Prediction of adverse perinatal outcomes among Gestational Diabetes complicated pregnancies

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This is to certify that the research work presented in this thesis, entitled "**Prediction of adverse perinatal outcomes among Gestational Diabetes complicated pregnancies**." was conducted by Mr. **Muhammad Shareef Sultan** under the supervision of **Prof Dr. Naima Iltaf.** No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the **Department of Computer Software Engineering** in partial fulfillment of the requirements for the degree of Master of Science in Field of **Computer Software Engineering** Department of Military College of Signals, National University of Sciences and Technology, Islamabad.

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DEDICATION

This thesis is dedicated to MY FAMILY, TEACHERS AND FRIENDS

for their love, endless support and encouragement

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I am grateful to Allah Almighty who has given me courage and strength to go through the complete journey. I am thankful to Him who shows his mercy and benevolence to me and my family in different shapes. Without his consent, it will not be on that place. My teachers also player a very crucial role in shaping my future particularly I am very thankful to Mam Naima for guiding me during the complete tenure. I am also grateful to my parents particularly my mother for praying at every point. I am also thankful to my sister for pushing me beyond the comfort zone.

ABSTRACT

This Research Aims to evaluate and predict the effects faced by women during maternity diagnosed with GDM. Adverse perinatal outcomes encompass multiple factors experienced during or after pregnancy and have a major impact on maternal and neonatal health. Timely identification and treatment can save major adverse outcome to occur. In recent years multiple issues are faced by women during the gestation period. Major outcomes may include but not limited to preterm or post-term delivery, shoulder dystocia, large or small at gestation period and fetal APGAR score measured multiple times after delivery. All above mentioned outcomes will be treated as dependent variables which have direct association with the other independent variables. Other independent variables which becomes the cause of these adverse effects also not limited to maternal age, height, weight resulted into BMI, obesity, ethnicity, previous obstetric history, parity, gravida, glucose tolerance test, folic acid dose, gestational diabetes and estimated total blood loss. The purpose behind this is to make an effective model which can determine the outcome and by analyzing the outcome the proactive measures can be taken on time to save any kind of maternal or neonatal casualty to occur. For this purpose, multiple techniques or prediction models are used. The objective of this research is to evaluate and predict the adverse effects experienced by women diagnosed with gestational diabetes mellitus (GDM) during maternity. The study aims to comprehensively assess adverse perinatal outcomes, which are influenced by various independent variables mentioned. By utilizing artificial intelligence (AI) techniques, the research seeks to develop an effective predictive model capable of analyzing multiple independent variables to accurately determine adverse outcomes. The ultimate goal is to facilitate timely identification and intervention to prevent maternal and neonatal casualties associated with GDM, thereby improving maternal and neonatal health outcomes.

Keywords: Gestational diabetes mellitus, Large for gestational age, Neonatal health, Body mass index, Adverse, Perinatal, Outcomes.

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

Gestational Diabetes Mellitus	GDM
Neonatal Intensive Care Unit	NICU
Index of Multiple Deprivation	IMD
Large for Gestational Age	LGA
Normal for Gestational Age	NGA
Small for Gestational Age	SGA
Oral Glucose Tolerance Test	OGTT
Body Mass Index	BMI
Convolutional Neural Network	CNN
Machine Learning	ML
Artificial Intelligence	AI
Oral Glucose Challenge Test	OGCT
World Health Organization	WHO
Time Above Range	TAR
Area Under the Curve	AUC
Mean Blood Glucose	MBG

CHAPTER 1: INTRODUCTION

The development and progress of the countries are directly associated with the maternal and neonatal health during and after pregnancy. Despite of the advancements and developments in Healthcare, the global burden of adverse perinatal outcomes still persists, this imposes a significant challenge on the healthcare system worldwide. Rendering to the WHO complications and adverse effects are the major factor in the death of the young women aged between 15-19 years globally. Additionally, 810 women dies every day which have some preventable diseases related to the pregnancy and child birth, with approximately 2.8 million neonatal deaths occurring every year, the mentioned figures are highlighting and urging the demand of more advance proactive predictive models for the prediction of these effects and their early treatment.

In result of the above figures, emerging technologies can be used for the effective predictability of the effects, like AI, ML and ANN, these technologies and predictive methods has entirely revolutionized the healthcare industry. These technologies use a vast range of dataset comprising of the multiple information from multiple perspective like general profile to previous medical history and some of the medical tests for the prediction of adverse perinatal outcome with high accuracy. By utilizing these models for predictive, healthcare provides can identify the high-risk pregnancies, implement the proactive measure for the treatment and optimize the neonatal and maternal health.

This research aims to give a broader exploration of the predictive technologies in maternity care while using their potential to evolve the prediction and prevention of adverse perinatal outcomes. By the integration of existing evidences, previous models and statistical insights of course seeks to transformative impact of predictive analytics on maternal and neonatal outcomes, while analyzing the opportunities and challenges in the existing diversity.

The initial phase of this research will provide a broader view of adverse perinatal outcomes and their effects of maternal and neonatal health. Globally, approximately 15 million of children born which SGA, and these are born with so often complications

which then becomes the major reason for the death of the kids under 5. Furthermore, maternal mortality rate also very high in most of the areas particularly in the low-resource settings, and place where quality healthcare services are limited or away from the patients. By elucidating the entire landscape of adverse perinatal outcomes, this section will cover the innovative predictive strategies to address challenges effectively.

Subsequently, we will then dive into the transformative applicability of artificial intelligence and machine learning in perinatal care. Recent research has revealed the durability and efficacy of AI-driven predictive models in finding females at high hazard of GDM, hypertensive disorders, and other gravidity related complications. Most of the researcher use the electronic databases normally maintained in the most of the healthcare hospitals related to the childcare and maternity with AI enabled algorithms for the prediction of adverse outcomes. Similarly, ML algorithms have shown tremendous results for monitoring the fetal heart rate pattern to detect signs of distress during labor, facilitating timely response to the neonatal outcome. So, by combining the real word data and AI models, this section will be the transformative potential of predictive technologies in enhancing the outcome prediction then the existing ones.

Moreover, multiple have explored the other predictive technologies, such as clinical decision support systems with health-related databases, like usage of the patient's previous history or data for the prediction of the disease and their timely management. These technologies empower the healthcare providers real time insights of the patients and make the decision making more effective than previous. AI enabled smart devices also enabled to monitor the different parameters of the patients related to particular disease and these wearables can continuously monitor the maternal vital signs and fetal movement. Health care providers can use the above mentioned for the better allocation of the resource, improve patient outcome, and enhance overall quality of maternity care.

However, the overall adaptability of these predictive technologies in the maternity and neonatal health care is not so easy. Data privacy and security concerns are the main considering for data to be used for the models. Data can be used after the approval of the ethical committee. Additionally, getting access to the health care resources impose

barriers to the smooth implementation of the predictive models. So that is very necessary to use the data solely for the deployment of predictive analytics. By critically examining the challenges and proposing strategies for ethical innovation and regulatory authorities, *this* research provides a broad view of the challenges and opportunities in implementing predictive technologies in maternal and neonatal health care.

As a result of the previous discussion, the prediction and prevention of adverse perinatal outcomes represent a critical frontier in maternity care, by convergence of technological innovation, clinical expertise, and public health databases belongs to patient's history. By utilizing the recent existing predictive models, including the AI, ML, ANN and other approaches, we can empower and assist the healthcare provider by providing the insights and tools needed to treat, mitigate and prevent the adverse perinatal outcomes effectively. This research further inspires the new innovation, collaboration to safeguard the health and wellbeing of mothers and newborns, every pregnancy and childbirth is characterized by safety, dignity, and composition.

1.1 Importance of Management:

The literature review revealed that GDM is an important health concern affecting both maternal and neonatal outcomes. Multiple studies emphasized the adverse effects of GDM on pregnancy, including increased risks of cesarean delivery, macrosomia, pre-term birth, and NICU admissions. The results demonstrating the importance of understanding and effectively managing GDM to improve outcomes for both mothers and newborns.

1.2 Research Gaps

The literature identified several gaps in existing knowledge, such as the need for further investigation into the specific risks and optimal management strategies for recurrent GDM pregnancies, particularly in women with prior adverse outcomes. Additionally, gaps were noted in understanding the significance of multiple factors in populations instead of using limited factors and the part of constantly glucose observance in GDM management. Continuous glucose monitoring is one of the multiple factors like others

are age, BMI, weight previous parity and gravida. Multiple authors just use a smaller number of variables instead of large variety as using large number of variables enable large population to be involved into the study, and by default the prediction model will predict the outcomes by considering a large variety. Along with the above-mentioned different authors do not use regional originality of patients which is very important to make the model which is not related to specific region. These research gaps indicating the areas where further study and exploration are warranted. Like some researchers used just three or four variables maximum and their results are on these bases, so a variety in variables will enhance the capability as well as the inclusion of entities into the model.

1.3 Different Fields coherence

The literature emphasized the importance of a multidisciplinary approach to GDM management, involving various healthcare professionals such as primary healthcare doctors, gynecologist, nutritionist, educators, social persons and pediatrist. This highlights the complexity of GDM management and the need for collaborative efforts to optimize perinatal care and reduce the hazard of contrary newborn results.

1.4 Potential for Impact

Results from preceding studies underscored the potential impact of addressing GDM through effective management strategies. By addressing hazard aspects such as maternal obesity, preceding diabetic records, and insulin treatment during pregnancy, interventions can potentially reduce the effect of contrary results in neonates complex by GDM. Implementing comprehensive care strategies informed by research findings has the potential to improve results for mothers and newborns resulted by GDM.

1.5 Goals to Deal the GDM

The purpose of this research is to evaluate and forecast the adverse consequences experienced by females identified with GDM during maternity. Study aims to comprehensively assess adverse perinatal outcomes, including preterm or post-term delivery, shoulder dystocia, LGA or SGA infants, and neonatal APGAR scores, which

are influenced by various independent variables such as maternal age, height, weight, BMI, obesity, ethnicity, obstetric history, parity, gravida, glucose tolerance test results, folic acid dose, and GDM diagnosis. By utilizing artificial intelligence (AI) techniques, the research seeks to develop an effective predictive model capable of analyzing multiple independent variables to accurately determine adverse outcomes. The ultimate goal is to facilitate timely identification and intervention to prevent maternal and neonatal casualties associated with GDM, thereby improving maternal and neonatal health outcomes.

1.6 Advantages

The proposed research on evaluating and predicting the effects faced by women during maternity diagnosed with gestational diabetes mellitus (GDM) offers several advantages with significant implications for maternal and neonatal health in Pakistan. Firstly, by comprehensively analyzing broader spectrum of factors contributing to risky perinatal results, comprising of preterm or post-term delivery, shoulder dystocia, and fetal APGAR scores, the research aims to provide a nuanced understanding of the complexities surrounding GDM management. This holistic approach allows health related professionals to demonstrate high risky cases before and implement targeted interventions to reduce adverse outcomes, thus potentially reducing parental and infant deaths and disease rates. Secondly, utilization of artificial intelligence (AI) models for outcome prediction enhances the precision and accuracy of risk assessment, allowing for more personalized and proactive maternal care strategies. AI-driven predictive models can leverage a multitude of independent variables, providing a comprehensive analysis that goes beyond conventional risk assessment methods. Moreover, by leveraging AI technology, the research aligns with global trends in healthcare innovation, positioning Pakistan at the front of advancements in mother and neonatal health. Ultimately, the research findings and AI-driven predictive models developed through this study have the potential to revolutionize GDM management practices in Pakistan moved to prioritized women and neonate health results and contributing to the achievement of national healthcare goals.

1.7 Areas of Application:

The areas of application for the proposed research on evaluating and predicting the effects faced by women during maternity identified as having GDM could include:

1.7.1 Programs for Maternal and Neonatal health

The study findings can help the development and implementation of Programs for mother and child health with the goal of lowering unfavorable perinatal consequences associated with GDM. Healthcare Policy and Guidelines. The research can aid in the creation of evidence-based healthcare policies and guidelines for the administration of GDM, leading to improved parental and neonatal health results at the national level.

1.7.2 Clinical Practice

Healthcare providers can utilize the AI-driven predictive models developed in the research to enhance risk assessment and personalized maternal care strategies for women diagnosed with GDM.

1.7.3 Medical Research

The research outcomes can serve as a framework for further medical studies in the domain of GDM management and predictive modelling, fostering advancements in maternal and neonatal healthcare.

1.7.4 Health Education and Awareness

The findings of the research can be incorporated into health education and awareness campaigns aimed at educating women about the dangers connected to GDM and the significance of early detection and intervention. Overall, the research has broad applications across various sectors of healthcare and public health, with the potential to positively impact maternal and neonatal health outcomes in Pakistan.

1.7.5 Healthcare Regulatory Authorities

Timely prediction of the outcomes in women would definitely assist the health care authorities to take some proactive measures by predicting the outcome timely.

CHAPTER 2: LITERATURE REVIEW

2.1 GDM patients which are medically treated and non-treated

GDM carries major dangers for mothers and their children if not treated well before. This paper specifically describes the effects to both mothers and infants if left untreated. This study compared the treated GDM with untreated GDM and nondiabetic pregnancies.

A study of mixed participants was conducted, involving 555 pregnant women with GDM diagnosed who do not received any kind of treatment up to 37 weeks, from which 1110 treated for GDM, and 1110 nondiabetic cases coordinated for overweightness, parity, origin, and gestating oldness at delivery. Non-diabetes topics and those who receive no medical attention for GDM stayed matched for prenatal appointments to control for healthcare access and surveillance bias.

The study describes significant differences in the perinatal outcomes among the groups. The entire adverse outcome was more elevated in the untreated GDM 59% pregnancies rather than the treated GDM 18% groups and nondiabetic pregnancies 11%. Untreated GDM pregnancies have major cause of metabolic worries and macrosomia/LGA infants. However, there is no major difference in the treated and nondiabetic pregnancies in these adverse outcomes. Comparisons based on the maternal factors like size, parity and disease severity showed a two to three times more severity for untreated groups rather than others.

The findings of this paper are that if GDM pregnancies treated on time then it reduces the adverse outcomes of all levels. Timely and effective treatment improve the perinatal outcome, if managed properly during pregnancy [1].

2.2 Infant mortality rate and GDM

This study includes the women with singleton pregnancies detected with GDM, carrying between thirty-six to forty-two weeks gestational oldness in California during the period since ninety-seven to six. Merged death percentage formulated toward assess the danger associated with hoping management at each gestational age. The composite rate incorporated the stillbirth risk and mortality risk during the gestational age.

The in-depth analysis of the data found that in females having GDM, the danger of hoping administration is lesser compared to the birth management at thirty-six weeks of gestation. However, by thirty-nine weeks of gestation, the risks of hopeful managing become advanced than the delivery management.

The findings suggest that among women with GDM, baby death ratio at thirty-nine weeks of gestational age is lesser than the general death risks associated with expected administration for an additional week. Additionally, the study revealed that the absolute risks of stillbirth and infant death in this population is very low. These conclusions underscore the importance of carefully evaluating the timing of delivery and expected outcome management in females diagnosed with GDM to maximize the maternal and neonatal outcome [2].

2.3 Adverse effects and their dependencies

This study's objective is to ascertain the accuracy of LGA and hazard of cesarean delivery diagnosed through sonography amongst females with GDM. This study manipulates nine hundred and three females with GDM who gave birth after 36 weeks of pregnancy and whose weight projected through ultrasound within thirty-one days of delivery. Delivery outcome linked with a sonography finding of LGA and non-LGA ultrasound finding.

The outcomes are founded on the sonography results, in this paper they recognized two hundred and forty-eight females with LGA embryo and six hundred and fifty-five females with a non LGA neonate. Form the females of LGA sonography analysis, fifty-six of two hundred and forty-eight delivered an LGA neonate as compared to the women non-LGA ultrasound diagnosed delivered 18 of 655 LGA neonate. Deliveries which are

diagnosed as LGA through ultrasound linked with bigger hazard for abdominal delivery irrespective of birth heaviness was among 2500 and 3499 g or between 3500 and 4500g.

The final results show that the sonography meaningfully overvalues the incidence LGA in females diagnosed with GDM, and sonography diagnosed LGA is connected with the cesarean delivery irrespective the neonate weight [3].

This study provides a detailed look over the postpartum hemorrhage during delivery, and analyzes multiple factors from which the most effective factors rather than the others are weight and weight at the admission. The data used for the prediction is clinical data most commonly collected by different healthcare providers. Two machine learning models and logistic regression models were employed to predict bleeding after childbirth from clinical data in order to see which performed better. The algorithm has been verified using data from the first and second halves of the research period, with the latter half being applied afterwards. Although other variables can also be used as better predictor then the existing ones, as gestational weight gain is a major variable but along with that if previous information regarding to the postpartum hemorrhage used then the prediction becomes more viable. Discovered that machine learning models are outperforming the rest by a small margin. There is also an association between the oxytocin and postpartum hemorrhage, it increased by multiple times if there is a prevalence of the oxytocin, so by introducing the duration of oxytocin as input variable the hemorrhage can be controlled [4].

Research stated that women with GDM have more chance of polyhydramnios and more probable to give birth via SC. Their offspring had greater rate of macrosomia and likely to require NICU [5].

The chances of cesarean delivery and LGA becomes double with pregnancy whose HbA1c >= 5.5% and BMI >= 25 kg/m^2 at the time of booking were compared to those with BMI <25 AND HbA1c <5.5. [6]. Machine Learning based triage model has been used to prioritize the children to critical and less critical categories and then allocate resources to them. These resources are allocated on the basis of criticality. Sometimes

model predicts the over triaging and under triaging but for a smaller number of cases [7].

The study's objective is to evaluate the risks and negative perinatal and maternal outcomes effected by gestational diabetes mellitus (GDM) by comparing the singleton and twin pregnancies. Through an organized evaluation and a meta-analysis of 27 twin births and 85 singleton births, it is analyzed that GDM raises the possibility of unfavorable results in both double as well as solo births. These outcomes included pregnancy-related hypertension problems, labor induction, and Delivery by cesarean section, low birth weight, premature delivery, and NICU admission. Notably, during twin gestations, the presence of GDM correlated with a diminished likelihood of certain negative outcomes such as the birth of SGA infants and newborn mortality, in contrast to singleton pregnancies. Furthermore, meta-regression analysis indicated that two births had a decreased relative chance of delivery via cesarean and reduced risks of entrance to the NICU, stillbirths, and neonatal death compared to singleton pregnancies. These results indicate that while there are hazards associated with GDM in single and twin pregnancies, its effect on certain unfavorable birth results might be less severe in twin pregnancies, highlighting further investigation and tailored management strategies [8].

GDM have pregnant women's and children's hazards, Nonetheless, nothing is understood regarding the specific risks in recurrent GDM pregnancies, particularly in women with prior adverse outcomes. Authors conducted a retrospective cohort study comparing 424 consecutive GDM pregnancies in pairs. Compared to index pregnancies, they discovered that subsequent pregnancies had reduced rates of instrumental and emergency Cesarean deliveries but greater rates of elective Cesarean sections. Importantly, A track record of unfavorable leads to the pregnancy index significantly increased the risk of repeat adverse outcomes in subsequent pregnancies, including delivering LGA or SGA infants. These findings underscore the need for personalized management strategies in high-risk women with recurrent GDM pregnancies to improve outcomes for both mothers and babies [9].

The occurrence of GDM is growing globally, needs effective management strategies to mitigate associated effects. In this prospective observational study spanning from 151 women between September 2016 and April 2018 with singleton GDM pregnancies were categorized into four treatment groups: "Diet," "Metformin," "Metformin and Insulin," or "Insulin alone." Baseline characteristics divided among groups, with notable differences observed in factors such as height, weight, timing of OGTT, blood glucose levels while fasting during OGTT, overall vitamin B12 intake, and a family record of diabetes. Interestingly, women treated with Metformin or Insulin underwent earlier OGTTs compared to those on dietary intervention alone. However, no discernible variations were observed in the mother and neonate composite outcomes among the therapy groups, indicating that pharmacological interventions did not confer significant advantages over dietary/lifestyle modifications in terms of these outcomes. Nonetheless, neonatal intensive care unit (NICU) admission rates varied, with infants of insulin-treated mothers exhibiting the highest proportion of hypoglycemic episodes. Furthermore, Mother factors of the need for medications were fasting blood glucose levels, history of losses or pregnancy dismissals, and the time of the OGTT, emphasizing the multifactorial nature of GDM management. The results of multivariate analysis showed that There was a negative correlation between the OGTT time and the history of terminations or losses, although the mother's BMI was not substantially linked to the requirement for medication, while fasting blood glucose levels were positively correlated. These findings underscore the necessity of personalized approaches to GDM management, considering various clinical and demographic factors to optimize maternal and neonatal outcomes. Additional investigation is necessary to clarify the most effective and safe management strategies for GDM within clinical settings [10].

Pregnancy-related GDM poses serious risks to the health of the mother and the fetus. In Germany, standard screening involves a 1-hour fifty-gram OGCT, after that a two-hour seventy-gram OGTT if initial results are abnormal. A retrospective study of 1664 participants from a Berlin GDM center looked at the connection between mother outcomes and glucose levels during the 75 g OGTT. Categorizing patients into subcategories based on their glucose response patterns (distinct hyperglycemia during fasting, distinct hyperglycemia following load, and mixed hyperglycemia), the study

found significant associations between specific glucose response patterns and unfavorable perinatal outcomes. Females with isolated fasting hyperglycemia and combined hyperglycemia exhibited greater BMI prior to conception and were more likely to need insulin treatment. Additionally, the risk of cesarean section delivery varied among subgroups, with the isolated fasting hyperglycemia group at greater risk of initial surgical delivery and An emergency cesarean section is more probable to be performed on the isolated post-load hyperglycemia group. Neonatal outcomes also differed significantly between subgroups, highlighting the importance of tailored prenatal care based on individual glucose response patterns to optimize outcomes for both mother and fetus in pregnancies complicated by GDM. To validate these results and improve clinical care guidelines, more investigation is required [11].

CGM has emerged as a promising means in handling diabetes during pregnancy, yet its application and impact in gestational diabetes mellitus (GDM) remain relatively unexplored. Based on information from 1302 GDM pregnant women, the results show a strong relationship between dangerous pregnancy outcomes (such as early birth, live birth, low-grade abortion, fetal distress, early membrane separation, and NICU hospitalization) and metrics obtained from CGM. Metrics that were specifically positively correlated with the likelihood of unfavorable outcomes included TAR, glucose AUC, MBG at night, MBG throughout the day, and MBG on a daily basis. LGA risk, on the other hand, was negatively correlated with time spent in range. These findings indicate the need for customized interventions to improve maternal and newborn health in this population and show the possibility of CGM-derived measures as useful markers for identifying persons at higher risk of unfavorable pregnancy outcomes in GDM pregnancies [12].

The significance of HbA1c in GDM management, specifically in Asian populations, remains unclear. This explained study describes 2048 Chinese women with GDM who gave birth to a single live child in order to investigate the relationship between high HbA1c levels and poor pregnancy outcomes, considering the GWG, pre-pregnancy BMI, and mother age. Preterm birth, primary CS, macrosomia, and pregnancy-induced hypertension (PIH) were all substantially linked with elevated HbA1c (≥5.5%). Their

correlation varied across mother age groups and BMI ranges, and GWG statuses. While older women showed correlations with macrosomia, PIH, and premature birth, younger women demonstrated a higher risk of primary CS. High HbA1c levels were associated with negative results in women with insufficient or excessive GWG, emphasizing the significance of taking maternal features into account in addition to HbA1c levels for customized GDM care[13].

Females with previous record of GDM face an increased hazard of GDM recurrence in subsequent pregnancies. This surveying group study, comprising one hundred and fifty-nine females with GDM and other future pregnancies, aimed to identify predictive factors for GDM recurrence. According to the study, there was a high overall probability of GDM recurrence, 72.3 Pregnancy BMI as high as or comparable to thirty kg/m2 before to the index pregnancy was one of the risk variables for recurrence, BMI greater than 25 kg/m2 before to the next pregnancy, positive diabetes mellitus in relatives, with the use of insulin throughout the index pregnancy. Furthermore, a cesarean section during the index pregnancy demonstrated marginal importance. Interestingly, during pregnancy mass increase, extreme mass gain throughout the index pregnancy, and neonatal outcomes were not projecting GDM recurrence. Compared to healthy controls, babies born to moms with GDM were more often admitted to the NICU. The study suggests that a helpful family past of GDM combined with weighty or obese significantly increases the danger of a GDM resurgence. Normalization of BMI prior to pregnancy is proposed as an operative strategy for minimizing the hazard of GDM reappearance in subsequent pregnancies [14].

The experiment, which included 175 pregnant women with GDM, found that most of the participants were over 30 (56%), of Saudi origins (92.6%), lived in cities (81.7%), and 6.3% had a family history of the disease. Remarkably, 78.3% of these mothers had previous cesarean deliveries, and 25.1% had four or more prior births. The results highlight the substantial influence of maternal variables on unfavorable infant outcomes and admissions to NICU, underscoring the significance of early identification and intervention through routine interactions with healthcare providers. To manage gestational diabetes comprehensively, ensure optimal prenatal care, and lower the risk

of risky neonatal outcomes, a collaborative, multidisciplinary approach involving primary healthcare doctors, obstetricians, dietitians, health instructors, social service providers, nursing staff and pediatricians must be put into practice[15].

Multiple factors have been mentioned like obesity, above normal weight gain during pregnancy and GDM on fetal overgrowth and other adverse effects. Women with 2-h OGTT 75-G and which are not treated through exercise, taking antidiabetic medicine increases the risk of being overweight or obese when a pregnancy first begins[16]. Adverse pregnancy outcomes are connected with BMI, higher HbA1c levels at diagnostic or delivery, greater fetal biometric results (large belly circumference), and estimated fetal weight are all associated with it, whether it occurs before or after pregnancy. [17]. Maternal weight increase over IOM recommendations are more probable to possess different complications related to the neonates along with the maternity health. Such as neonates born to these women are large for gestational age, maternal have increased likelihood of preterm birth and cesarean delivery. Women who weigh less than the recommended amount for their gestational age are more likely to give birth to SGA neonates and have very little chance of giving birth to LGA neonates [18]. Research work formulated that singleton pregnancies have more gestational age as compared to the multiple pregnancies. Similarly birth weight is more for singleton pregnancies as compared to multiple pregnancies [19]. Women with GDM-1 have more chances of polyhydramnios, neonates born with macrosomia, large for gestational age, delivery through cesarean and also having more chances that these neonates require NICU (neonatal intensive care unit) after delivery [20].

One-hour sugar after OGTT and pre-pregnancy BMI were found to be linked with cesarean delivery in another investigation. Macrosomia & LGA are associated with the HbA1c and gestational weight growth during the last trimester of pregnancy, however the SGA was negatively correlated with pre-pregnancy BMI. Neonatal hypoglycemia and the mother's therapy were connected. The odds of a cesarean section and lower gastric band (LGA) are twice in patients with BMI >= 25 and HbA1c > 5.5% compared to those with BMI < 25 and HbA1c < 5.5% [21].

Another study concluded the results and checking the relationship between GDM and consumption of protein from animals and plants. There is a connection between GDM and the general consumption of animal protein. During pregnancy, each additional 5% increase in energy consumption from total protein increases the risk of GDM by 20%. Furthermore, no non-linear relationship has been found between the plant protein intake and GDM [22]. Two different groups have been studied effected by preeclampsia and GDM. They stated that advanced maternal age has a positive effect on the preeclampsia and GDM. Similarly, there is a positive impact of obesity on preeclampsia and GDM [23]. Patients which are already diagnosed with the GDM have 48% chance of getting GDM again as compared to the non GDM history patients which have chances of 16%. Higher age, body mass index and oral glucose tolerance are found to be the major causes of GDM. Normally age more than the 35 years are considered higher one [24]. At different points ultrasonography overrates the existence of LGA in females with GDM and sonography diagnosed LGA remains more linked with cesarean delivery independent of birth weight [25].

CHAPTER 3: METHODOLOGY

We base our model proposal on the GDM dataset. Rochan Agha-Jaffar and Srirangan Jeyaparam prepared the dataset. The hospital in London owns the dataset. And they conducted an in-depth observational study using the CERNER pregnancy data that were regularly tracked at St. Mary's Hospital in London between the months of April 2016 and the end of 2019. The first search results included 26063 patients, selected based on criteria including zip code, height, weight, BMI at registration, ethnicity (self-reported), availability of a glucose tolerance test, and test results (taken after 75g glucose load and after 0 minutes and 120 minutes), Various delivery techniques, total expected blood loss, gestational age, infant weight, necessity for or lack of a SCBU, length of hospital stay following delivery, gender, and stillbirth are among the additional factors taken into account. The patients who lacked data for any number of critical variables have been eliminated from the analysis. and did not fill out the data that isn't really accessible. Rechecking the original patient data was not practicable, thus datasets were removed and significantly outlier values were modified. Inconsistencies in unit measurements have been corrected.

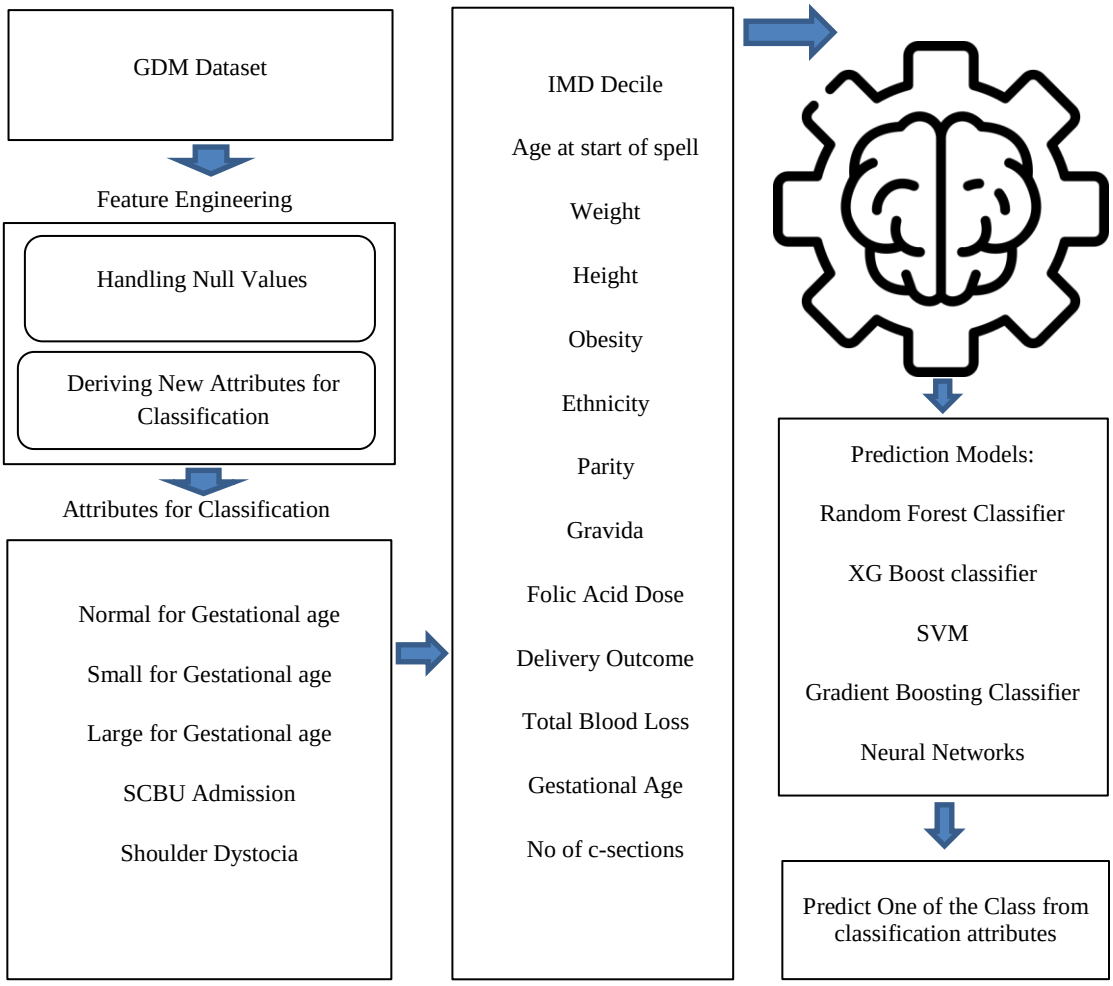

Figure 3-1: Feature Selection Techniques

3.1 EDA (Exploratory Data Analysis)

Exploratory data analysis has been used to determine the feature importance and removing the null values. Below mentioned techniques has been used for this purpose.

3.1.1 Handling Missing Values

Dataset consists of large number of columns and multiple of them have missing values. Features which have a smaller number of missing values treated and filled by considering the previous values. Just filled those values which have missing values from 4 to 10 instances. These are filled which have less importance in the dataset. But if some important values are missing from the dataset then these are deleted.

3.1.2 Eliminating Null value features

There are a number of features which have null values. Features consisting of null values and have less importance regarding to the prediction of the adverse effects have been removed from the dataset. The representation of such columns are as follows.

Table 3.1: Null values feature elimination

Features	Count of Missing Values from Total of 1847
Risk Factors	1457
AntenatalMedicalFactors	1359
PreviousObstetricHistory	1610
Glucoselevelblood	1065
GlucoseToleranceTest	485
SystolicBloodPressureCuff	833
Diastolic Blood Pressure	833
VitaminDlevelblood	1555
O_Thyroidfunctionblood	1854
Contraction frequency prior to delivery	1083
Category Caesarean Section	1118

3.2 Feature Engineering for Target variables

In this study five labels are used for the prediction purpose which are SCBU admission needed, LGA, NGA, SGA and shoulder dystocia. Basically, the size of the baby such as

small, normal and large have been determined from the BW Centile column under the below mentioned mechanism.

Table 3.2: Classification of neonates according to weight

Baby Size	Percentile
SGA	<10th
NGA	>=10th AND <=90th
LGA	>90th

Neonates having percentile less than 10 these are categorized as small for gestational age. Those which have percentile more than or equal to 10 and less than or equal to 90 are treated as normal for gestational age. At last those whose percentile is more than 90 are treated as large for gestational age.

3.3 Feature Selection

The features which we use for the training and testing of the model are below mentioned. Furthermore, statistical tests are also used to check the association between independent variables and final predicted feature which is named as effect and non-effected patients.

3.3.1 Statistical tests to check the association

This data on which the experimental study has been carried out comprising of both instances like those which observed gestational diabetes mellitus and those which do not during the gestational age. But we do select the appropriate class of patients for which we want to predict the adverse effects like those patients which have observed gestational diabetes mellitus during the pregnancy. Form that one multiple instance has been removed because of missing data in important features. Some of the derived instance has been used like obesity rather than the complete independent variables of BMI like height age and weight.

3.3.2 Hypothesis formulation on the basis of questions

- Which columns shows association with target columns?
- Which columns have difference of means with target column like effected/non-effected?
- Either there is any association between the input features and target column such as effected/non-effected.

Data Preprocessing and finding relationship among different variables. The most of the description has been already given. Here the relationship among different variables has been found and their results will be interpreted. These Associations has been found in two ways.

- Through ANOVA
- Through chi-square

Both of these tests are run on different features of Dataset First like patients which have status effected/non-effected and find the association among variables. The purpose behind checking of these associations is to find that either variables are associated on the basis of gestational diabetes status Yes and No. For example, we create a null hypothesis that there is no association between obesity and gestational diabetes. And on the basis of the null hypothesis we accept or reject our assumption.

3.3.3 ANOVA

Basically, ANOVA is utilized to examine if the mean values of two samples differ from one another. There are two types of ANOVA such as Single-way ANOVA and 2-way ANOVA. In one-way AONOVA the means difference has been checked horizontally or vertically. Like values corresponds to different variables like IMD decile and GDM. Here we make premise that there is no variation in the means. And after that check their values like F-Calculated and F-Critical value comparing these values if F-Calculated>F-

Critical then we will reject H0 else accept H1. P value can also be compared with level of significance used in the statistical analysis in the comparison if P-Value>0.05 then we will accept H0 else reject H0.

3.3.4 Difference between gestational age and status effected/non-effected

H0: There is no difference between means of Gestational age and status effected/non-effected

H1: Both means Gestational age and status effected/non-effected are different

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Effected(Gestation)	786	29702	37.7888	3.838142		
Non Effected (Gestation)	1064	40679	38.23214	3.077762		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	88.85132	1	88.85132	26.12691	3.53E-07	3.846496
Within Groups	6284.602	1848	3.400759			
Total	6373.454	1849				

Figure 3-2: Gestation and Effected/Non-Effected

Decision: As F-Calculated>F-critical, 26.12>3.84 Consequently, We reject the null H0 and adopt the H1, which states that there is a difference in the means. It means that the means are not same for both like for gestational age and status effected/non-effected.

3.3.5 Difference between blood loss and status effected/non-effected

H0: There is no difference between means of estimated blood loss and status effected/non-effected

H1: Both means of estimated blood loss and status effected/non-effected are associated

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Effected (EstimatedTotalBloodLoss)	786	476823	606.645	146731.3		
Non Effected (EstimatedTotalBloodLoss)	1060	580642.7	547.7761	115511.6		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	1564115	1	1564115	12.14356	0.000504	3.846507
Within Groups	2.38E+08	1844	128802			
Total	2.39E+08	1845				

Figure 3-3: Blood Loss and Effected/Non-Effected

Decision: As F-Calculated>F-critical, 12.14>3.84 Consequently, rejecting the H0 and accepting the H1 that there is a difference in the means. It means that the means are not same for both like for estimated blood loss and status effected/non-effected. This is due to the reason that the chances of blood loss in effected patients is more than the other patients such as non GDM patients.

3.3.6 Difference between age at start of spell and status effected/non-effected

H0: There is no difference of means between age at start of spell and status effected/non-effected

H1: Both means age at start of first spell and GDM are different

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Effected (AgeAtStartOfSpell)	789	27067	34.30545	28.18958		
Non Effected (AgeAtStartOfSpell)	1064	35941	33.77914	28.86274		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	125.4972	1	125.4972	4.391674	0.03625	3.846488
Within Groups	52894.48	1851	28.57617			
Total	53019.98	1852				

Figure 3-4: Age at start of spell and Effected/Non-Effected

Decision: As F-Calculated>F-critical, 4.39>3.84 Thus, The H0 is rejected in favor of the H1, which holds that there is a difference between the means. It clarifies that the means are not same for both like for age at start of spell and status effected/non-effected.

3.3.7 Difference of means between no of c-sections and status effected/non-effected

H0: There is no difference of means between Glucose level 0 min Blood and status effected/non-effected

H1: Both means no of Glucose level 0min Blood and status effected/non-effected are different

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
Effected (Glucoselevel0minblood)	788	3937	4.996193	1.183696		
Non Effected(Glucoselevel0minblood	1064	5105.8	4.798684	0.780375		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	17.66034766	1	17.66035	18.55177	1.74E-05	3.84649
Within Groups	1761.106737	1850	0.95195			
Total	1778.767084	1851				

Figure 3-5: Glucose Level 0minblood and Effected/Non-Effected

Decision: As F-Calculated>F-critical, 18.55>3.84 so that there is a disparity between the means, we accept the H1 and reject the H0. It indicates that the means differ for both like Glucose level 0min blood and status effected/non-effected.

3.3.8 Chi-Square Test

For comparing the two nominal variables the chi-square test has been used. This is basically used to check the association between the columns like if we have two columns one is for gestation and its status is yes and No. and second one is for obesity whose status is yes and no. Our main purpose is to find that either there is any kind of relationship exists or not such as in that example Our H0 is that there is no connection between obesity and GDM status. After implementing the statistical formula, we conclude on the basis of Chi-square calculated and its critical value or p value with level of significance. We accept the H1 and reject the H0 if the Chi-square value is greater than the critical threshold. We accept the null hypothesis if we are comparing other numbers, such as if P>0.05.

3.3.9 Association between Obesity and status effected/non-effected

H0: Status affected/non-effected and obesity do not correspond.

H1: The afflicted/non-effected state and obesity are correlated.

The level of significance is alpha=0.05

P-Value=0.0079

Decision: since P-Value!>0.05 Thus, we reject the H0 and accept the H1, which states that obesity and status effected/non-effected are related.

3.3.10 Association between delivery outcome and status effected/non-effected

H0: There is no association between delivery outcome and status effected/non-effected

H1: There is association between delivery outcome and status effected/non-effected

Alpha=0.05 is the significance level

P-Value=0

Decision: since P-Value!>0.05 Since there is a relationship between the delivery outcome and the status effected/non-effected, we reject the H0 and accept the H1.

3.3.11 Association between shoulder dystocia and status effected/non-effected

For shoulder dystocia and status effected/non-effected P= 0.000108779 since P!>0.05 Therefore, we accept H1 and reject H0, i.e., that shoulder dystocia and status effected/non-effected are related.

3.3.12 Association between SCBU admission and status effected/non-effected

For SCBU admission and status effected/non-effected P= 0 We accept H1—that there is a relationship between SCBU admittance and status affected/non-effected—and reject H0 since P!>0.05.

3.3.13 Association between Still birth and status effected/non-effected

For Still birth admission and status effected/non-effected P= 0.0306 as P!>0.05 As a result, we accept H1 and reject H0, or the idea that stillbirth and affected/non-effected status are related.

3.3.14 IMD Decile

Based on 39 separate indices of deprivation, which are then weighted into seven different categories known as the domains of the deprivation, the disparate places and

locales have been ranked. The IMD are essentially a collection of descriptive data that are produced every three to four years by the office for national statistics. Average rank and average score can be any which can be further simplified by dividing it into percentile or decile.

3.3.15 Age at start of spell and its effects

Age is an important component in the prediction and recurrence of the GDM. As with the increasing of age the chances of GDM increased as compared to the other patients with less age. That's why this is used in the dataset.

3.3.16 Obesity

Table 3.3: Recommended weight gain on the basis of BMI

Category of Pregnancy Weight	BMI	Total Weight Gain	Average Weight Gain Suggested for the Second and Third Trimesters
Underweight	< 18.5	12.5–18 kg (28–40 lb)	0.4 kg/week (1 lb/week)
Normal weight	18.5–24.9	11.5–16 kg (25–35 lb)	0.4 kg/week (1 lb/week)
Overweight (0.5–0.7)	25.0–29.9	6.8–11.3 kg (15–25 lb)	0.27 kg/week (0.6 lb/week)
Obese (includes all classes)	≥ 30.0	5–9 kg (11–20 lb)	0.23 kg/week (0.5 lb/week)

Obesity is closely linked with the gestational diabetes mellitus. Obese patients are most likely to experience GDM in contrast to the patients which are not obese due to this reason this feature is incorporated into the dataset.

3.3.17 Ethnicity

An important factor in the formation of the GDM is ethnicity. Specific ethnicities are more likely to develop GDM due to some environmental or lifestyle factors.

3.3.18 Parity

Parity refers to the number of times a woman has given birth. Below are some of the points relevant to the association of parity and gestational diabetes mellitus.

3.3.19 Gravida

The Number of times a woman conceive is known to be gravida, to find an association between gravida and gestational diabetes mellitus is very important although other factors are influencing a lot.

3.3.20 Folic Acid Dose

Although there is not any direct association between the folic acid dose received by women during pregnancy on gestational diabetes mellitus but it has some of the further association with other variables such as on the weight of the neonates.

3.3.21 Delivery Outcome

There is a direct impact of gestational diabetes mellitus on delivery outcome. There are multiple associations which are demonstrated and identified between GDM and delivery complications. There are some of the associations as below.

3.3.22 Total Blood Loss

The association between gestational diabetes mellitus and total blood loss is not extensively studied but this feature has been used in the model training and testing. With the expectation that if it contributes to the accuracy of the results.

3.3.23 Gestational Age

As previously indicated, a number of other factors are also crucial in the development of GDM. But gestational age is also carrying more importance. The Associated factors are mentioned below.

3.3.24 No of C sections

The number of previous cesarean deliveries or C-sections, may have associations with GDM in further pregnancies. That’s why this is used in the dataset.

3.4 Model interpretation

Diagram of the overall model is below mentioned from initial to the final process. At first point the dataset has been processed against missing and null values. Then splitting has been done into training and testing. As there are five labels to which our model classifies each data instance. There are three labels which are derived from the one column named as birth weight centile and derived attributes are named as SGA, NGA and LGA. Other two labels are derived from the existing columns of shoulder dystocia and SCBU admission. Then AI model has been implemented for checking the correctness of the models.

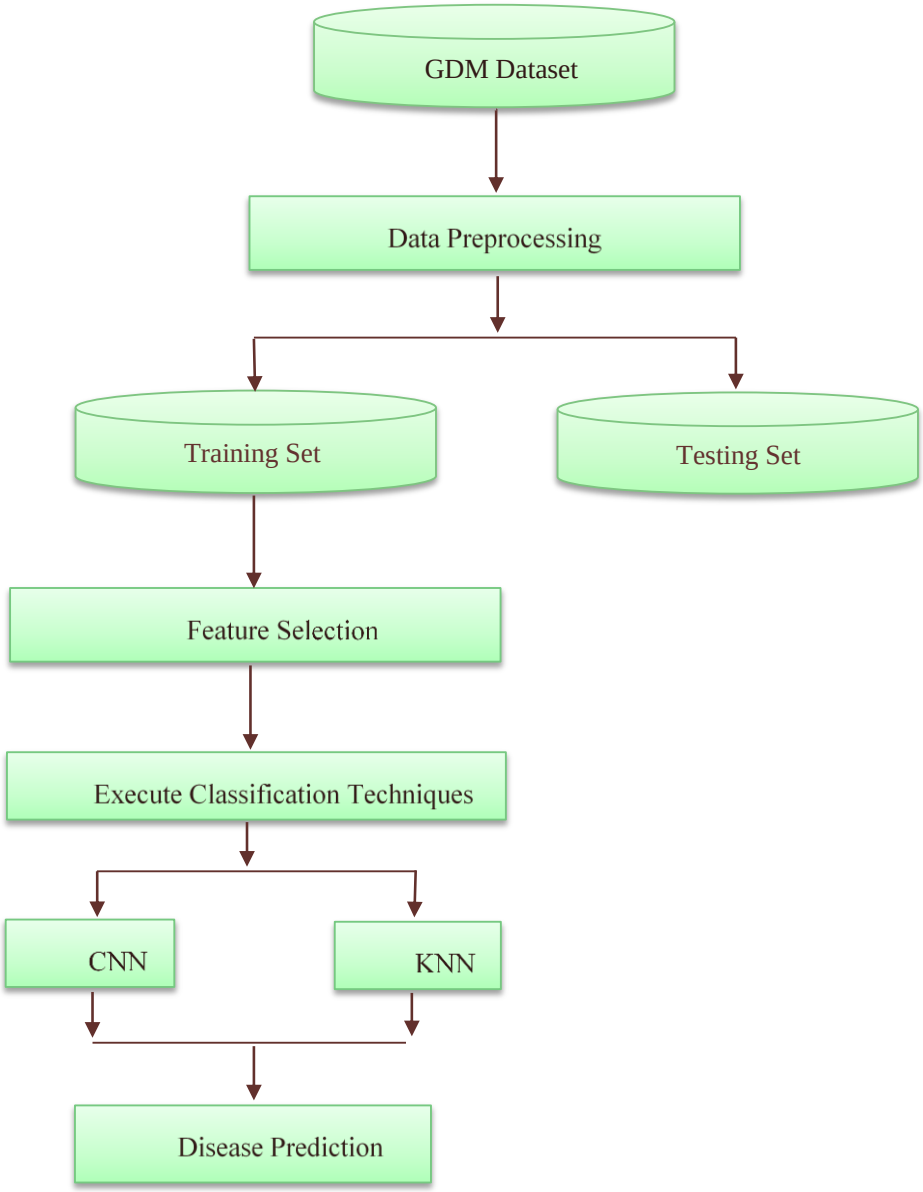

Figure 3-6: Model Overview

3.5 Random Forest Classifier

The random forest classifier is a collaborative learning approach for regression and classification that works by building a large number of decision trees during the training phase. The average of each tree's projections or the majority vote are used to illustrate its outcomes.

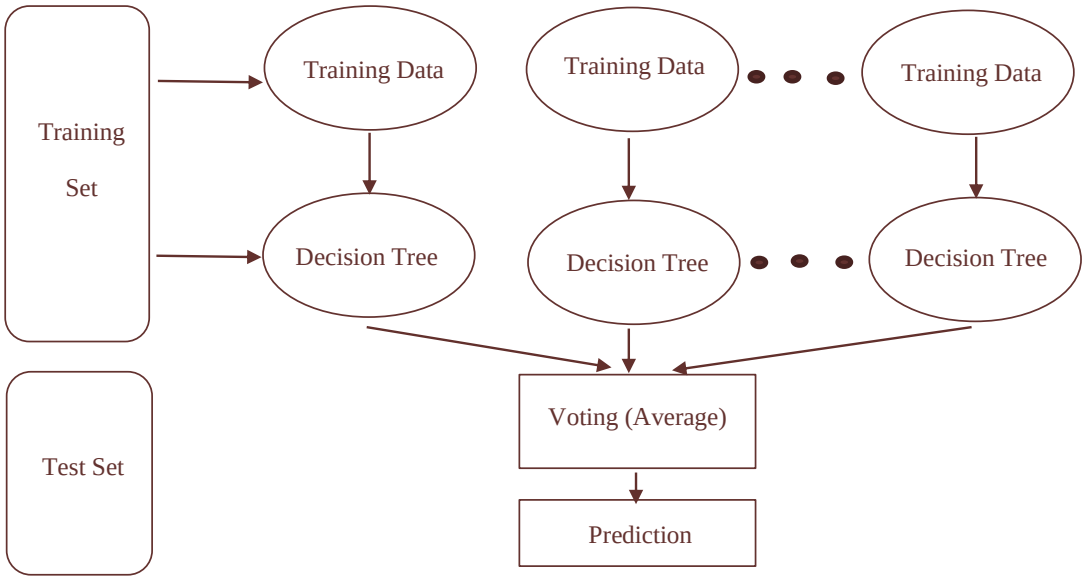

Figure 3-7: Random Forest Classifier Diagram

- Ensemble learning: Creates a more reliable model by combining several decision trees.
- Randomness: Introduces randomness in the selection of features and data samples, which helps in creating diverse trees and reducing overfitting.
- Bagging (Bootstrap Aggregating): Every tree is trained using a randomized, replacement-sampled subset of the data.
- Feature Randomness: To ensure that trees are diverse, a random subset of traits is considered at each split in the tree.

The class and probability are used in the random forest classifier formula to calculate the Gini of each branch on a node. It is basically calculated to determine that which branch is more likely to take place. The relative frequency of each class we are witnessing in the dataset is represented by pi in this case. While the number of classes is represented by c.

$$Gini = 1 - \sum_{i=1}^{c} (p_i)^2$$

Entropy can also be used in this regard to ascertain the decision tree's node branching pattern. In essence, it determines the likelihood of a specific result.

$$Entropy = \sum_{i=1}^{c} -p_i * \log_2(p_i)$$

This model has been performing better than the other models for the prediction of the adverse effects. Basically, it predicts multiple adverse outcomes like LGA, SGA, SCBU admission needed, shoulder dystocia and NGA. This model shows an accuracy of up to 72.43%. Accuracy just shown to those values which are used for the testing purpose.

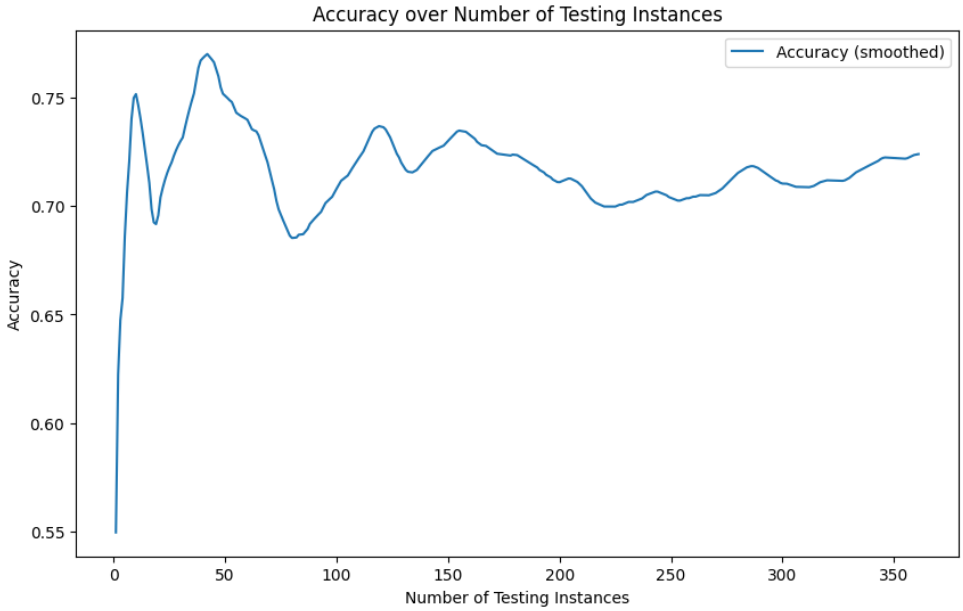

Figure 3-8: Accuracy Graph

3.1 XG Boost Classifier

Based on the gradient boosting framework, Extreme Gradient Boosting is a sophisticated machine learning algorithm. It is highly efficient, flexible and portable and making it first choice for many machine learning tasks. It has steps like previous one like boosting, gradient boosting and other one is regularization adds terms to the loss function to reduce

overfitting. Extreme boosting also applied to the GDM dataset with a final accuracy of 72%. the graph is below mentioned.

XG-Boost is an ensemble additive model and composed of multiple base learners the below mentioned equation representing the set base learners.

$$F = \{F_1, F_1, F_1, F_1, \ldots, F_m\}$$

Final prediction

$$y_i = \sum_{t=1}^{m} f_t(x_i)$$

Loss function is basically used to check the error of training set and then finally reducing the error. Firstly, we calculate the error function and then minimizing this error using different methodologies like tuning the hyperparameters.

$$L^{<t>} = \sum_{i=1}^{n} l(y_{i,} y_i^{<t-1>} + f_t(x_i)) + \Omega(f_t)$$

3.2 SVM

To classify data, a support vector machine, an N-dimensional supervised machine learning method, determines the optimal line or hyperplane to maximize the distance between each class. The model accuracy is standing at 71.62%.

For multiclass classification problem One-vs-Rest (OvR) SVM. The decision function for each class c, where c = 1, 2, 3,... and C is the total number of classes, is listed below.:

$$f_c(x) = \sum_{i=1}^{n} a_i^c * y_i^c * K(x_i, x) + b_c$$

- a_i^c: Langrage multiplier for the i-th training when classifying for class c.
- y_i^c: Label for the i-th training example, and $y_i^c = +1$ if belongs to the same class, else $y_i^c = -1$.
- $K(x_i, x)$, Kernel function
- b_c: Bias term for class c.

The final class label $\overline{c}$ for new point data is determined by selecting the class with highest decision function value:

$$\hat{c} = arg\ max_c\ f_c(x)$$

3.3 Gradient Boosting Classifier

Predictive models are constructed using the Gradient Boosting classifier approach. It is mainly utilized for problems involving regression and classification. Combining the predictions of numerous base estimators to increase overall performance is the primary motivation for using or developing this approach. General steps in the gradient boosting classifier are mentioned below:

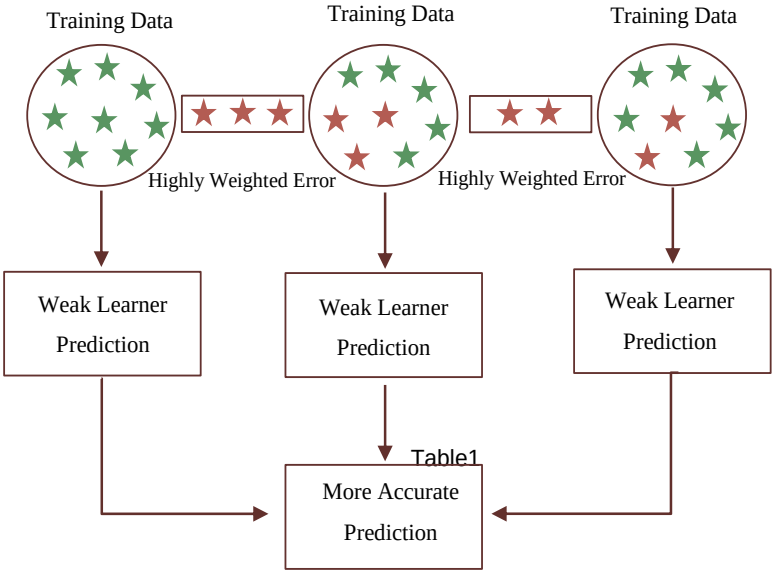

Figure 3-9: Gradient Boosting Classifier Diagram

An ensemble technique which combines the results of multiple weak learners (models performing slightly better than the random) to create a strong predictive model. Improve the results gradually. Each new model removes the errors from the previous one. Typically, shallow decision tress, these are simple models which prone to overfitting individually but perform well when combined. This model also has been used on the GDM dataset. Its accuracy is quite better than the neural networks which is 70%.

For multiclass classification problem with c classes, the model estimates a function F(x) that provides a vector of predictions for each class:

$$F(x) = [F_1(x), F_2(x), F_3(x), \ldots, F_c(x)]$$

Below mentioned is the formula for the prediction of each class c:

$$F_c(x) = F_c^{(0)} + \sum_{m=1}^{M} \nu h_m(x; \gamma_{c,m})$$

Where

$F_c(x)$: The prediction results for class c for input x

$F_c^{(0)}$: The initial prediction (often set as the log of the class prior probabilities).

M: Total number of boosting iterations (or trees)

ν: This is the learning rate which contributes to the value of each weak learner.

$h_m(x;\gamma_{c,m})$: The m-th weak learner (e.g. decision tree) for class c, parameterized by $\gamma_{c,m}$

The final class label $\hat{c}$ for a new data is determined by taking the class with highest score.

$$\hat{c} = arg\ max_c F_c(x)$$

3.4 Neural Networks

An artificial intelligence technique called a neural network trains computer to function in a manner modeled after the human brain. A type of machine learning called deep learning connects nodes or neurons in a layered pattern that resembles the organization of the human brain. This model has been implemented on the GDM dataset and it has an accuracy of 62.16% which is much lesser then the other ones.

There are four parts of neural networks:

1. Input layer: The input feature vector is passed through multiple layers of the network.
2. Hidden layers: Each hidden layer performs the below mentioned operations:

$$z^{(\ell)} = W^{(\ell)} a^{(\ell-1)} + b^{(\ell)}$$

Where:

- $z^{(\ell)}$: The linear combination of inputs at layer ℓ.
- $W^{(\ell)}$: Weight matrix at layer ℓ.
- $a^{(\ell-1)}$: The activation from the previous layer (or input x for the first previous hidden layer).
- $b^{(\ell)}$: The bias vector at layer ℓ.

Then activation function (e.g. RELU) has been applied:

$$a^{(\ell)} = \sigma(z^{(\ell)})$$

Where σ is the activation function

3. Output Layer: The final layer computes the unnormalized scores for each class c.

$$Z_c = W_c a^{(L-1)} + b_c$$

Where

- Z_c: The logit for class c.
- W_c: The weight vector associated with class c.
- $a^{(L-1)}$: The activation from the last hidden layer.
- b_c: The bias term for class c.

4. SoftMax Activation: The anticipated probability for each class are then obtained by running the logits through a SoftMax algorithm.

$$P(y = c|x) = \frac{e^{\mathcal{Z}_c}}{\sum_{k=1}^{c} e^{\mathcal{Z}_k}}$$

Where:

- $P(y = c|x)$: The probability that input x belongs to class c.
- $\mathcal{Z}_c$: The logit for class c.
- c: The total number of classes.

Prediction:

The final predicted class $\hat{c}$ for input x is those with highest probability.

$$\hat{c} = arg\ max_c\ P(\mathcal{Y} = c|x)$$

3.5 Model Evaluation Metrics

Our dataset consists of 1847 instances was served as the model's training data and data has been tested. The most commonly used metrics is accuracy. Models are tested on this basis. Other metrics like precision, recall and F score against each class.

3.5.1 Precision:

Precision are used to measure how much results are relevant. The ration of True positive and sum of True positive and False positive.

$$Precision = \frac{TP}{TP + FP}$$

3.5.2 Recall:

Recall represents how many returned results are relevant. It estimates how many actual samples belonging to a certain class were correctly predicted by the model.

$$Recall = \frac{TP}{TP + FN}$$

3.5.3 F1 Score:

A metric for evaluating the model it basically combining the results of both models like Precision and Recall. This model basically evaluated that for how many times this model gives the accurate results.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall}$$

3.5.4 Accuracy

The degree of closeness of model prediction and actual values. Accuracy has been used as an evaluation measure. It basically combines overall effect of the values such as TP, TN, FN and FP.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

CHAPTER 4: RESULTS AND DISCUSSION

The motivation behind the selection of this topic is to determine the adverse effects proactively in neonates. In previous studies single factor analysis of the adverse effects has been discussed instead of collective prediction and different authors used just statistical tests for finding the associations. Our model is able to predict five different labels through multi class classification problem. We use both of the strategies in our model such as statistical analysis and prediction through the AI models. For statistical analysis relationship has been checked between different input features and the final output label where each instance categorized as effected/Non-effected.

The results of the ANOVA are mentioned above. In this statistical test difference of means has been observed between the features named gestational age, blood loss, age at start of spell and No of c-sections with final column which needs to be predicted with AI models.

Table 4.1: Associated features found through ANOVA

ANOVA	
Feature	Effected/Non-Effected
Gestational Age	There is a Difference of Means (Associated)
Blood Loss	There is a Difference of Means (Associated)
Age at Start of Spell	There is a Difference of Means (Associated)
No of c-Sections	There is a Difference of Means (Associated)

The results mentioned above are derived after implementing chi-square test on the input features and final labelled feature consisting of adverse effects labelled as effected and non-effected. Association has been checked one by one by taking one input feature and second labeled feature and results formulated. Features named obesity, delivery outcome,

shoulder dystocia, SCBU admission and still birth are directly associated with the output/labeled feature as effected/non-effected.

Table 4.2: Associated features found through chi-square

Chi-Square	
Feature	Effected/Non-Effected
Obesity	Obesity and Status are Associated
Delivery Outcome	Delivery Outcome and Status are Associated
Shoulder Dystocia	Shoulder Dystocia and Status are Associated
SCBU Admission	SCBU and Status are Associated
Still Birth	Still Birth are Associated

Evaluation metrics table has been mentioned below consisting of accuracy, precision, recall and specificity. Evaluation metrics consisting of accuracy, recall and specificity are at higher for Random Forest Classifier. Precision results are not much better for Random Forest but these are good for XG Boost.

Table 4.3: Accuracy Table of all models

Classifier	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**Specificity(%)**	**F.1 Score(%)**
Random Forest Classifier	72.43	62	72.73	99.61	63.36
XG Boost	72	67	72	99	64
Support Vector Machines	72	59	72	81	61
Gradient Boosting	70	59	70	83	63
Convolutional Neural Networks	69.46	49	69	80	58
K Nearest Neighbor	69.19	63	69	83	63
Deeper Neural Network	70.54	63	71	84	65

4.1 Results after Hyperparameter Tuning

Grid search CV is used for hyperparameter tuning and by using these results significantly improved. This is basically a hyperparameter tuning function used for

machine learning models to improve the results. Below mentioned are the results of random forest classifier after hyperparameter tuning.

Metric	Before Tuning	After Tuning
Accuracy (%)	72.43	84.93
Precision (%)	62	85
Recall (%)	72.73	85
Specificity (%)	99.61	89
F.1 Score (%)	63.36	85

Below mentioned is the bar chart of top important features in the dataset. The most important feature is weight measured followed by gestational age and then glucose level at 0 min and at 120 min.

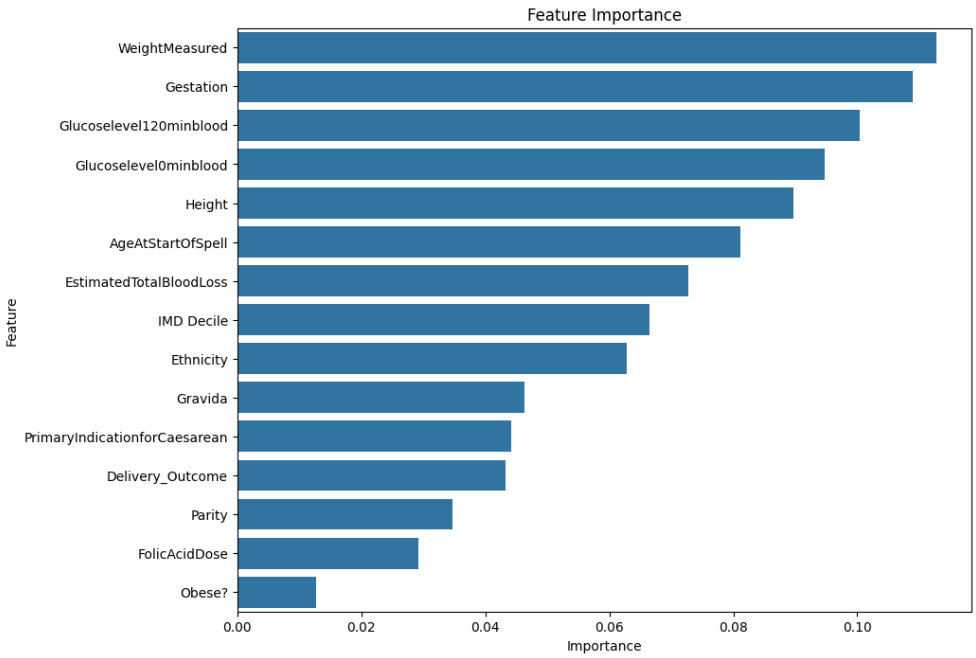

Figure 4-1: Features importance

CHAPTER 5: CONCLUSION AND FUTURE WORK

5.1 Future Work

Our main concentration during this work is to determining or predicting the adverse effects in the neonates before it occurring and we are succeeded in this part. But still there is need of certain aspects to consider for some of the adverse effects belongs to the both like maternal and neonates proactively. Below mentioned are some of the suggestions for future work.

5.1.1 Including more features

In future work our aim is to predict more adverse effects and include some of the other genetic tests which will be helpful to more generalization of the model. By inclusion of some genetic tests will help to predict more specific disease of the neonates and help to mitigate it before it become more adverse for their health.

5.1.2 Specific location-based data

For implementation-based purpose that is necessary to use the specific location based for better prediction of the adverse effects.

5.1.3 Prediction of future maternal diseases as well

Our proposed model predicting the neonatal adverse effects but in future that is also very necessary to predict the maternal diseases as well which may arise in the future.

5.2 Conclusion

Overall all model's performance is very well for the prediction. As in the previous literature work they predict just limited or desired variables. Maximum work has been done on retrospective study instead of the prospective study but our models predicts up to variables. That is the main difference among this and other models.

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