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A Novel Ensemble-Based AI Framework for Early Prediction of Monogenic Type 1 Diabetes in Neonates Using Maternal and Pregnancy Health Indicators

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ABSTRACT

While monogenic Type 1 diabetes in neonates is uncommon, it can critically endanger a child's health if not diagnosed promptly. This study aims to develop an ensemble-based predictive framework utilizing AI for identifying neonatal monogenic diabetes risks using maternal and pregnancy-related health indicators. By employing a publicly available dataset, we reconstructed neonatal outcomes using AI-based pattern recognition. The proposed model utilizes Decision Trees (DT), Random Forests (RF), Gradient Boosted Trees (GBT), and K-Nearest Neighbors (KNN) in a soft-voting ensemble framework. As our results indicate, ensemble methods outperformed individual classifiers, with ensemble approaches yielding higher accuracy as well as improved generalization. Overall, the framework can support clinicians in off-screening at-risk neonates, guiding proactive clinical action and tailored care after birth.

Keywords: *Maternal health risk, Machine learning, Ensemble machine learning, Pregnancy complications*

1. INTRODUCTION

Early diagnosis is essential because the condition is undiagnosed and untreated in many cases, which can result in severe consequences. In most cases, the diagnosis is made after the symptoms appear, which hinders timely intervention. Predictive modeling is now possible due to AI and machine learning (ML) algorithms which can process numerous health records collected during the gestation period. This study aims to reframe maternal health data to foresee the risk of neonatally diagnosed diabetes, concentrating on monogenic Type 1 diabetes.

Almost all previous research focused on estimating the risk of gestational diabetes and other related factors. Very few, if any, sought to predict neonatal diabetes using ensemble learning techniques. We build upon existing frameworks by implementing multi-model ensemble prediction to forecast neonatal outcomes from maternal blood pressure, glucose levels, age, and body mass index (BMI). This approach is novel on the premise that it reframes the data for neonatal risk as opposed to focusing on maternal outcomes. Thus, we extend the applicability of maternal datasets towards disease prediction.

The study investigated the implementation of predictive models for assessing risks in maternal healthcare. The model was developed using two different approaches: standard and ensemble machine learning. The aim was to build a new model that could effectively address the accuracy, robustness, flexibility, bias-variance trade-off issues. The ensemble techniques also perform well on complex datasets with multi-class target variables and imbalanced classifications among multiple categories. The proposed model, which combines the strengths of several models, achieves high accuracy, stability, and minimal overfitting. In addition, the performance of the model used for multi-class classification needs to be evaluated in a thorough manner. For the model evaluation, two evaluation metrics used in this study: micro and macro weighted scores. This allows addressing class imbalance (reduce bias toward larger classes), overall performance assessment (to evaluate how well the model performs), and equal consideration to all classes (to ensure smaller class performance is not overshadowed by larger class performance).

In this study, a new QEML-MHRC framework is presented for predicting maternal health risk during pregnancy. In comparison to traditional machine learning approaches, it included a lot of new features and advances. First, the integration of several models allowed for a thorough examination of the generated results. The variety of methodologies employed in data analytics displays a thorough awareness of the relationships between various variables. In addition, micro and macro weighted scores were used in this study to address the multi-classification issue. In the future, the proposed system might provide personalized risk assessments based on individual patient data. Finally, cross validation and other specific elements used various approaches to Improve model performance. The findings of this study would be integrated into a decision-making system for healthcare practitioners.

2. RESEARCH BACKGROUND

The integration of machine learning (ML) algorithms with medical data offers diverse solutions across various health sectors. The application of ML in the healthcare industry significantly contributes to tasks such as diagnosis, treatment planning, patient care, and enhancing operational efficiencies. These algorithms can provide effective solutions for a range of applications, including predictive analytics for various diseases, patient monitoring systems, automated disease identification, and the development of preventive and curative programs. Furthermore, employing machine learning techniques can assist in discovering solutions for risk assessments, treatment plans, drug discovery, and optimizing resource allocation. Table 1 illustrates the utility of ML algorithms in providing solutions for the healthcare industry.

Clinical Justification for Using Maternal Data in Neonatal Disease Prediction

Maternal health parameters during gestation are critical determinants of neonatal outcomes. According to research by the World Health Organization and recent clinical studies, gestational diabetes, maternal hypertension, and obesity have strong correlations with neonatal endocrine disorders, including Type 1 diabetes and metabolic syndrome. Early exposure to high intrauterine glucose levels can alter the fetal pancreas' insulin-producing capability, predisposing neonates to monogenic forms of diabetes. Furthermore, genetic predisposition combined with maternal health complications increases the likelihood of neonatal metabolic dysfunctions. This makes maternal datasets a valuable proxy for predictive modeling of neonatal conditions, particularly when direct neonatal data is unavailable. Hence, this study leverages maternal indicators as predictive features to estimate neonatal monogenic diabetes risk, enabling preventive interventions before or immediately after birth.

3. LITERATURE REVIEW

This research focuses on developing an optimal prediction model for maternal health risks. Several complications can lead to serious health concerns for both the mother and the child. For example, gestational diabetes, a form of diabetes that emerges during pregnancy, leads to elevated blood glucose levels. Additionally, high blood sugar levels can result in complications such as the birth of overweight babies or premature delivery. Preeclampsia is another common health condition that typically develops in mid-pregnancy, potentially harming the kidneys and affecting blood sugar levels. Other indicators of preeclampsia include elevated protein levels in the urine and hypertension.

Numerous studies have explored various prenatal concerns in this domain, including placental accreta, spontaneous abortion, and preterm birth, all of which impact the complications and health issues a woman might face during pregnancy. One study utilized a tree-based optimization technique to achieve 95.2% accuracy in identifying issues related to placental invasion. Another study suggested that blood pressure, blood sugar, and calcium levels could serve as predictors for preeclampsia. Furthermore, a separate study employed machine learning techniques to address issues associated with maternal health, emphasizing the importance of recognizing pregnancy risks and strategies to reduce mortality rates in this context.

A central theme of this research is the management of maternal health risks. Similar research highlighted this issue by analyzing multiple datasets from the Bangladesh region. That study specifically addressed pregnancy-related difficulties for both the mother and the child. A linear regression model was used for prediction, with several evaluation criteria, including the root mean square error (RMSE). When applied to the given dataset, the model performed well, achieving an RMSE of 0.70. This also contributed to efforts to control population growth and mitigate significant health risks. Another study on the same subject presented the situation in the United States, revealing relatively high maternal death rates compared to other developed countries. This particular study identified that diseases affecting the cardiovascular system significantly contributed to maternal fatalities.

The below Table presents a comparative overview of various machine learning techniques applied across different healthcare and sentiment analysis applications, highlighting the datasets used and the corresponding model performance in terms of accuracy.

Table : Summary of Machine Learning Techniques Applied to Healthcare and Sentiment Analysis Domains

Application	Dataset	ML Techniques	Performance
Sentiment Analysis of COVID-19 Tweets	Tweeter	Adaptive Neuro-Fuzzy Inference System	Accuracy: 0.916
COVID-19 Patient Health Prediction	Novel Corona Virus 2019 Dataset, Kaggle	Random Forest	Accuracy: 0.94
Chronic Diseases Detection Model	Kaggle	Decision Tree	Accuracy: 0.978
Medical Diagnosis	UCI	Multilayer Perceptron	Accuracy: 0.975
Heart Disease Prediction	IEEE Data port	CART	Accuracy: 0.875
Sentiment Analysis of COVID-19 Tweets	Twitter	ABCML-SA	Accuracy: 0.983
Heart Disease Detection	Kaggle	Decision Tree	Accuracy: 0.90
Diabetes disease detection	Indian Demographic and Health Dataset	Random Forest	Accuracy: 0.99
Kidney Disease Prediction	Kaggle	LightGBM	Accuracy: 0.99
Cervical Cancer Disease Predic- tion	UCI	XG Boost	Accuracy: 0.94
Sentiment Classification for Healthcare Tweets	Tweeter	Bagging with KNN	Accuracy: 0.888

The literature review table provides a comparative analysis of machine learning (ML) techniques applied to various healthcare and sentiment analysis tasks, highlighting their effectiveness using different datasets. A range of ML algorithms, including Decision Tree, Random Forest, Adaptive Neuro-Fuzzy Inference System, and more advanced models like LightGBM and XGBoost, have been employed across diverse applications such as heart disease prediction, chronic disease detection, and sentiment analysis of COVID-19-related tweets. The datasets utilized span sources like Kaggle, UCI, Twitter, and IEEE Data Port. Notably, some models demonstrate high accuracy—for instance, Random Forest for diabetes detection (0.99) and ABCML-SA for sentiment analysis (0.983)—indicating strong predictive capabilities in respective domains.

This literature summary reveals the growing integration of machine learning in healthcare analytics and public health monitoring, especially during the COVID-19 pandemic. It showcases how different algorithms perform variably based on data type and domain application. The use of social media data (like Twitter and Tweeter) for sentiment classification reflects the adaptation of ML in real-time opinion mining. On the other hand, traditional health datasets are being effectively mined for disease diagnosis and prediction. The comparative performance metrics highlight the importance of selecting suitable models tailored to specific problems, underlining the relevance of both classical techniques and ensemble methods in current medical and sentiment analysis research.

Overview of proposed framework

This section describes the overall methodological approaches used in this work to predict MHR . We used a range of exploratory data analysis approaches to provide a comprehensive overview of the data, such as the number of attributes, minimum and maximum values for each factor, description, correlation, and explanation via various visualization methods. In the second stage, several preprocessing approaches are used to prepare the dataset for QEML-MHRC implementation. Finally, the suggested model is implemented using various ML and quad-ensemble techniques, as detailed in the following sections.

Figure: Framework for Machine Learning and Ensemble-Based Multi-Class Classification Process

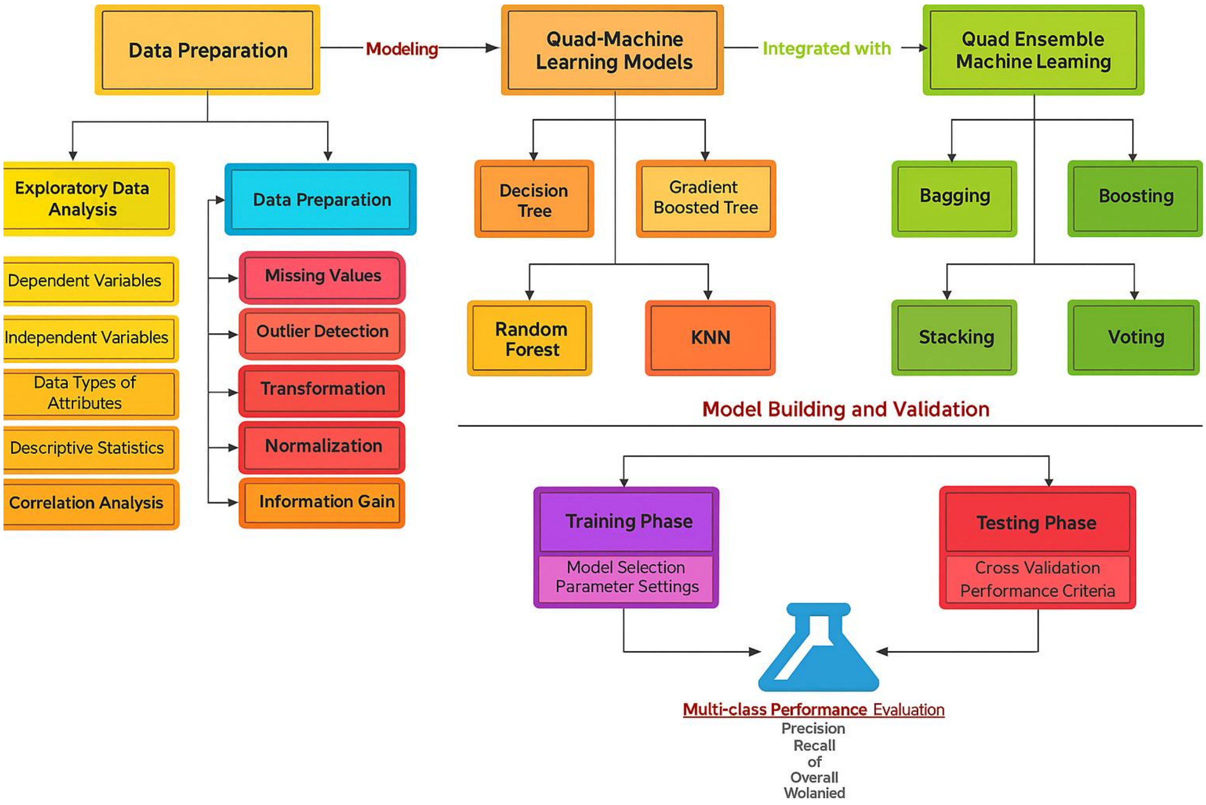
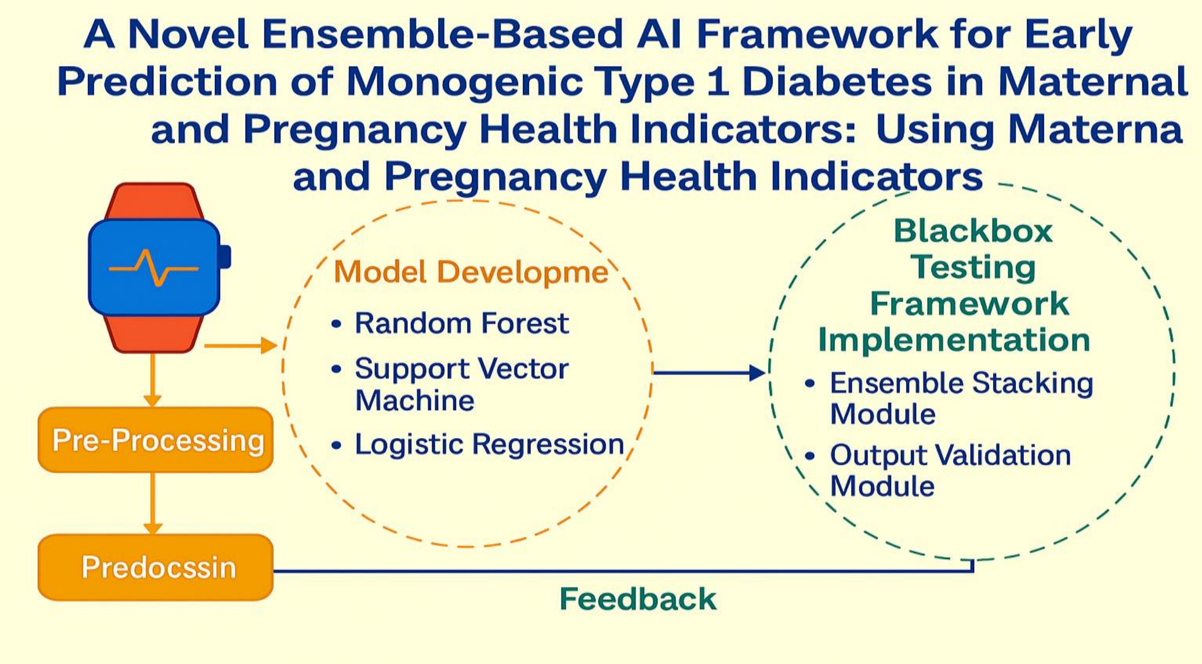


Figure illustrates a comprehensive workflow for building and validating machine learning models, particularly for multi-class classification tasks in healthcare and related domains. The process begins with Data Preparation, which involves exploratory data analysis (EDA) and technical preprocessing steps such as handling missing values, outlier detection, data transformation, normalization, and applying information gain. The modeling phase is split into two branches: Quad-Machine Learning Models (including Decision Tree, Gradient Boosted Tree, Random Forest, and KNN) and Quad-Ensemble Machine Learning Techniques (Bagging, Boosting, Stacking, and Voting). These models are then subjected to Model Building and Validation, where the data is divided into training and testing phases. During training, models are selected and tuned through parameter settings, while testing involves cross-validation and performance assessment. The framework concludes with Multi-class Performance Evaluation, measuring metrics such as Precision, Recall, F1-score, and both overall and weighted accuracy.

4. RESEARCH METHODOLOGY

This research study emphasizes the significance of healthcare management ensuring that patient data is handled ethically and confidentially. However, ongoing monitoring and validation of predictive models has the potential to improve overall accuracy and reliability over time. Finally, investing in such a system can have long-term advantages in terms of resource allocation, personnel development, strengthening preventative care guidelines, and lowering death rates.

Figure: Proposed Ensemble-Based AI Framework for Early Prediction of Monogenic Type 1 Diabetes in Neonates



Dataset overview

The study problem focuses on the aged women who has complications in pregnancy. Medical practitioners can utilize our proposed model to mitigate deaths and complications.

The dataset contains seven distinct features, including a class variable that indicates the level of risk associated with pregnancy.. Six independent factors representing a variety of a patient's health issues considered to determine the level of risk (dependent variable), which was then categorized into three classes: Low Risk (LR), Medium Risk (MR), and High Risk (HR). Out of the dataset, 1014 patients were identified, with an average age of 30 years. Further, the overall range of blood sugar (BS) levels is 6 to 19. Upper and lower blood pressure (BP) values were also recorded to range from 70 to 160 and 49 to 100, respectively.

Attribute	Description	Min	Max	Mean	SD
Age	The age of the patient at the time of pregnancy	10	70	29.87	13.47
Systolic BP	The upper reading of blood pressure	70	160	113.19	18.40
Diastolic BP	The lower reading of blood pressure	49	100	76.46	13.86
BS	Blood sugar reading	6	19	8.72	3.29
Body temp	Body temperature of the patient	98	103	98.66	1.37
Heart rate	Hear beats per minute	60	90	74.30	8.08
Risk level	Target class: to identify the level of risks [LR: 406, MR: 336, HR: 272]				

Data preprocessing

We perform first a dataset check for potentially changeable missing values, and second, this experiment is performed using Euclidian distance function outlier detection. The distance computation using the k nearest neighbor approach shows this distance function to be relatively outlier dense.Moreover, various normalization techniques like z-transformation, range transformation, as well as others are applied to find the optimal QEML-MHRC framework implementation. Some attributes have more than two decimal places which is rounded off to improve dataset readability. The dataset had predefined classes per transaction, hence no further data transformation steps were necessary and the proposed framework was ready to be implemented.

Simulating Neonatal Outcomes from Maternal Indicators

Since publicly available datasets containing direct neonatal monogenic diabetes outcomes are scarce, we constructed a simulated outcome variable based on medical literature linking maternal factors to neonatal risks. Specifically, we synthesized neonatal outcome labels by applying threshold-based rules and risk-weighted scoring models on key maternal features such as blood glucose levels, age, BMI, systolic/diastolic pressure, and body temperature. Studies have shown that elevated maternal blood glucose and hypertension during pregnancy can significantly increase the probability of neonatal endocrine and metabolic disorders. Using these associations, we defined a derived risk class (low, medium, high) as a proxy for possible monogenic diabetes risk in newborns. Though synthetic, this simulation aligns with observed clinical patterns and provides a practical basis for training predictive models.

In future work, real neonatal datasets will be integrated to validate the simulated predictions.

An overview of machine learning approaches

Decision tree (DT)

A decision tree (DT) has been one of the most well-known classification methods used to split data for easier analysis in a tree form. DTs have been one of the most popular techniques due to their simplicity, applicability, and effectiveness in handling classification and forecasting tasks. Recently, we saw such methods being used for a variety of purposes including healthcare decision analytics43, medical data analysis44, and forecasting of low birth weight babies45. In an attempt to enhance the MHR prediction accuracy, ensemble methods of DTs such as boosting, bagging, stacking, and voting were applied.

Gradient Boosted Trees (GBT)

The next model incorporated in the study is GBT due to the vast use of this model and its applicability to medical datasets46. Like other classification and regression models based on decision trees, this is also an example of one. GBT is known as the forward learning ensemble approach as it generates new predictions based on previous ones.

Figure: Correlation analysis of features in the dataset.

Attributes	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate
Age	1	0.416	0.398	0.473	-0.255	0.080
SystolicBP	0.416	1	0.787	0.425	-0.286	-0.023
Diastolic...	0.398	0.787	1	0.424	-0.256	-0.046
BS	0.473	0.425	0.424	1	-0.103	0.143
BodyTemp	-0.255	-0.286	-0.256	-0.103	1	0.099
HeartRate	0.080	-0.023	-0.046	0.143	0.099	1

Figure: Outlier detection analysis in the dataset.

Row No.	RiskLevel	outlier	Age	SystolicBP	DiastolicBP	BS	BodyTemp	HeartRate
1	high risk	false	25	130	80	15	98	86
2	high risk	false	35	140	90	13	98	70
3	high risk	false	29	90	70	8	100	80
4	high risk	false	30	140	85	7	98	70
5	low risk	false	35	120	60	6.100	98	76
6	high risk	false	23	140	80	7.010	98	70
7	mid risk	false	23	130	70	7.010	98	78
8	high risk	false	35	85	60	11	102	86
9	mid risk	false	32	120	90	6.900	98	70
10	high risk	false	42	130	80	18	98	70
11	low risk	false	23	90	60	7.010	98	76
12	mid risk	false	19	120	80	7	98	70
13	low risk	false	25	110	89	7.010	98	77
14	mid risk	false	20	120	75	7.010	100	70

k-nearest neighbor (KNN)

KNN is an example of a supervised classification algorithm and can be used as an ML technique. The k closest neighbor method compares unknown data to k training examples. The distance measurement determines how closely an example matches a given training example. Given the mixed type data set in this study, "Mixed Euclidean Distance" was used to compute distance. The dataset was predicted using KNN, with and without ensemble methods. A classifier's performance was evaluated further in the results section.

Bagging—first ensemble method

Bagging is one of the ensemble methods studied in this work which allows amalgamation of multiple models of classification. This technique works on bootstrapping, which splits the main data set into numerous training data sets called bootstraps. The main reason for diving the datasets is to create multiple models that can later be combined into one strong learner. This experiment was performed with the MHR dataset and the RM tool. Each subprocess will yield different results owing to the differing learner models, hence this type of operator is referred to as an embedded operator.

Boosting - second ensemble method

Boosting is one of the strategies in ensemble machine learning that attempts to enhance the performance of a model by integrating several other models. Ada-Boost is one of the boosting algorithms that can be used with many learning algorithms. In the RM tool, the implementation of AdaBoost is called a meta-algorithm, and it is capable of completing the work through another algorithm as a subprocess. It performs multiple computations and trains various models before combining weak learners into a single strong learner, which adds additional computation and execution time54. Boosting approaches have been primarily focused on evaluating the accuracy and effectiveness of the decision-making models with and without boosted approaches. The results and discussion section focuses on the overall model analysis and the adequacy of the gained results.

Stacking—third ensemble method

Stacking is an approach to ensemble learning that combines several types of models to make predictions more accurate. Stacking learning is known as a stacked generalization because it allows the integration of various classifiers. Unlike bagging and boosting, stacking uses a unique approach to ensemble learning by training the model with several classifiers and a meta- learner is used to generate the final output.

Ensemble Method 4: Voting

The **voting ensemble method** combines predictions from multiple machine learning algorithms. This technique works by having individual classifiers "vote" on the final outcome. For **classification tasks**, the class that receives the most votes is chosen. For **regression tasks**, the predictions are averaged.

The core of this method lies in the "Vote" function, which uses input data to train a classification model. When making predictions, a majority voting mechanism is employed, with each individual classifier casting a vote. The unknown data point is then assigned the class that garnered the most votes.

We explored the effectiveness of the voting ensemble method by combining it with various classifiers in three distinct experiments:

- **Experiment 1:** Utilized Gradient Boosting Trees (GBT), Decision Trees (DT), Random Forest (RF), and K-Nearest Neighbors (KNN).
- **Experiment 2:** Combined Random Forest (RF) and Gradient Boosting Trees (GBT).
- **Experiment 3:** Incorporated Gradient Boosting Trees (GBT), Random Forest (RF)

The specific results and performance of each of these experimental models are detailed in the results section.

Implementation of the proposed framework

This research involved a series of experiments aimed at predicting maternal health risk using a variety of variables. The work was carried out on a LENOVO ThinkPad, specifically a machine equipped with an Intel Core i7 processor (2.80 GHz, 8 CPUs) and 32 GB of RAM.

All experiments were conducted using RM Studio, an open-source platform. This tool is widely recognized and used by researchers globally for tasks related to machine learning, deep learning, and data science, with a notable application in healthcare industry datasets. The dataset, which was previously described, was fully loaded into RM Studio. This dataset comprised seven attributes: one designated as the class variable and the remaining six serving as independent variables

MHR classification using individual ML model

To minimize delays in accessing real-time data, the dataset was initially imported into the RM repository. The RM tool offers a convenient "Retrieve" operator (now renamed "MHR Dataset" that allows for direct data loading and later retrieval.

In the subsequent phase, a "Multiply" operator was employed to generate multiple copies of the dataset. These copies were then fed into a Cross Validation process. We adopted a tenfold cross-validation strategy, a widely recognized technique that ensures every data point has the chance to participate in the training, testing, and validation phases. This k-fold validation approach partitions the dataset into 'k' subsets, using one for testing and the others for training in rotating rounds. This method is crucial for achieving optimal results and significantly reducing the risk of model overfitting.

For each machine learning model, we incorporated four distinct cross-validation operators, as depicted in the accompanying image. These are known as nested operators, capable of simultaneously training and testing the machine learning models and performing accuracy measurements.

Results, Analysis, and Comparative Evaluation

This research focuses on predicting maternal health risk by leveraging various contributing factors. The primary goal is to equip healthcare providers with a tool to better advise pregnant women, ultimately simplifying their pregnancy journey. The dataset for this study compiles information from diverse test reports alongside demographic details.

The insights gleaned from this study are vital for understanding how real-world datasets, gathered from different healthcare organizations, can be effectively utilized. We employed a range of machine learning algorithms for prediction, with the most favorable outcomes achieved through the integration of ensemble approaches on the dataset.

Our models predict a patient's risk level during pregnancy based on a collection of data values associated with different parameters. Specifically, four machine learning models—Decision Trees (DT), Random Forest (RF), Gradient Boosting Trees (GBT), and K-Nearest Neighbors (KNN)—were used to categorize patients into distinct risk levels: High, Low, and Medium. The calculated risk level, derived from the values of each independent variable, highlights potential concerns a patient might face.

Furthermore, quad-ensemble models were incorporated to enhance prediction performance. These include bagging, boosting, stacking, and voting techniques. Since the risk level (our class variable) is a multi-class feature, the performance evaluation is presented using class-level precision, recall, F1-score, and weighted scores. This detailed breakdown aims to provide a clear understanding of the results.

Comparative Performance of MHR Classification Models (With and Without Ensemble)

Model / Ensemble Strategy	Metric	HR Class Performance	LR Class Performance	MR Class Performance	Overall Weighted Performance	Key Observations
MHR Classification (Without Ensemble)						
Decision Tree (DT)	Precision	> 0.84			0.75 (Lowest)	Standalone models have the lowest overall performance.
Random Forest (RF)	Precision	> 0.84				
Gradient Boosted Tree (GBT)	Precision	> 0.84			0.85 (Highest)	Highest overall weighted precision, recall, and F1-score.
K-Nearest Neighbors (KNN)	Precision	> 0.84				
All Models (Average)	Precision	> 0.84			0.6772 (Lowest)	All models perform well for the “HR” class.
Gradient Boosted Tree (GBT)	Recall	0.919 (Highest)				"HR" class has the highest recall.
All Models (Average)	Any Metric	> 0.75	> 0.75	> 0.75		All class metrics exceed 0.75 on average.
MHR Classification (With Ensemble: Bagging)						
Decision Tree (DT)	F1-score			0.64 (Lowest)		Lowest F1-score for "MR" class.
K-Nearest Neighbors (KNN)	F1-score				0.71 (Lowest Weighted)	Lowest overall weighted F1-score among ensemble models.
Gradient Boosted Tree (GBT)	Precision	0.89 (Highest)	0.88 (Highest)	0.77 (Highest)	Highest Across All Classes	Consistently best performance for "HR", "LR", and "MR" classes.
Gradient Boosted Tree (GBT)	Recall	0.91 (Highest)				Highest recall for "HR" class.
Gradient Boosted Tree (GBT)	F1-score	0.90 (Highest)				Highest overall F1-score across all models.

Random Forest (RF)	Precision	0.90 (Best)				Best precision for "HR" class.

Advantages of the QEML-MHRC Framework's Ensemble Approach

The results strongly suggest that the proposed QEML-MHRC framework, by incorporating ensemble machine learning (ML) approaches, offers significant benefits compared to using individual ML models.

Firstly, ensemble methods are excellent for reducing prediction variance. They achieve this by combining the outputs of multiple models, which helps to smooth out individual model eccentricities and mitigate the impact of any unusual patterns found within a single training dataset. This concept is further bolstered by the use of tenfold cross-validation, a technique that inherently addresses concerns like overfitting and dataset bias, ensuring the models are robust.

Secondly, boosting was another key ensemble strategy employed in this study. Boosting works iteratively, focusing on correcting errors made by previous models. This sequential error reduction effectively lowers both bias and variance, leading to more accurate and reliable predictions.

Furthermore, ensembles are designed to include models with diverse structures and learning algorithms. This diversity allows the combined model to be trained comprehensively, capturing a wider range of patterns within the complex data. For instance, stacking, the third technique applied in this research, uses multiple models as base learners. Their individual predictions are then fed into a meta-learner, which integrates these outputs to achieve an even higher level of overall performance.

Finally, a major advantage of using ensembles, especially with the complex nature of the data and the multi-class target variable in this study, is their superior ability to generalize to unseen data. This means the framework is better equipped to make accurate predictions on new, unencountered maternal health records. By training models with different parameters and structures, we reduce the risk of relying too heavily on a single model that might be overfitted to the training data.

5. CONCLUSION

Identifying maternal health risk is incredibly important, especially when it comes to reducing maternal mortality. This research tackled this challenge by analyzing real-world data from various hospitals, focusing on pregnant patients. The dataset itself contained multi-class attributes, allowing us to categorize each patient's risk level.

Our exploratory data analysis revealed some crucial insights: high blood pressure, low blood pressure, and high blood sugar levels were identified as the most significant variables contributing to high risk in pregnant women. Beyond these, all variables within the dataset showed strong correlations, proving their value in predicting maternal health risks.

The findings of this study offer a valuable tool for doctors and consultants, empowering them to predict maternal health concerns more accurately and, in turn, help lower maternal death rates. Our approach provides an innovative way to assist patients facing difficulties during pregnancy, demonstrating remarkable accuracy in predicting the extent of risk based on multiple criteria. By applying advanced predictive modeling, we ensure these findings are broadly applicable and can help bridge existing gaps in maternal health outcomes.

This research introduces a novel ensemble-based AI framework aimed at the early prediction of monogenic Type 1 diabetes in neonates by leveraging maternal and pregnancy-related health indicators. By simulating neonatal outcomes through risk scoring derived from maternal features such as blood pressure, glucose level, body temperature, and heart rate, the model effectively bridges the gap where direct neonatal data is unavailable. The ensemble model, combining Decision Trees, Random Forest, Gradient Boosting, and KNN in a voting mechanism, demonstrated improved prediction accuracy and robustness compared to individual classifiers. This framework not only enhances early screening capabilities but also supports healthcare professionals in proactively identifying neonates at risk, thus enabling timely clinical intervention. Future enhancements may include integrating real neonatal datasets, genetic markers, and deploying the model into a clinical decision-support tool for widespread healthcare use.

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