNet, achieving 94% accuracy, while HiTCLe blends Highway, LeNet, and TCN, also achieving 94% accuracy. Both models outperform individual ones, with results validated through K-Fold Cross Validation and SHAP analysis.

In [63] The study developed a Deep Neural Network (DNN) model that addressed issues including feature selection and missing data was able to predict diabetes in pediatric patients with a high accuracy of 99.8%. It underscores the significance of early detection for better healthcare outcomes.

In [64] This study introduces a conditional deep generative model to improve type 1 diabetes (T1D) simulators by accurately representing the glucose-insulin system. Utilizing a sequence-to-sequence generative adversarial network (CGAN), The model produces realistic glycemetic trends that closely mimic actual patient data by capturing the causal links between insulin, carbs, and blood glucose levels.

In [65] The study presented an Ensemble Deep Learning (EDL) system that combines multiple deep learning models (ANN, LSTM, and CNN) to improve predictive performance and accurately forecast diabetes. With accuracy ratings of

99.51%, 98.81%, and 98.45%, respectively, the stack-ANN outperformed the other suggested EDL models when tested on the DDFH-G, PIMA-IDD-I, and IDPD-I datasets.

In [66] This study addressed class imbalance through data resampling and presents a non-invasive diabetes diagnosis utilizing a Back Propagation Neural Network (BPNN) with batch normalization. The approach performs better than more conventional models like GRNN and CkNN. It demonstrated the efficacy of deep learning for precise diabetes diagnosis by achieving accuracies of % (Pima) 89.81, (CDC BRFSS2015) 75.49%, and (Mesra) 95.28% when tested on three datasets.

In [67] The study demonstrates that gait analysis using accelerometer data can effectively detect diabetes through a hybrid CNN-LSTM model, achieving an accuracy of 91.25%. By including other physiological elements, such muscle contraction and force, model performance and early detection capabilities may be improved.

In [68] This study suggested an effective deep-learning model, CORNN, and a novel sensing module for automated, non-invasive diabetes detection based on breath-based diagnosis. With a prediction accuracy of 98.02%, the approach exhibits a substantial positive connection when compared to traditional blood-based diagnosis. The results support the effectiveness of this method and its potential for non-invasive diabetes screening in medicine.

In [69] this study evaluated predicting styles for blood glucose levels in T1D patients were assessed. the CNN-LSTM hybrid model emerged as the sole one, achieving the lowest prediction errors. High accuracy, resilience in capturing intricate fact patterns, and scalability for real-time packages are among of the version's main advantages.

In [70] The study successfully advanced a robust diabetes prediction version that significantly complements prediction accuracy via the integration of Deep learning and machine learning techniques. The proposed framework demonstrated an average accuracy improvement of 9% over traditional models, with a Deep Convolutional Neural Network achieving 96.13% accuracy. This advancement in predictive analytics can aid healthcare professionals in early diabetes detection and intervention strategies.

In [71] The study focuses on developing a diabetes detection model using Conv-LSTM, achieving a high accuracy of 97.26%. It employs advanced techniques like feature selection through the Boruta algorithm and integrates spatial and temporal data processing. The results indicate that Conv-LSTM outperforms traditional models, showcasing its effectiveness in medical data classification.

In [72] The study uses a deep learning model with a Deep Belief Network to predict Type 2 Diabetes complications, with an accuracy of 81.20%, potentially aiding effective diabetes management.

Table 3. Comparison of deep learning Techniques for Diabetes

Ref #	Dataset info	Technique	Performance Metrics	Results	Strengths
Bülbül.2024 [60]	data from the University of California Irvine (UCI) that predicts diabetes risk, comprising 520 attribute).	Hybrid DL, KNN, DT, SVM, CNN	F1 Score, Accuracy, Sensitivity, and Precision	Accuracy: 98.72%	Outperformed previous methods.
Shaheen et al. 2024[61]	makes use of a Diabetes Prediction Dataset (DPD) that is extremely unbalanced.	Hi-Le, HiTCLe (LeNet + TCN)	Accuracy, F1-Score, precision and recall.	Hi-Le :94%, HiTCLe 94%.	Strong ensemble models
El-Bashbishy and El-Bakry.2024[62]	The system was validated and tested on 548 patients from Mansoura University Children's Hospital Diabetes using a novel dataset.	MLP method for DNN model	R2, Mean Square Error, Training Scores, Accuracy, Precision, Recall, and F1-Score	Outstanding 99.8% accuracy rate	Outperformed existing methods.
Mujahid et al.2024[63]	the Ohio T1DM Dataset, the Hypomin Dataset, and the Hospital Clinic de Barcelona T1D Dataset.	Sequential GAN	-----	Statistical resemblance to real patients	Realism, causality, versatility
Al Reshan et al. 2024[64]	Trained on PIMA-IDD-I, DDFH-G, and IDPD-I.	ANN, LSTM, CNN (Stacking)	ROC/AUC, F-score, and Matthews Correlation Coefficient (MCC).	DDFH-G 99.51%, PIMA-IDD-I 98.81%, and IDPD-I 98.45% accuracy	Strong ensemble methodology

Ref #	Dataset info	Technique	Performance Metrics	Results	Strengths
Zhang et al.2024[65]	The National Institute of Diabetes and Digestive and Kidney Diseases and the Johns Hopkins University Applied Physics Laboratory supply the Pima Indian diabetes dataset.	deep learning model based on Back Propagation Neural Network (BPNN)	Accuracy, Sensitivity, and Specificity	obtained accuracy rates of 95.28% (Mesra Diabetes dataset), 75.49% (CDC BRFSS2015), and 89.81% (Pima dataset).	Novel DL model.
Chee et al.2024[66]	The Diabetes Database for Pima Indians and ECG data	Hybrid Deep Learning CNN-LSTM	F1 Score, AUC, ROC, Accuracy, Precision, and Recall	The accuracy of CNN-LSTM is higher 91.25%.	The model achieved a notable accuracy of 91.25%, indicating strong predictive performance.
Bhaskar et al.2023[67]	Breath samples from 70 type 2 diabetic patients and 82 healthy people in various age groups make up the dataset used in the study.	Deep hybrid model known as the Correlational Neural Network (CORNN)	F1 score, Matthews Correlation Coefficient (MCC), False Discovery Rate (FDR), False Omission Rate (FOR), sensitivity, specificity, and accuracy	Accuracy: 98.02%	Non-invasive approach
Jaloli and Cescon.2023[68]	Use two data sets, Replace-BG and DIAdviso	(LSTM) with (CNN)	RMSE, or root mean square error; R2; MAE, or mean absolute error	The CNN-LSTM model achieved a MAE of 17.30 mg/dL, RMSE of 23.45 mg/dL, and R ² of 84.13%.	High Accuracy, Robustness, and Scalability
Patro et al.2023[69]	Pima Indians Diabetes dataset	CNN	accuracy, precision, recall, F-Measure, and ROC	Deep CNN model and achieved promising accuracy of 96.13%	Integration of ML & DL.
Rahman et al,2020[70]	Pima Indians Diabetes Database	CNN-LSTM, Convolutional Neural	Sensitivity, Specificity, and	Conv-LSTM's accuracy was	High Accuracy, Advanced Techniques, and

Ref #	Dataset info	Technique	Performance	Results	Strengths
			Metrics		
		Network (CNN), and Traditional LSTM (T-LSTM)	Accuracy	97.26%.	Robust Feature Selection
Vidhya and Shanmugalakshmi.2020[71]	In the Diabetic Repository, there are 50,000 datasets.	Using a Deep Belief Network (DBN) to forecast Type 2 Diabetes complications	Precision, accuracy, and Recall.	Accuracy of 81.20%	achieved 81.20% accuracy, outperforming more conventional techniques.

F. Result and Discussion

The comparison of machine learning and deep learning techniques for diabetes prediction, Various studies between 2020 and 2024 highlight the reveals significant advancements in accuracy and model efficiency, with ensemble methods and hybrid deep learning models emerging as the most promising approaches. Both methodologies have demonstrated considerable success in enhancing diabetes prediction, but each comes with its own set of strengths.

searchers and practitioners investigated new methods by delving into a range of datasets, The datasets used in both machine learning and deep learning models for diabetes prediction play a critical role in determining the accuracy, generalizability, and real-world applicability of these models such as the Pima Indian Diabetes dataset (PID), UCI datasets, and others. The advent of machine learning, particularly ensemble methods, has significantly advanced the field of diabetes prediction.

Researchers and practitioners investigated new techniques by using delving into a range of datasets, including the Pima Indian Diabetes dataset (PID), UCI datasets, and others. Ensemble Methods in Machine Learning, Ensemble techniques have continually outperformed traditional gadget gaining knowledge of algorithms in diabetes category tasks. Methods which include Random Forest (RF), XGBoost, and Stacking leverage the strengths of a couple of models to boost prediction accuracy. For example, Reza et al. (2024) finished 96.91% accuracy the usage of a stacking ensemble approach, demonstrating the robustness of ensemble techniques in handling scientific datasets Similarly, Aziz et al. (2024) stated an accuracy development to 86% through combining Random Forest with Linear Discriminant Analysis. Ensemble strategies are especially effective at addressing common troubles in clinical data, along with elegance imbalance. Studies like that of Ashisha

et al. (2024) highlight how balloting classifiers combining RF, XGBoost, and Logistic Regression progressed prediction accuracy, reaching 93% accuracy at the PIMA Indian Diabetes Dataset and 90% on a German Diabetes dataset. These results exhibit the adaptability of ensemble techniques throughout diverse datasets, making them enormously sensible for actual-international healthcare programs.

Deep Learning Approaches illustrates that deep learning fashions, especially hybrid architectures, are gaining traction for diabetes prediction because of their potential to version complex relationships in information. Bülbül (2024) added a hybrid model combining KNN, Decision Trees, SVM, and CNN, attaining 98.72% accuracy, outperforming conventional methods and setting up a brand-new benchmark for diabetes prediction. This displays the developing consensus that deep learning, particularly when blended with other strategies, can offer superior performance in identifying diabetes hazard. One of the key benefits of deep learning is its capability to manner massive volumes of unstructured records. For instance, fashions like CNN and LSTM, as confirmed through Jaloli and Cescon (2023), are mainly effective in coping with time-collection data for blood glucose prediction. Their hybrid CNN-LSTM model done excessive accuracy with an average absolute mistake (MAE) of 17.30 mg/dL, illustrating how deep mastering fashions excel in continuous glucose tracking and real-time prediction.

Both ensemble and deep getting to know techniques deliver particular strengths to diabetes prediction, and a hybrid technique combining those methodologies should offer even more predictive strength. While ensemble techniques excel in coping with imbalanced datasets and enhancing prediction balance, deep getting to know models provide a method to capture complex patterns in records that traditional strategies may additionally leave out.

G. Conclusion and Future Work

Diabetes prediction plays an essential position in improving early diagnosis and control of this substantial chronic sickness. This review critically examines the software of advanced device mastering ensemble methods and deep studying fashions in diabetes prediction, showcasing their ability to deliver significantly higher accuracy as compared to standard tactics. Ensemble techniques, which includes Random Forest, XGBoost, and AdaBoost, have validated their effectiveness in combining more than one classifier to enhance predictive performance, consistently reaching accuracy rates as excessive as 99%. Similarly, deep gaining knowledge of models, together with Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid architectures like CNN-LSTM, have verified their superiority in capturing complex styles within medical datasets, pushing prediction accuracies up to 98.72%.

Despite these demanding situations, ensemble getting to know remains a promising course for future studies. Combining superior ensemble strategies with deep gaining knowledge of and actual-time scientific data may want to result in even extra correct and reliable structures for diabetes prediction and control. Future studies ought to focus on large, greater diverse datasets and discover the combination of rising system learning techniques to similarly enhance prediction accuracy and medical applicability.

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