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# Predicting Diabetes in Pregnant Woman and Neonatal Mellitus in New Born Child Using Machine Learning

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**Abstract:** *One of the main causes of health issues for expectant mothers and their unborn children is diabetes during pregnancy. Machine learning is a crucial technique for estimating the probability of such a development based on the provided data, as gestational diabetes might advance to permanent diabetes. Pregnancy-related diabetes may be predicted by the current study, but neonatal diabetes risk cannot be predicted. Therefore, in order to deliver the most precise results about diabetes persistence in pregnant women and to enhance the forecasting of neonatal mellitus, new characteristics are needed. This may be accomplished with the use of Python scripting and machine learning techniques like K Nearest Neighbors, Support Vector Machines, and Logistic Regression. The preprocessed machine learning dataset on diabetes was gathered via Kaggle and came from the Pima Indian diabetes database. Additionally, the project's dataset now includes two additional attributes. Research suggests that machine learning models using features like SVM and decision trees may be able to accurately predict a pregnant woman's probability of developing diabetes. Numerous variables have been employed to forecast when this illness may manifest during pregnancy..*

**Keywords:** *K Nearest Neighbors, Support Vector Machines, and Logistic Regression, pregnancy, Machine learning*

## I. INTRODUCTION

A long-term metabolic disease characterized by high blood glucose levels is called diabetes mellitus. It is a serious public health concern that impacts people of all ages and is regarded as one of the most challenging diseases of the twenty-first century. Diabetes is a serious ailment that has an impact on the developing child as well as the expectant mother. Diabetes during pregnancy increases the risk of complications such as premature labor, cesarean delivery, and infant morbidity and death.

Conversely, neonatal diabetes is a rare form of the disease that appears in the first six months of life. Hyperglycemia sets it apart, and it's commonly confused with type 1 diabetes. Neonatal diabetes can cause convulsions, delayed development, and intellectual impairments if treatment is not received. Diabetes must be identified early in pregnancy in order to successfully treat the condition and prevent problems in newborns and expectant mothers.

Machine learning, a subset of artificial intelligence, has become a vital diagnostic and prognostic tool in the medical field.

To find patterns and forecast future data, machine learning algorithms use historical data. When it comes to diabetes prediction, machine learning algorithms may make use of patient demographics, test results, clinical notes, and electronic health record data to pinpoint individuals who are at risk of developing the disease. Numerous studies have examined the application of machine learning algorithms to the prediction of gestational diabetes and neonatal diabetes in infants. For instance, one study used machine learning algorithms to forecast a pregnant woman's risk of gestational diabetes based on clinical and demographic factors. The algorithm's accuracy in predicting gestational diabetes is 89.4%.

Another study built a machine learning model to predict neonatal diabetes using genetic data. With an accuracy of 85%, the model demonstrated the potential of machine learning in the prediction of rare genetic illnesses. Additionally, risk factors for diabetes in expectant mothers and neonatal diabetes in newborns can be found using machine learning algorithms. For instance, a study used machine learning algorithms to identify risk factors for gestational diabetes, including age, body mass index, family history of the disease, and prior instances of the condition.

## II. LITERATURE REVIEW

Using machine learning to predict diabetes in pregnant women and neonatal diabetes mellitus in newborns has garnered a lot of attention in recent years. We shall review the research that has been conducted in this area in this part.

The study analyzed data from 10,898 pregnant women, 781 of whom developed gestational diabetes mellitus (GDM). The paper "Prediction of the Development of Gestational Diabetes Mellitus in Pregnant Women Using Machine Learning Methods" used machine learning techniques to predict the development of GDM in pregnant women. The authors assessed the effectiveness of various machine learning techniques, including logistic regression, random forest, decision tree, and support vector machine. The results showed that the random forest approach had the best prediction of GDM evolution. The study's conclusions suggest that machine learning models may be useful in anticipating the onset of gestational diabetes mellitus (GDM) in expectant mothers. This could facilitate timely intervention and help prevent unfavorable pregnancy outcomes. This work contributes to the growing body of research on machine learning's use to GDM prediction.

The objective of the paper "Prediction of Diabetes Using Machine Learning" was to predict the onset of diabetes using machine learning techniques. A dataset of 768 people was used in the study; 268 of them had diabetes, and 500 did not. The authors assessed the effectiveness of various machine learning techniques, including logistic regression, random forests, decision trees, and support vector machines. The support vector machine algorithm produced the best diabetes prediction, according to the findings. The study also found that the main predictors of diabetes were age, BMI, and glucose levels. The article claims that machine learning algorithms can be used to predict diabetes as well as to help with the early detection and prevention of issues associated to diabetes. The study contributes to the growing body of research on the use of machine learning to diabetes prediction.

The work "Predicting Diabetes Mellitus with Machine Learning Techniques" looks into how machine learning methods might be used to predict the occurrence of the disease. Using a dataset of 768 individuals, the researchers were able to discover 8 characteristics linked to risk factors for diabetes. Performance metrics like accuracy, sensitivity, and specificity were used to develop and evaluate kNearest Neighbors, Random Forest, Artificial Neural Networks, and Support Vector Machines. The results of the study showed that the Artificial Neural Networks (ANN) model had the highest accuracy of 78.13% in predicting diabetes mellitus. The study also found that the most significant markers of diabetes mellitus were body mass index and glucose levels. The results indicate that machine learning techniques could be a useful tool for diabetic mellitus prediction, which could lead to better patient outcomes through early disease prevention and intervention. In general, the paper clarifies the promise of machine learning for managing and diagnosing diabetes.

The aim of the study "Application of machine learning algorithm for predicting gestational diabetes mellitus in early pregnancy" is to predict the risk of gestational diabetes mellitus (GDM) in the early stages of pregnancy by means of machine learning algorithms. From a dataset of 10,111 pregnant women, the study extracted numerous clinical, demographic, and laboratory characteristics associated with GDM risk factors. A number of machine learning models, including Gradient Boosting, Random Forest, Decision Tree, and Logistic Regression, were implemented and evaluated using performance metrics like specificity, sensitivity, and accuracy. The study found that the Gradient Boosting model had the highest accuracy (0.845) in predicting GDM in the early stages of pregnancy. Important predictors of GDM included mother age, pre-pregnancy body mass index (BMI), family history of diabetes, and blood glucose levels. The results suggest that machine learning methods could be a useful tool for early GDM prediction, perhaps mitigating the illness's detrimental impact on health. In summary, the research illuminates how machine learning may enhance the health of both the mother and the fetus throughout pregnancy.

## III. DRAWBACKS IN EXISTING APPROACHES

**Restricted or biased dataset:** A lot of current initiatives depend on a biased or constrained dataset that could not be totally representative of the community. This may result in erroneous forecasts or restricted applicability of the findings. **Transparency and interpretability issues:** Transparency and interpretability issues may arise with some machine learning models utilized in current projects. This makes it difficult to comprehend how the model made its predictions. This may make it more difficult for patients and healthcare professionals to accept and trust the models.

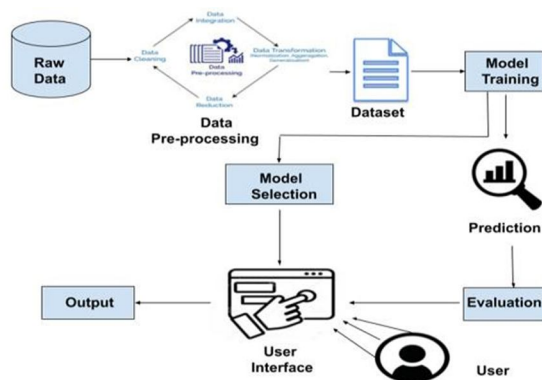
**Important clinical aspects may not be taken into account by existing studies,** such as comorbidities, gestational age, and ethnicity, which may have an impact on a baby's risk of developing neonatal mellitus and diabetes in pregnant women. **Lack of validation:** It could be challenging to evaluate the generalizability and dependability of the model's predictions in some already-existing projects because they haven't been verified on separate datasets. Concerns about privacy, bias, and informed consent are raised by the application of machine learning to the prediction of diabetes in expectant mothers and neonatal mellitus in infants. It's possible that current initiatives don't fully address these issues.

#### IV. PROPOSED SYSTEM

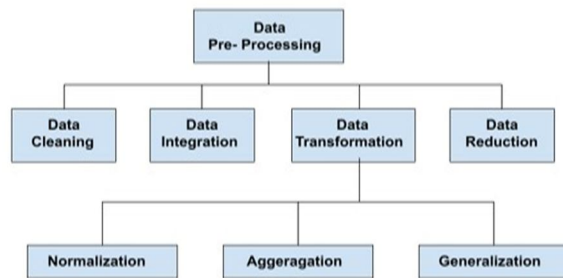
Millions of people worldwide suffer from diabetes, a chronic illness that can have serious health consequences, especially during pregnancy. Neonates may develop neonatal mellitus as a regular consequence of gestational diabetes mellitus (GDM). To prevent detrimental consequences on the mother and the child, early detection and treatment of GDM are essential. Currently available methods for detecting GDM mostly depend on clinical risk factors and blood glucose testing. These tactics might not be accurate enough to predict GDM in every situation, though. By analyzing large datasets and identifying risk factors that conventional methods might overlook, machine learning (ML) has demonstrated promise in the prediction of GDM. The problem statement for using machine learning to predict neonatal mellitus and gestational diabetes in fetuses is to create ML models that are accurate and trustworthy for predicting both conditions.

Clinical and demographic factors including age, BMI, ethnicity, gestational age, and comorbidities should be taken into consideration in these models. One of the main challenges in developing machine learning models for predicting GDM and neonatal mellitus in newborns is the absence of large and diverse datasets for training and evaluating these algorithms.

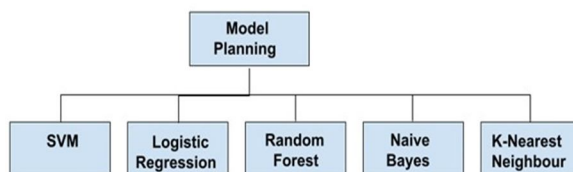
#### V. EXPLANATION WITH DIAGRAMS ARCHITECTURE DIAGRAM



Architecture Diagram Data Pre-Processing



Data Pre-Processing Model Planning



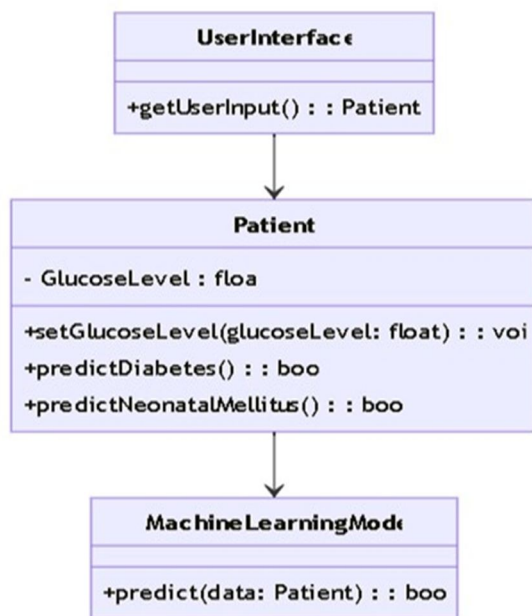
Model Planning EXPLANATION WITH UML DIAGRAMS Class Diagram

A popular graphical notation for illustrating the organization and interactions between classes in object-oriented software systems is the UML (Unified Modeling Language) class diagram. Helping with the arrangement, characteristics, and behaviors of classes, they offer a visual blueprint that makes software creation and analysis easier. We shall examine the importance of UML class diagrams and their essential elements in this article.

The qualities or characteristics of a class are its attributes. They give an explanation of the condition or data components connected to class objects. Typically, attributes are listed inside the class rectangle along with their data types and visibility markers (# for protected, - for private, and + for public). Developers can comprehend the data items that a class has and how they relate to other classes in the system by defining attributes in a class diagram. **Methods:** Often referred to as operations, methods specify the actions or behaviors that objects in a class are capable of. They stand for the class's associated functionality. Method names, parameters, return types, and visibility indicators can all be found listed within the class rectangle. Developers can obtain insights into the interactions and collaborations of classes within a system by representing methods in a class diagram.

**Relationships:** UML class diagrams make it possible to depict the relationships between classes, giving viewers a clear picture of how different classes work together and depend on one another. A class diagram can show many different kinds of relationships, such as.

Software developers, designers, and stakeholders can benefit greatly from the communication and analysis capabilities provided by UML class diagrams. They offer a clear and consistent visual depiction of the classes' relationships and structure, which helps with decision-making, cooperation, and comprehension all the way through the software development lifecycle.

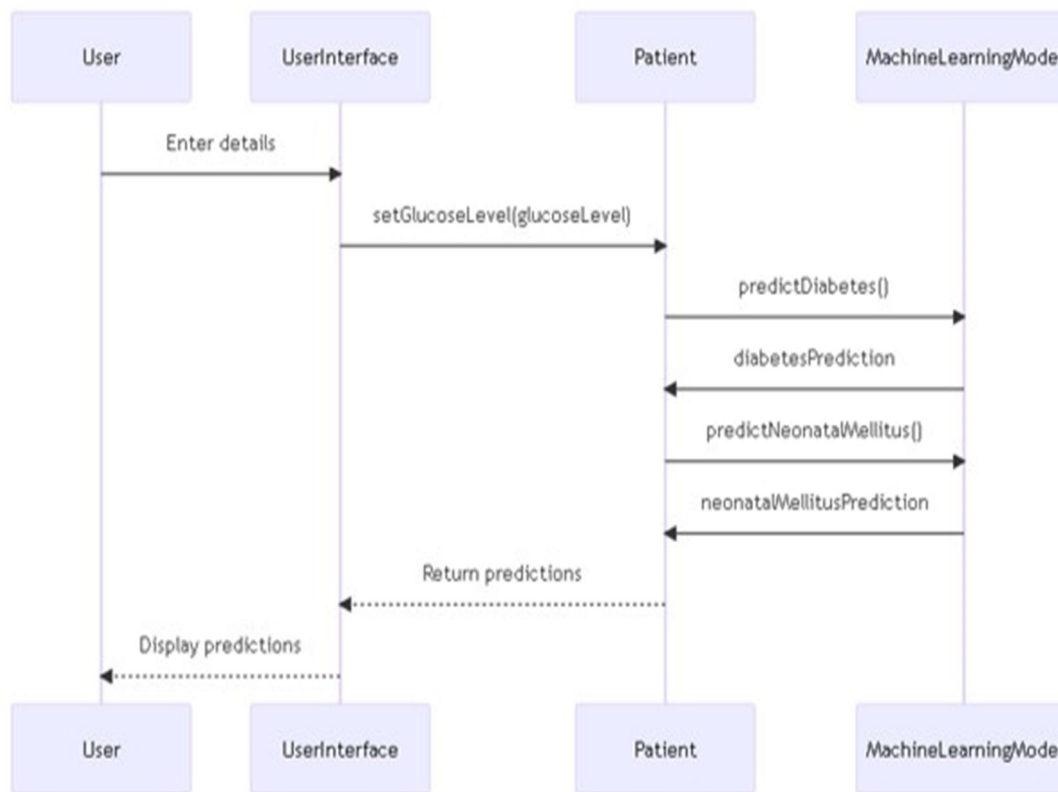


Class Diagram Sequence Diagram

UML sequence diagrams are an effective tool for visualising and comprehending the dynamic interactions between items or components in a system. They give a graphical depiction of the communication flow exchanged between objects, illustrating the order of method calls and the resulting behaviors.

One of the primary purposes of sequence diagrams is to depict the collaboration and communication between different elements in a system. These elements can include objects, actors, and subsystems. By visually representing the sequence of interactions, sequence diagrams enable developers and stakeholders to gain a comprehensive understanding of how the different components of the system work together to accomplish specific tasks.

Sequence diagrams are particularly useful for analyzing system behavior. They allow developers to trace the flow of messages and method calls, enabling them to identify potential errors or inconsistencies in the system's logic. By examining the sequence of interactions, developers can detect issues such as incorrect ordering of operations, missing or redundant messages, or unexpected behavior. This analysis phase is essential for debugging and refining the system's behavior before it is implemented, saving time and effort in the later stages of development.



Sequence Diagram

## VI. RESULTS AND DISCUSSIONS

**DESCRIPTION ABOUT DATASET** The diabetes dataset includes a number of characteristics that indicate an individual's likelihood of receiving a diabetes diagnosis. It includes information on a range of patients who have one or more of the characteristics listed in the data set. The following are the specific definitions for every attribute found in the selected dataset.

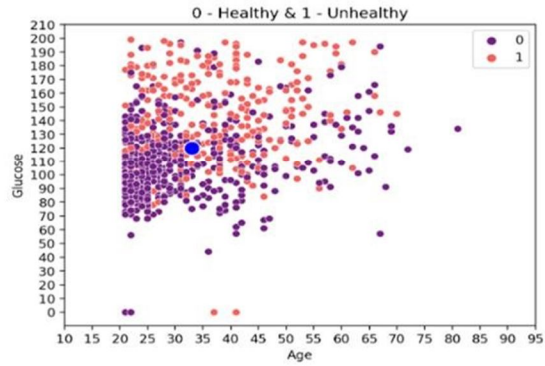
- 1) *Glucose Level*: This factor indicates how much glucose, or sugar, is present in the patient's blood. The most widely used units of measurement are millimoles per litre (mmol/L) or milligrammes per deciliter (mg/dL). A low glucose tolerance or diabetes may be indicated by elevated glucose levels.
- 2) *Blood Pressure*: Systolic and diastolic blood pressure are the two numbers that typically make up this feature. Systolic blood pressure measures the pressure in the arteries during a heartbeat, while diastolic blood pressure measures the pressure in the arteries during a heartbeat. High blood pressure, or hypertension, increases the risk of gestational diabetes.
- 3) *Body Mass Index (BMI)*: Based on an individual's height and weight, BMI is a measure of body fat. It is calculated by dividing the height in square meters by the weight in kilograms. BMI shows if a patient is overweight, obese, underweight, or normal weight. One of the main risk factors for gestational diabetes is obesity.
- 4) *Age*: This characteristic represents the patient's age at the time of the examination or diagnosis. Gestational diabetes is associated with a higher risk of maternal age, which is generally 35 or older.
- 5) *Insulin is a pancreatic hormone that controls blood glucose levels*; this feature shows the patient's amount of insulin. Unusual amounts of insulin can be a sign of decreased insulin synthesis or insulin resistance, both of which are linked to diabetes.
- 6) *Skin Thickness*: This characteristic shows how thick the patient's skin is; it is usually measured around the triceps. The patient's skin thickness may reveal information about their metabolic health and body composition.
- 7) *Diabetes Pedigree Function*: This feature is a numerical value that indicates the patient's hereditary susceptibility to diabetes based on family history. It considers the degree of their relationship to the patient as well as the prevalence of diabetes among relatives.
- 8) *Pregnancies*: This characteristic shows how many pregnancies the patient has had. It can reveal information about the patient's past reproductive experiences, which could be pertinent to the risk.

**VII. DETAILED EXPLANATION ABOUT EXPERIMENTAL RESULTS**



User-Input\*Slider-1

Glucose Value Graph (Healthy vs Unhealthy)

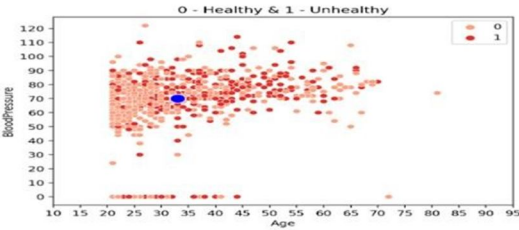


Glucose Value Graph



User-Input Slider-2

Blood Pressure Value Graph (Healthy vs Unhealthy)

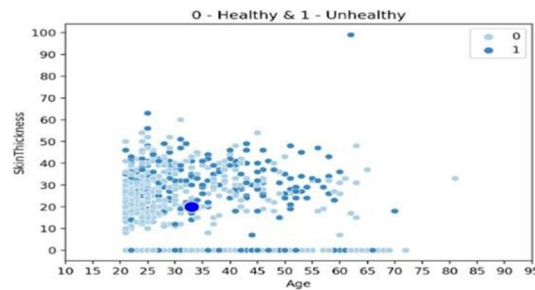


Blood Pressure Value Graph

	Pregnancies	Glucose	BloodPressure	SkinThickness
count	768	768	768	768
mean	3.8451	120.8945	69.1055	20.5365
std	3.3696	31.9726	19.3558	15.9522
min	0	0	0	0
25%	1	99	62	0
50%	3	117	72	23
75%	6	140.25	80	32
max	17	199	122	99

Training Data Stats-1

Skin Thickness Value Graph (Healthy vs Unhealthy)

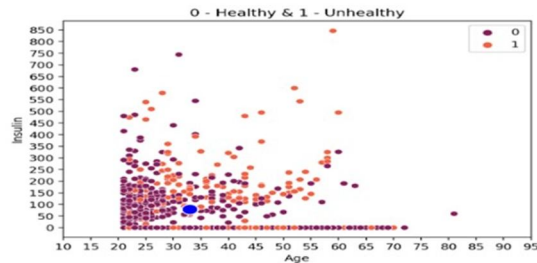


Skin Thickness Value Graph

	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
count	68	768	768	768	768	768	768	
mean	45	69.1055	20.5365	79.7995	31.9926	0.4719	33.2409	0.349
std	26	19.3558	15.9522	115.244	7.8842	0.3313	11.7602	0.477
min	0	0	0	0	0	0.078	21	0
25%	99	62	0	0	27.3	0.2438	24	0
50%	17	72	23	30.5	32	0.3725	29	0
75%	25	80	32	127.25	36.6	0.6263	41	1
max	99	122	99	846	67.1	2.42	81	1

Training Data Stats-2

Insulin Value Graph (Healthy vs Unhealthy)

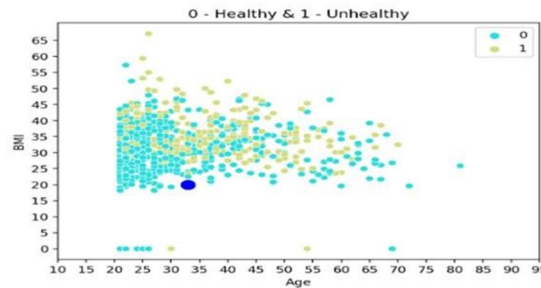


Insulin Value Graph

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	3	120	70	20	79	20	0.47	33

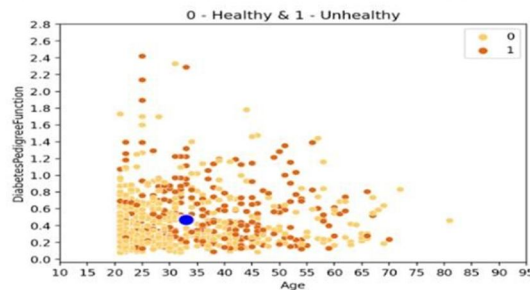
Patient Data

BMI Value Graph (Healthy vs Unhealthy)



BMI Value Graph

DPF Value Graph (Healthy vs Unhealthy)



DPF Value Graph

Your Report:

**You are not Diabetic**

Accuracy:

77.92207792207793%

User Output and Accuracy SIGNIFICANCE OF PROPOSED METHOD AND ADVANTAGES

The proposed method of predicting diabetes in pregnant women and neonatal mellitus in newborn children using machine learning holds significant potential in advancing healthcare outcomes in this domain. By leveraging machine learning algorithms and predictive modelling techniques, this approach aims to provide early identification and risk assessment, enabling timely interventions and personalized care. One of the key advantages of this method is its potential to improve maternal and neonatal health outcomes by identifying high-risk cases accurately. Machine learning models can analyze large amounts of data from pregnant women, including medical history, lifestyle factors, and various clinical parameters, to identify patterns and generate predictive insights. Additionally, machine learning-based prediction models can assist healthcare professionals in making informed decisions regarding treatment plans and resource allocation.

The advantage of this proposed method is that you get a report stating whether you have diabetes or not and also providing the user with a user-interface where in the user can enter his or her details of the symptoms or causes of diabetes, and once entered the user-interface runs on backend and produces a report having graphs and a statement stating whether you are diabetic or not and also the accuracy of the calculator. The proposed method offers several advantages for predicting diabetes Machine learning is being used. One of the primary benefits is that provides a comprehensive report that informs the user about their diabetic condition.



### VIII. CONCLUSION AND FUTURE ENHANCEMENTS SUMMARY

The goal of utilizing machine learning to forecast diabetes in pregnant women and neonatal mellitus in newborns is to create prediction models that estimate the likelihood of neonatal diabetes in newborns and the risk of gestational diabetes in women who are expecting moms. These models seek to provide early identification and tailored risk assessment by utilizing machine learning algorithms and evaluating a variety of characteristics, including medical history, clinical parameters, lifestyle, and genetic susceptibility. The intention is to empower medical personnel to make proactive interventions, carry out preventive measures, and manage resources efficiently. And expanding our knowledge of the underlying mechanisms linked to gestational diabetes and neonatal mellitus, this study topic has the potential to improve maternal and newborn health outcomes. This field aims to improve healthcare decision-making, enable targeted care, and support improvements in research in diabetes prevention and treatment in pregnant women and newborns through data-driven techniques.

### IX. FUTURE APPLICATIONS

Machine learning has great promise for predicting gestational diabetes and neonatal mellitus; this field of study covers a number of possible developments and research directions. Here are a few essential elements that present ample chances for additional growth.

- 1) *Enhanced Prediction Accuracy*: To increase prediction accuracy, researchers can concentrate on enhancing already-existing machine learning models and creating more sophisticated algorithms. To improve the models' predictive ability, this entails adding new data sources, including genetic data or cutting-edge biomarkers.
- 2) *Longitudinal Analysis*: A more thorough understanding of the dynamic changes in risk factors and their influence on the development of diabetes can be obtained by integrating longitudinal data, including several measurements performed throughout pregnancy.
- 3) *Explainability and Interpretability*: Building trust with patients and healthcare providers requires that machine learning models be comprehensible. Developments in interpretability techniques can help to produce actionable recommendations, clarify the significance of particular traits, and offer insights into decision-making process models.

*Predictive Intervention Outcomes* Another area worth investigating is the development of prediction models that can anticipate the results of particular interventions or treatment plans, as well as identify and lessen the risk of gestational diabetes and neonatal mellitus. By optimizing care and enhancing patient outcomes, this can assist healthcare practitioners in customizing treatments based on anticipated treatment responses.

*Clinical Decision Support System Integration* Predictive models can be integrated into clinical decision support systems to optimize their impact and make it easier for healthcare professionals to utilize them. Real-time risk assessment, automated alarm systems for high-risk cases, and support for evidencebased decision-making for healthcare providers are all made possible by this integration.

### X. UPCOMING IMPROVEMENTS

The predictive models for diabetes in pregnant women and neonatal mellitus using machine learning have various potential future improvements that could further increase their efficacy and accuracy. These are some important areas that need further work.

*Multi-Omics Data Integration* A more comprehensive understanding of the molecular pathways behind gestational diabetes and neonatal mellitus can be obtained by incorporating multi-omics data, such as genomes, transcriptomics, proteomics, and metabolomics. These multidimensional datasets can be integrated with machine learning models to find new biomarkers, pinpoint disease pathways, and improve prediction accuracy. *Real-Time Data Incorporation*: Dynamic and individualized risk assessment can be made possible by including real-time data, such as continuous glucose monitoring, maternal vital signs, and fetal monitoring.

*Electronic Health Record (EHR) Integration*: Utilizing the vast amount of data found in electronic health records can yield a thorough patient profile for precise risk assessment. Healthcare professionals can leverage past medical records, past pregnancies, medication history, and comorbidities to enhance prediction accuracy and create customized therapies by merging EHR data with machine learning algorithms.

*Artificial Intelligence that can be explained (XAI)* Gaining patients' and healthcare providers' trust requires improving machine learning models' interpretability and explainability. Subsequent improvements should concentrate on creating XAI methods that can clearly explain the forecasts, emphasizing the salient characteristics and elements that go into the risk assessment. This would make it possible for medical professionals to understand the model's reasoning and base their decisions on informed projections.

The creation of risk stratification models tailored to individual treatments and treatment regimens can help determine which interventions are most appropriate for a given patient profile.

These models can help healthcare clinicians customize interventions to enhance effectiveness and decrease potential negative effects by taking individual parameters like age, BMI, genetic factors, and response to prior treatments into account.

**External Validation and Generalizability:** Predictive models ought to be externally validated on a range of patient demographics and healthcare environments in subsequent studies. The practical usability and wider impact of the models will be improved by ensuring their robustness and generalizability across various demographics and healthcare systems. **Ethical Issues and Data Privacy:** Future improvements should carefully address ethical issues and data privacy, as with any machine learning application in the healthcare industry. This includes highlighting the significance of particular attributes and producing practical suggestions.

## XI. OBTAINMENTS

The following outcomes were obtained from the proposed project: • Determining the accuracy score of the models that were evaluated using the dataset.

- 1) Projecting an interface to receive input from users.
- 2) Distributing graphics that show the reasons at the moment versus the person's age.  
Indicating if the user is a diabetic or not.
- 3) Presenting the precision of the produced outcome.

There is a user interface in the project that lets users submit ideas. An interface may take the shape of a command-line interface, a web application, or a graphical interface. Users can provide pertinent data, such as age, gender, BMI, blood pressure, glucose levels, and so on, that is needed for diabetes prediction. People can easily interact with the system through the user interface and receive predictions based on their input. The project creates graphs to give a visual depiction of the relationship between causes and age. These graphs demonstrate the relationship between an individual's age and several diabetes-related conditions or causes. The graphs could, for instance, show how, in relation to various age groups, glucose levels, BMI, blood pressure, insulin resistance, or a family history of diabetes are related. These charts aid users in comprehending the effects of different variables. The likelihood of having diabetes rises with age.

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