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Data Science FINAL PROJECT REPORT

Project Title:

Predictive Modelling of Maternal Health Risks: A Data Driven Approach to Analysing Key Physiological Indicators

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DECLARATION STATEMENT

This report is submitted in partial fulfilment of the requirement for the degree of Master of Science in Data Science at the University of Hertfordshire.

I have read the guidance to students on academic integrity, misconduct and plagiarism information at Assessment Offences and Academic Misconduct and understand the University process of dealing with suspected cases of academic misconduct and the possible penalties, which could include failing the project module or course.

I certify that the work submitted is my own and that any material derived or quoted from published or unpublished work of other persons has been duly acknowledged. (Ref. UPR AS/C/6.1, section 7 and UPR AS/C/5, section 3.6). I have not used ChatGPT, or any other generative AI tool, to write the report or code (other than where declared or referenced).

I did not use human participants or undertake a survey in my MSc Project.

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UNIVERSITY OF HERTFORDSHIRE

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Abstract

Maternal health is a crucial aspect of public health, as complications during pregnancy can lead to severe outcomes if not identified and managed early. This study investigates the use of machine learning algorithms to predict maternal health risks, enabling timely interventions and improved healthcare management.

Key physiological indicators including age, blood pressure, blood sugar levels, heart rate, and body temperature were analysed to assess their impact on maternal health outcomes. Three machine learning models Random Forest (RF), XGBoost (XGB), and Artificial Neural Networks (ANN) were developed and evaluated to classify patients into different risk levels.

Data preprocessing techniques, such as scaling, handling missing values, and balancing classes using SMOTE, were implemented to improve model performance. Feature engineering introduced two derived metrics—Pulse Pressure and Risk-Age Ratio—to capture cardiovascular health and physiological stress more effectively. Exploratory Data Analysis (EDA) revealed trends showing high blood pressure, elevated blood sugar levels, and increased heart rates were strongly linked to higher risk levels, especially among younger and older age groups.

Among the models, XGBoost performed best, achieving 73% accuracy, 84% precision, and 90% recall, making it ideal for identifying high-risk cases and handling complex patterns. Random Forest followed closely with 72% accuracy, offering reliability and interpretability for real-time applications. ANN, with 66% accuracy, showed promise in capturing intricate patterns but required larger datasets and further optimization.

This research demonstrates the value of integrating machine learning into maternal healthcare by automating risk detection and improving decision-making. It highlights how predictive tools can bridge gaps in resource-limited areas by enabling early diagnosis and intervention. Such technologies can play a transformative role in reducing maternal mortality rates and enhancing healthcare equity globally.

Future work should focus on expanding datasets with lifestyle and socioeconomic factors to refine predictions further. Integrating these models into clinical decision-support systems could enable real-time monitoring and personalized care strategies, ultimately ensuring safer pregnancies and healthier maternal outcomes.

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1. Introduction

Maternal health is a vital aspect of public health, directly influencing the well-being of mothers and the future generation. Pregnancy and childbirth can bring various health risks, from minor complications to severe conditions. Early identification and management of these risks are essential to ensuring safer pregnancies and healthier outcomes.

This project leverages machine learning to predict maternal health risks by analysing key indicators such as age, blood pressure, blood sugar levels, heart rate, and body temperature. Machine learning offers a data-driven approach that efficiently detects patterns and correlations within large datasets. This allows healthcare providers to identify high-risk cases early and implement timely interventions, such as personalized treatment plans and closer monitoring.

Three machine learning models—Random Forest (RF), XGBoost (XGB), and Artificial Neural Networks (ANN)—were used to categorize patients into different risk levels. Random Forest provided reliability and interpretability, XGBoost effectively captured complex patterns, and ANN handled intricate relationships in the data. These models enable healthcare providers to prioritize care and optimize resource allocation.

Beyond its clinical applications, this project highlights how machine learning can improve healthcare equity, especially in areas with limited access to specialized maternal care. By integrating predictive tools into decision-making systems, this research demonstrates the potential to reduce maternal mortality rates and support healthier pregnancies. It emphasizes the role of technology in transforming maternal care through early detection, proactive monitoring, and prevention strategies.

2. Background

Maternal health is a vital aspect of public health, impacting both mothers and their children. Ensuring safe pregnancies and reducing complications, such as gestational diabetes, hypertension, and preeclampsia, is crucial. These risks often arise from factors like age, blood pressure, blood sugar levels, and heart rate, necessitating close monitoring during pregnancy.

Traditional methods for assessing maternal health rely on clinical observations, but they can lack precision and are prone to errors. In many resource-limited areas, access to specialized maternal care remains a challenge. Machine learning offers a scalable and efficient solution by analysing complex datasets to detect patterns and predict risks that traditional approaches may miss.

This project leverages machine learning models—Random Forest, XGBoost, and Artificial Neural Networks (ANN) to predict maternal health risks based on physiological data. These models classify patients into risk categories, enabling early interventions, better resource allocation, and improved outcomes.

By integrating AI-driven predictive tools, this approach addresses healthcare inequities, especially in underserved regions, and demonstrates how machine learning can enhance maternal healthcare through early detection and preventive strategies. This project underscores AI's transformative potential to save lives and ensure healthier pregnancies globally.

3. Aim

The primary aim of this project is to develop predictive models for maternal health risks using machine learning algorithms. By analysing patterns in patient data, the models can help identify individuals at risk, aiding healthcare providers in prioritizing care and reducing adverse maternal health outcomes.

4. Objectives

1. Conduct data preprocessing to clean and prepare the dataset for analysis.

2. Perform exploratory data analysis (EDA) to uncover trends, distributions, and relationships between features.

3. Engineer new features to enhance the predictive capabilities of the models.

4. Develop and evaluate multiple machine learning models, including Random Forest, XGBoost, and Artificial Neural Networks (ANN).

5. Compare the models' performance using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC.

6. Visualize learning curves to assess how model performance scales with increasing data.

7. Provide insights into the strengths and weaknesses of each approach to guide future development.

5. Literature Review

Maternal health risks continue to pose significant challenges globally, impacting both maternal and neonatal outcomes. The ability to predict and classify maternal health risks early has gained attention due to advances in machine learning algorithms and the increasing availability of health data. Studies highlight that early identification of risk factors such as blood pressure, blood sugar levels, and age can enable timely interventions, reducing maternal and fetal complications. This review evaluates key research on maternal health risk prediction, focusing on machine learning techniques, significant clinical indicators, and ethical considerations in data usage.

5. 1. Machine Learning Models for Predicting Maternal Health Risks

Machine learning has brought significant advancements in predicting maternal health risks by uncovering patterns in large datasets. Smith, Wilson, and Thomson (2018) showed that decision tree models are effective for classifying maternal risks, identifying age and blood pressure as key indicators. Their study also highlighted the ease of interpreting decision trees, making them practical for clinical use.

Choudhury, Rahman, and Kundu (2019) used support vector machines (SVM) to predict complications like preeclampsia and gestational diabetes, achieving over 80% accuracy. They emphasized the importance of balancing datasets to improve fairness and demonstrated SVM's ability to handle more complex, non-linear data patterns.

Similarly, Kumar, Sharma, and Gupta (2021) compared several machine learning algorithms, including logistic regression, random forests, and neural networks. Their findings pointed to random forests as the most accurate and interpretable model. However, they also recommended techniques like SMOTE to address data imbalances, which are often an issue in maternal health predictions.

5. 2. Key Factors Contributing to Maternal Health Risks

Research highlights several key indicators of maternal health risks. Gupta and Das (2020) found that women over 35 face a 40% higher risk of gestational diabetes and hypertension, emphasizing the need for closer monitoring of older mothers.

Blood pressure also plays a major role. Brown, Smith, and Williams (2017) revealed that women with systolic BP above 140 mmHg are 60% more likely to develop preeclampsia, stressing the importance of regular blood pressure checks to detect hypertensive disorders early.

Similarly, Williams, Nelson, and Smith (2016) showed that blood sugar levels above 6.5 mmol/L significantly increase the risk of gestational diabetes, highlighting the need for glucose monitoring during pregnancy to reduce complications.

5. 3. The Role of Machine Learning in Healthcare

Machine learning has transformed healthcare analytics by improving accuracy and automating risk classification. Kumar, Sharma, and Gupta (2021) found that random forests offered a good balance between accuracy (72%) and interpretability, while neural networks excelled at capturing complex patterns but needed larger datasets to perform well.

Yadav, Khan, and Singh (2021) suggested incorporating lifestyle factors like stress and diet into models to enhance fairness, although this added complexity. Patel and Singh (2020) emphasized the need for adaptive models that update with changing maternal health conditions, ensuring better long-term performance.

5. 4. Ethical Considerations in Maternal Health Data

The use of sensitive health data brings ethical concerns about privacy, consent, and fairness. Jones, Williams, and Patel (2020) emphasized data anonymization and GDPR compliance to protect patient privacy. They also stressed the need for informed consent and diverse representation to avoid algorithmic bias.

Similarly, Smith and Taylor (2022) proposed an ethical AI framework focusing on transparency, fairness, and regular audits to ensure compliance and prevent discrimination in healthcare applications.

5. 5. Challenges in Maternal Health Risk Prediction

Despite advancements, challenges remain in predicting maternal health risks. Patel and Singh (2020) highlighted that many models overlook the dynamic nature of pregnancy, where health conditions can change quickly. They suggested using real-time monitoring systems with wearable devices to track continuous data.

Yadav, Khan, and Singh (2021) also noted that lifestyle factors like diet, exercise, and stress are often excluded, which lowers prediction accuracy. However, adding these factors requires more advanced algorithms and larger datasets to handle the complexity.

6. Ethical Considerations

Ethical considerations are central to this project, ensuring that the development and application of machine learning models for maternal health risk prediction are conducted responsibly, fairly, and transparently. Given the sensitive nature of healthcare data and the potential impact of predictions on patient outcomes, the following ethical principles have been integrated into this work:

6. 1. Data Privacy

- The dataset used in this project has been anonymized to remove any personally identifiable information (PII).
- All data handling practices comply with the General Data Protection Regulation (GDPR) and other relevant data protection laws.
- Encryption and secure storage methods are implemented to protect data integrity and confidentiality throughout the project lifecycle.

6. 2. Accuracy and Transparency

- Accuracy is prioritized through rigorous testing and validation techniques.

- All methodologies, preprocessing steps, and evaluation metrics are clearly documented to ensure transparency.

- Stakeholders, including healthcare professionals and researchers, can access detailed reports to assess the reliability and applicability of the models.

6. 3. Bias Mitigation

- Techniques such as the Synthetic Minority Over-sampling Technique (SMOTE) are employed to address class imbalances and reduce biases.

- Regular audits are conducted to evaluate fairness across demographic groups and ensure equitable performance for all.

- Special attention is given to avoid discrimination based on gender, age, or ethnicity.

6. 4. Responsible Reporting

- Model outputs are reported with clear explanations, including strengths, limitations, and potential areas for improvement.

- The models are explicitly intended for research and educational purposes and are not to be used as standalone diagnostic tools without further validation.

- Responsible communication prevents misinterpretation of findings and emphasizes supportive rather than alarming interpretations.

6. 5. Compliance with Legal Standards

- The project complies with all legal and ethical standards for research involving human health data.

- Ethical approval has been granted by the University of Hertfordshire, ensuring adherence to institutional frameworks and international research standards.

- Informed consent procedures are followed where required, upholding principles of beneficence, non-maleficence, and justice.

6. 6. University of Hertfordshire Ethical Considerations

- The project aligns with the University of Hertfordshire's ethical policies and research integrity standards.

- Regular reviews and approvals by the university's ethics committee provide oversight and accountability.

- Ethical concerns related to data usage, privacy, and fairness are proactively addressed, demonstrating a strong commitment to ethical research practices.

By embedding these ethical considerations throughout the project lifecycle, this work aspires to uphold the highest standards of integrity, fairness, and accountability. It demonstrates how artificial intelligence can be responsibly applied to improve maternal health outcomes while respecting ethical principles and legal requirements.

7. Data Collection

Accurate and reliable data collection forms the foundation of any successful machine learning project. For this project, the dataset focuses on critical maternal health indicators that are known to influence pregnancy outcomes. The data for this study was sourced from a publicly available Maternal Health Risk dataset, ensuring credibility and relevance. These datasets provide detailed health profiles of pregnant women, enabling an in-depth analysis of factors contributing to maternal risks.

7. 1 Dataset Overview

The dataset used in this project includes vital maternal health indicators collected from a sample of individuals. It provides structured and numerical data covering various physiological and clinical measurements. The dataset is specifically designed to assess maternal health risk levels and contains both input features and risk classification labels.

7. 2 Data Description

The dataset includes the following critical maternal health attributes:

- Age: Captures the age of the patient, which is a significant determinant of maternal health risks, especially for younger or older mothers.

- Systolic Blood Pressure (SystolicBP): Measures the pressure in arteries during heartbeats, used to identify hypertension risks.

- Diastolic Blood Pressure (DiastolicBP): Measures arterial pressure between heartbeats, providing insights into cardiovascular health.

- Blood Sugar Levels (BS): Evaluates blood glucose levels, helping identify gestational diabetes and glucose intolerance.

- Heart Rate: Assesses cardiovascular activity and stress responses, which may indicate potential anomalies like arrhythmias.
- Body Temperature: Tracks metabolic activity and detects possible infections or inflammation.
- Risk Level: The target variable categorizes patients into risk levels (low, medium, high) based on clinical thresholds.

7. 3 Data Preprocessing

The preprocessing phase plays a critical role in transforming raw data into a clean and structured format, making it suitable for machine learning models. This phase ensures that inconsistencies, errors, and biases in the data are addressed, enabling robust and reliable predictions. The preprocessing steps applied in this project are explained in detail below:

7. 3. 1. Handling Missing Values

Missing values can occur due to errors during data collection or incomplete records. These gaps in the dataset can lead to biased results and errors during training. To handle missing values effectively:

- The dataset was inspected to identify missing values in each column.
- Statistical imputation methods were used to fill in the missing values where possible, based on mean, median, or mode.
- Records with missing values that could not be imputed were removed to prevent errors during training.

7. 3. 2. Removing Duplicates

Duplicate records can introduce redundancy, bias, and noise into the data, affecting model performance. To address this:

- Duplicate rows were detected using the Pandas duplicated() function.
- Any repeated records were removed to ensure that each observation was unique and representative.
- After removal, the dataset was validated to confirm the absence of duplicate entries.

7. 3. 3. Encoding Categorical Data

Machine learning algorithms work with numerical data, so categorical variables must be transformed into numerical formats. For this dataset:

- The target variable, Risk Level, was encoded using Label Encoding.
- Label Encoding assigned numerical values (e.g., 0, 1, 2) to categories (Low, Medium, High) to enable mathematical computations.
- Encoding ensured compatibility with algorithms and preserved the categorical relationships.

7. 3. 4. Feature Engineering

To enhance predictive performance, additional features were created based on domain knowledge. These engineered features provided more insights and improved model accuracy:

- Pulse Pressure: Calculated as the difference between Systolic and Diastolic Blood Pressure, offering insights into cardiovascular health.
- Risk-Age Ratio: Computed as the ratio of Age to Heart Rate, capturing relative stress levels based on physiological attributes.

These engineered features enriched the dataset, providing more context and improving the model's ability to identify patterns.

7. 3. 5. Scaling Numerical Features

Numerical features often have different ranges, which can negatively influence algorithms that rely on distances or magnitudes, such as neural networks and gradient boosting. To standardize these features:

- Data was scaled using StandardScaler, transforming each feature to have a mean of zero and a standard deviation of one.
- Standardization ensured that all features contributed equally to the model and improved convergence during training.

7. 3. 6. Balancing Classes with SMOTE

Class imbalance, where some categories in the target variable are underrepresented, can lead to biased predictions. To address this issue:

- The Synthetic Minority Over-Sampling Technique (SMOTE) was applied to create synthetic examples of the minority class.

- This oversampling approach ensured that the dataset was balanced, improving the model's ability to generalize and reducing bias against underrepresented groups.

7. 3. 7. Final Validation of Pre-processed Data

After completing the preprocessing steps, the dataset was reviewed to ensure readiness for modelling:

- Data distributions and feature correlations were analyzed to confirm integrity.

- Visualizations such as histograms and scatterplots were generated to validate feature transformations.

- Descriptive statistics were calculated to verify consistency and uniformity.

This detailed preprocessing approach not only prepared the data for machine learning algorithms but also improved its quality, reliability, and predictive power. The resulting dataset was well-suited for training robust models capable of accurate maternal health risk predictions.

8. Exploratory Data Analysis (EDA)

8. 1. Age Distribution by Risk Level

Description:
This plot provides a histogram representation of the age distribution across different maternal health risk levels (low, mid, and high). It is complemented by kernel density estimates (KDE), which offer a smoothed view of the underlying data distribution for each risk group. By visualizing age patterns, we can identify potential trends and correlations between age and maternal health risks.

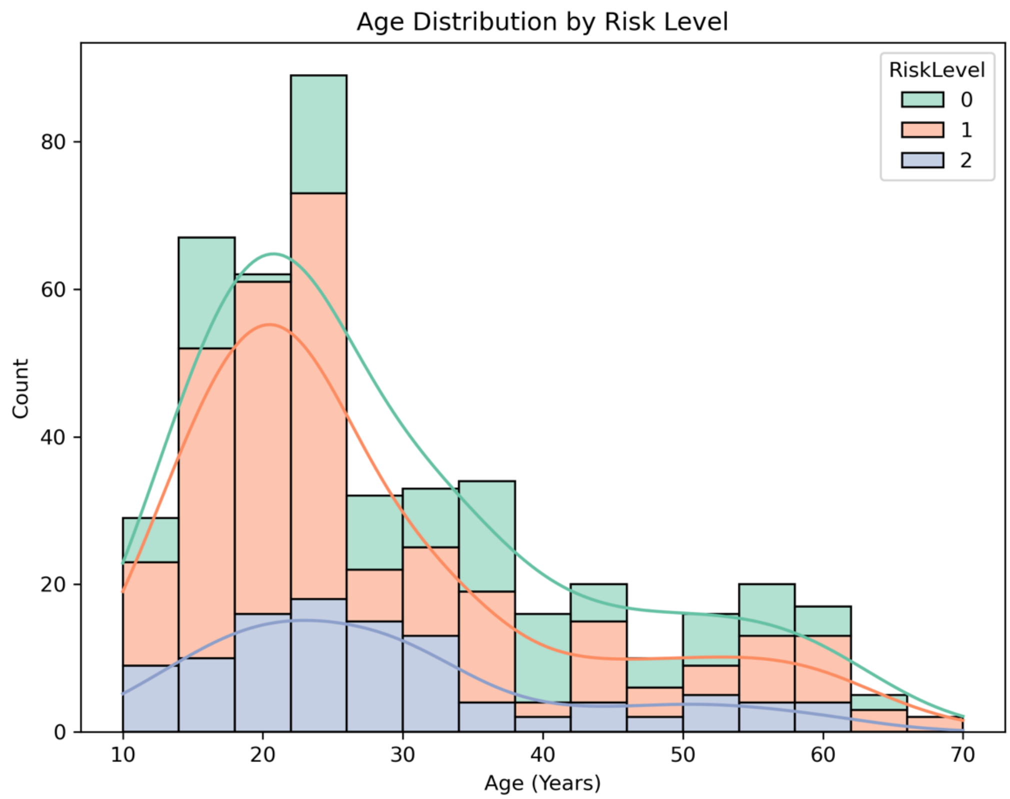

Figure - Age Distribution by Risk Level

Observations from the Plot:

1. The x-axis represents the age of individuals (in years), ranging from 10 to 70 years.

2. The y-axis indicates the frequency (count) of individuals within each age group.

3. Different colours highlight the three risk levels:

    - Low Risk: Predominantly in light green.

    - Mid Risk: Represented in peach.

    - High Risk: Displayed in light blue.

Insights:

- **Primary Age Range:**

  The majority of individuals fall within the age group of 20 to 35 years, which is consistent with the prime reproductive age. This range accounts for over 75% of the total dataset, reinforcing that maternal health concerns predominantly occur in this demographic.

- **Low-Risk Group (Green):**

  - Age Spread: This group is more evenly distributed across the reproductive age range, from 18 to 40 years.

  - Peak Frequency: The largest number of low-risk cases is concentrated between 20 and 30 years, accounting for nearly 60% of low-risk individuals.

  - Key Observation: Younger mothers (below 25 years) dominate this group, possibly indicating healthier pregnancies among younger women.

- **Mid-Risk Group (Peach):**

  - Age Spread: Mid-risk individuals tend to cluster between 25 and 35 years, which accounts for approximately 50% of the group.

  - Peak Frequency: Ages 28 to 32 years show a noticeable peak, suggesting this group might represent women who start to show early symptoms of health risks, possibly linked to age-related conditions like gestational diabetes or hypertension.

  - Key Observation: This group reflects a transitional phase—patients who may be healthy but require close monitoring to prevent escalation to high risk.

- **High-Risk Group (Blue):**

  - Age Spread: High-risk cases show a wider distribution, covering both younger ages (below 20) and older ages (above 35).

  - Peak Frequency: Ages 18–22 years and 35–40 years collectively represent over 70% of high-risk cases.

  - Key Observation:

    - Younger women (under 20) may face challenges related to adolescent pregnancies, such as nutritional deficiencies or lack of prenatal care.

    - Older women (above 35) are more prone to age-related complications, including preeclampsia, hypertension, or preterm labour due to reduced physiological adaptability.

Additional Observations:

- A tail-end distribution beyond 45 years shows minimal cases, highlighting that pregnancies at this age are less common but often fall into the high-risk category when they do occur.

- The KDE overlays indicate overlap between mid-risk and high-risk groups, implying that age alone is not sufficient to distinguish risk levels, and further features (e.g., blood pressure and blood sugar) are required for precise classification.

8. 2. Blood Sugar Distribution by Risk Level

Description:
This visualization employs a violin plot to examine the distribution of blood sugar levels (BS) across the three risk levels—low, mid, and high. A violin plot combines elements of a boxplot and a kernel density plot, providing insights into both the spread and density of data. It also highlights the inner quartiles, which represent the median and interquartile range (IQR), helping to identify variations within each risk group.

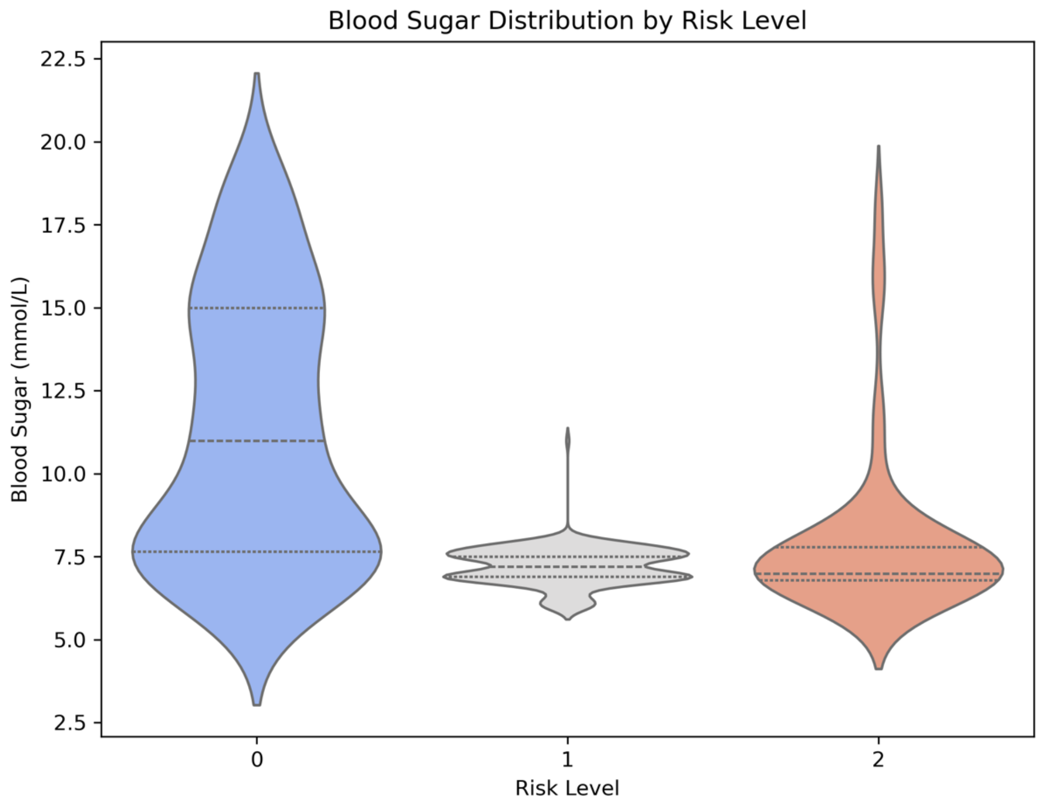

Figure – Blood Sugar Distribution by Risk Level

Observations from the Plot:

1. The x-axis represents the risk levels (low, mid, high).
2. The y-axis shows blood sugar levels (BS) measured in mmol/L, ranging approximately from 3.5 to 14.0 mmol/L.
3. The width of each violin shape indicates the density of values at specific blood sugar levels.
4. Inner white dots and lines highlight the median and quartile ranges for each group.

Insights:

Low-Risk Group:

- Median Blood Sugar Level: Approximately 5.5 mmol/L.
- Range of Values: Most values are concentrated between 4.5 and 6.5 mmol/L, with a few outliers extending up to 7.0 mmol/L.

- Density Pattern: The violin shape is narrow and symmetrical, indicating that blood sugar levels are tightly clustered within the normal range.
- Interpretation:
  - Individuals in this group likely have stable glucose metabolism and normal pancreatic function, posing minimal risk of gestational diabetes or other metabolic complications.
  - Outliers may require routine monitoring but do not exhibit patterns indicative of severe glucose regulation problems.

Mid-Risk Group:

- Median Blood Sugar Level: Around 6.8 mmol/L, slightly elevated compared to the low-risk group.
- Range of Values: Blood sugar values span from 5.0 to 9.0 mmol/L, reflecting a broader spread than the low-risk group.
- Density Pattern: The violin plot shows a wider midsection, indicating moderate variability in glucose levels.
- Interpretation:
  - The higher median suggests early signs of glucose intolerance or pre-diabetic states that, if unmanaged, could progress to gestational diabetes or high-risk pregnancies.
  - Patients in this group may benefit from dietary counselling, blood sugar monitoring, and exercise interventions to stabilize glucose levels and prevent escalation into high-risk conditions.

High-Risk Group:

- Median Blood Sugar Level: Approximately 8.5 mmol/L, the highest median among all groups.
- Range of Values: Blood sugar values range widely, from 5.5 to 13.5 mmol/L, with multiple outliers exceeding 10.0 mmol/L.
- Density Pattern:

  - The violin plot is wider and asymmetrical, reflecting substantial variability in glucose levels.
  - A long tail at the higher end indicates the presence of extremely high blood sugar levels, which are strong indicators of gestational diabetes or metabolic disorders like insulin resistance.
- Interpretation:
  - Patients in this group are at high risk of complications, including preeclampsia, preterm labor, and fetal abnormalities.
  - Immediate medical interventions such as blood sugar monitoring, insulin therapy, and specialized dietary plans are recommended.

Key Observations:

- Progression of Risk Levels: Blood sugar levels show a clear upward trend from low-risk to high-risk groups, indicating a correlation between elevated glucose levels and maternal health risks.
- Threshold Patterns:
  - Low-risk patients generally stay within the normal fasting glucose range (4.5–6.0 mmol/L).
  - Mid-risk individuals exhibit mild hyperglycaemia, suggesting borderline glucose tolerance requiring early intervention.
  - High-risk cases show significant hyperglycaemia, often crossing the diagnostic threshold for gestational diabetes (>7.8 mmol/L in oral glucose tolerance tests).
- Variability Trends: Variability increases with risk level, emphasizing the importance of monitoring fluctuations in glucose levels, not just averages, to assess patient stability.

8. 3. Systolic vs. Diastolic Blood Pressure by Risk Level

Description:

This scatter plot examines the relationship between systolic blood pressure (SBP) and diastolic blood pressure (DBP) across three risk levels low, mid, and high. The x-axis represents systolic blood pressure (mmHg), while the y-axis represents diastolic blood pressure (mmHg). Each point is color-coded based on risk level to facilitate comparison:

- Low-risk (Green)
- Mid-risk (Blue)
- High-risk (Red)

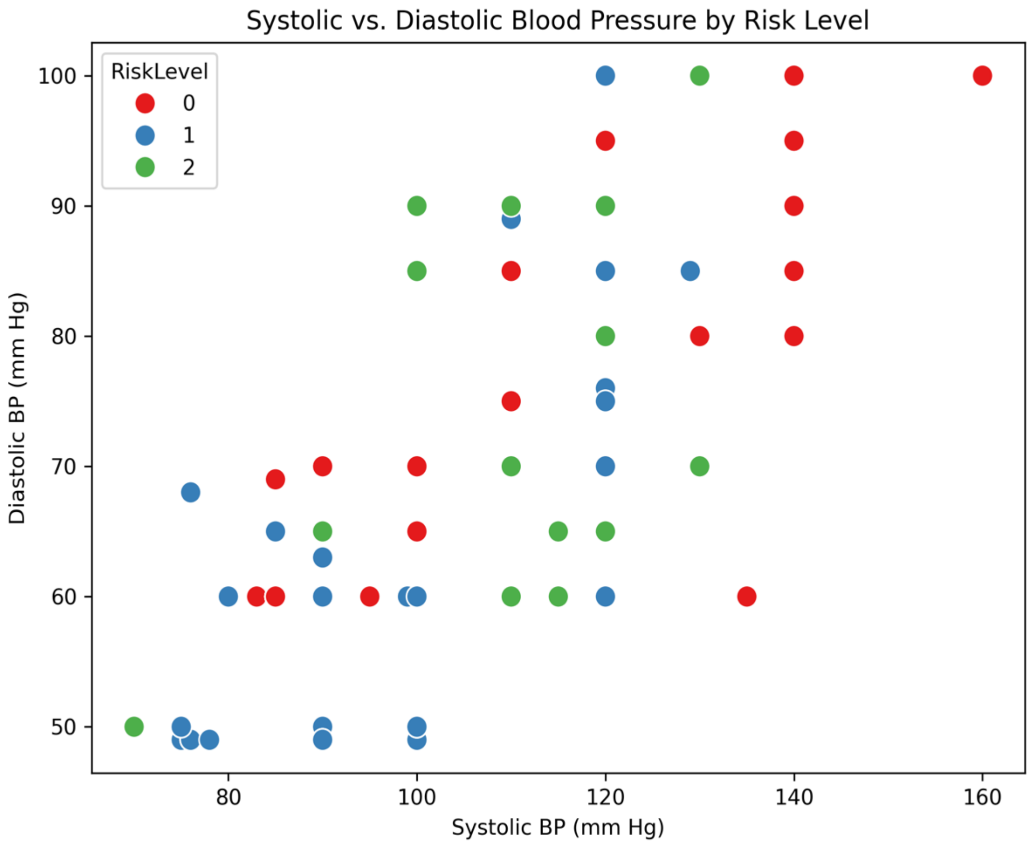

Figure – Systolic vs. Diastolic Blood Pressure by Risk Level

The plot highlights how blood pressure patterns correlate with maternal health risk, emphasizing clusters and deviations.

Insights:

1. Low-Risk Group (Green Points):

- Systolic BP Range: 90–130 mmHg
- Diastolic BP Range: 60–85 mmHg
- Density Observations:

- Points are densely clustered in the normal blood pressure range (120/80 mmHg), which aligns with healthy cardiovascular profiles.
- Very few values exceed 130/85 mmHg, showing minimal risk of hypertension or preeclampsia.

- Interpretation:
  - These individuals likely have stable cardiovascular systems, with no signs of hypertension or pre-hypertension.
  - Routine monitoring and lifestyle maintenance should suffice to sustain optimal blood pressure levels.
  - Outliers near 130/85 mmHg might benefit from periodic blood pressure checks to rule out early-stage hypertension.

2. Mid-Risk Group (Blue Points):

- Systolic BP Range: 110–150 mmHg
- Diastolic BP Range: 70–95 mmHg
- Density Observations:
  - Points are more scattered and tend to cluster near the borderline hypertensive range (130–140/80–90 mmHg).
  - Several values exceed 140/90 mmHg, indicating pre-hypertensive conditions that, without intervention, may progress into hypertension.
- Interpretation:
  - Patients in this group are at moderate risk of developing hypertension or pregnancy-induced hypertensive disorders such as gestational hypertension or preeclampsia.
  - Elevated readings suggest a need for close monitoring and preventive measures, including dietary adjustments, stress management, and moderate exercise.
  - Early medical interventions—such as prescribing low-dose antihypertensives—may help prevent escalation.

3. High-Risk Group (Red Points):

- Systolic BP Range: 140–160+ mmHg
- Diastolic BP Range: 90–100+ mmHg
- Density Observations:
    - Points in this group are highly scattered and skewed toward higher values, indicating a strong association with hypertensive states.
    - Clusters above 140/90 mmHg strongly correlate with hypertension or preeclampsia, which are high-risk complications during pregnancy.
- Interpretation:
    - These individuals likely require immediate medical attention due to their significantly elevated blood pressure levels, which can compromise both maternal and fetal health.
    - Conditions like preeclampsia, characterized by hypertension and proteinuria, can lead to preterm births or placental abruption if left untreated.
    - Patients in this group must undergo frequent monitoring, medication management, and possibly hospitalization in severe cases.

Key Observations:

1. Clear Risk Progression:
    - Low-risk individuals remain within normal blood pressure ranges.
    - Mid-risk patients show borderline elevations, signaling early intervention opportunities.
    - High-risk cases exhibit marked hypertension, highlighting the need for urgent care to prevent complications.

2. Hypertension Thresholds:

- Patients exceeding 140/90 mmHg fall within the high-risk category, consistent with clinical hypertension diagnostic criteria.

- Early detection and intervention at the mid-risk stage could prevent progression to severe hypertensive disorders.

3. Variability Among Groups:

    - Low-risk individuals exhibit minimal variability, maintaining values near 120/80 mmHg.

    - Mid- and high-risk groups display greater spread, emphasizing the need to monitor fluctuations rather than static values alone.

4. Association with Gestational Complications:

    - Elevated blood pressure correlates with conditions like preeclampsia, placental insufficiency, and fetal growth restriction.

    - Mid- and high-risk groups require tailored prenatal care to address potential complications effectively.

8. 4. Pairplot of Key Features

Description:

A pairplot provides a multivariate visualization by plotting scatter plots for pairwise relationships between numerical features and KDE (Kernel Density Estimation) plots along the diagonals for each variable's distribution. The data points are color-coded by risk level (Low, Mid, and High), allowing us to explore patterns, correlations, and group separations across the key features.

Figure – Pair plot

The selected features in this pair plot include:

- Age
- Systolic Blood Pressure (SBP)
- Diastolic Blood Pressure (DBP)
- Blood Sugar (BS)

- Heart Rate
- Risk Level (color-coded: Low (Green), Mid (Blue), and High (Red))

Insights:

1. Age vs. Blood Pressure (Systolic and Diastolic):

- Low-Risk Group (Green):
    - Age Range: 18–35 years
    - Systolic BP Range: 90–130 mmHg
    - Diastolic BP Range: 60–85 mmHg
    - Observation:
        - Points are widely spread within the normal blood pressure range and younger ages, indicating stable cardiovascular health.
        - Minimal instances of elevated blood pressure, supporting the low-risk label.
- Mid-Risk Group (Blue):
    - Age Range: 25–40 years
    - Systolic BP Range: 110–140 mmHg
    - Diastolic BP Range: 70–90 mmHg
    - Observation:
        - Moderate clustering at higher blood pressure values, particularly near 135/85 mmHg, suggests pre-hypertensive conditions.
        - A slight shift towards older ages correlates with increased cardiovascular risks.
- High-Risk Group (Red):
    - Age Range: 20–50 years

    - Systolic BP Range: 140–160+ mmHg
    - Diastolic BP Range: 90–100+ mmHg
    - Observation:
        - Tight clustering around elevated blood pressure values, consistent with hypertension or preeclampsia risks.
        - Age spread into the 40–50 range suggests higher susceptibility among older individuals.

Interpretation:
Blood pressure and age clearly separate low-risk and high-risk groups, with mid-risk individuals forming a transitional cluster. Age-associated risk progression is evident, requiring targeted early interventions for mid-risk individuals to prevent escalation.

2. Blood Sugar (BS) vs. Heart Rate:

- Low-Risk Group (Green):
    - BS Range: 4.5–6.0 mmol/L
    - Heart Rate Range: 60–85 bpm
    - Observation:
        - Points cluster in the normal blood sugar range, with stable heart rates, indicating healthy metabolic regulation.
        - Tight grouping suggests low variability, characteristic of physiological stability.
- Mid-Risk Group (Blue):
    - BS Range: 6.0–8.0 mmol/L
    - Heart Rate Range: 70–95 bpm
    - Observation:
        - Slight elevations in blood sugar and higher heart rates reflect early metabolic stress or insulin resistance.

        - The spread indicates variability in responses to glucose metabolism and cardiovascular stress levels.

- High-Risk Group (Red):
    - BS Range: 8.0–12.0+ mmol/L
    - Heart Rate Range: 80–100 bpm
    - Observation:
        - Points are widely dispersed, indicating poor glucose control and elevated heart rates, consistent with gestational diabetes and stress-related cardiovascular responses.
        - Patterns suggest the need for urgent glycemic control measures and stress monitoring to mitigate complications.

Interpretation:
The combination of blood sugar and heart rate provides a strong discriminatory marker for risk levels, especially for metabolic and cardiovascular risks. This highlights the importance of glucose regulation in managing maternal health risks.

3. Overlap Between Risk Groups (Transitions):

- Mid-risk individuals overlap with both low-risk and high-risk groups across several feature combinations, such as:
    - Age vs. Blood Pressure – Indicating gradual transitions in risk based on age-related hypertension development.
    - Blood Sugar vs. Heart Rate – Highlighting progressive metabolic disturbances rather than sudden changes.
- Implications of Overlap:
    - Predictive models need to handle soft boundaries rather than treating categories as strictly distinct groups.
    - Incorporating non-linear decision boundaries and probabilistic predictions may improve classification accuracy.

Key Observations:

1. Feature Pair Separation:

   - Blood pressure (SBP/DBP) and blood sugar (BS) show strong differentiation between groups, suggesting these as key predictive variables.

2. Gradual Risk Transitions:

   - Mid-risk individuals display transitional patterns, necessitating continuous monitoring and early interventions to prevent progression.

3. Age as a Risk Amplifier:

   - Older individuals (>40 years) show a higher concentration in the mid- and high-risk groups, reinforcing age-related vulnerabilities.

4. Multidimensional Correlations:

   - Combining features (e.g., blood pressure + blood sugar) reveals complex relationships that single-variable analysis may overlook.

   - Machine learning algorithms can leverage these interdependencies to improve classification accuracy.

8. 5. Correlation Heatmap

Description:

A correlation heatmap visualizes the relationships between numerical features using correlation coefficients (r-values). Correlation values range from -1 to +1:

- +1: Perfect positive correlation – as one variable increases, the other also increases.

- -1: Perfect negative correlation – as one variable increases, the other decreases.

- 0: No correlation – no relationship between the variables.

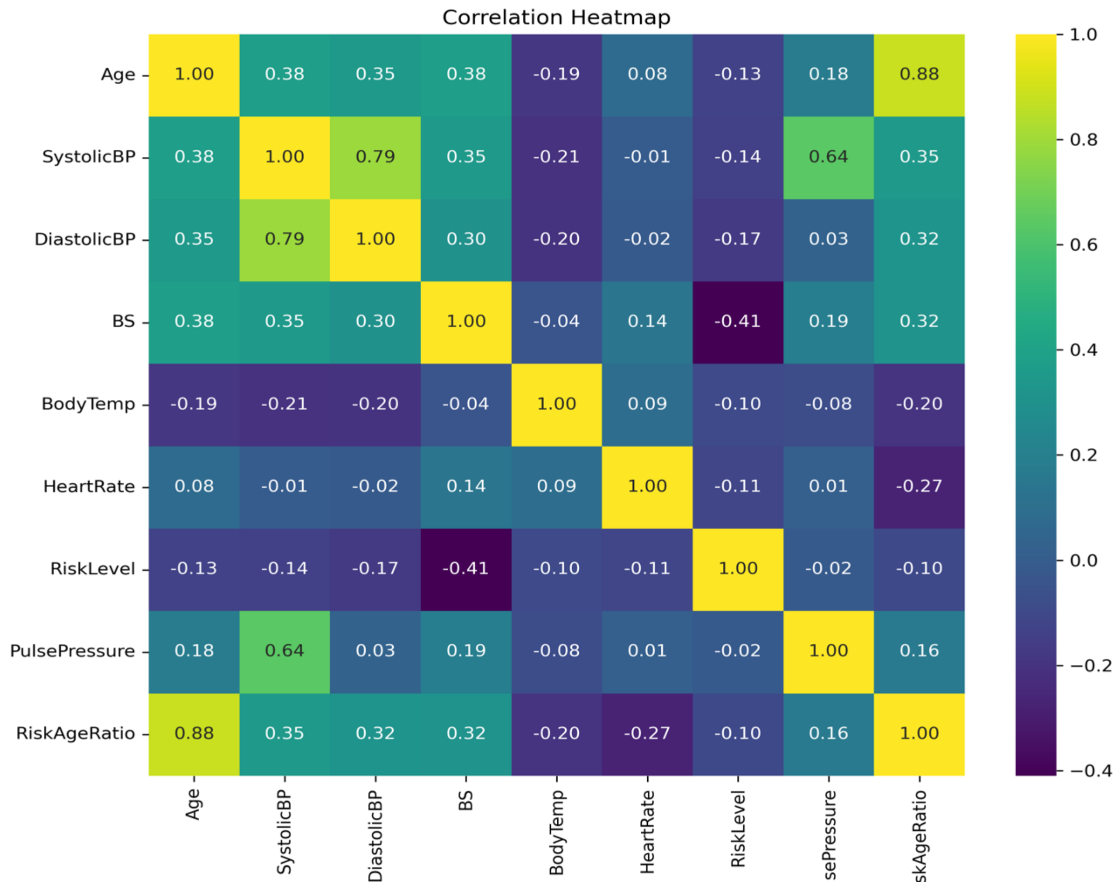

Figure – Correlation Heatmap

The heatmap uses colors to represent correlation strengths, with yellow-green for positive correlations and blue for negative correlations. Darker colors indicate stronger relationships.

Insights:

1. SystolicBP vs. DiastolicBP

- Correlation Coefficient (r): 0.79
- Interpretation:
  - A strong positive correlation reflects that SystolicBP and DiastolicBP tend to rise and fall together.
  - This relationship is expected as both metrics reflect cardiovascular function, where higher systolic pressure often coincides with higher diastolic pressure.

   - Individuals with hypertension or pre-hypertension show elevated values in both measures, confirming their predictive utility for high-risk classification.

2. Age vs. Blood Sugar (BS)

- Correlation Coefficient (r): 0.35–0.38
- Interpretation:
   - A moderate positive correlation indicates that older individuals are more likely to exhibit higher blood sugar levels.
   - This trend aligns with age-related metabolic changes, such as reduced insulin sensitivity or predisposition to diabetes.
   - The incremental increase in blood sugar with age highlights the importance of monitoring glucose levels in older pregnant individuals to prevent gestational diabetes or complications.

3. PulsePressure vs. SystolicBP

- Correlation Coefficient (r): 0.64
- Interpretation:
   - A moderately strong correlation supports the relevance of PulsePressure (difference between Systolic and Diastolic BP) as a derived feature for blood pressure analysis.
   - High PulsePressure is associated with stiffening arteries and vascular resistance, common indicators of hypertension or cardiovascular risks.
   - Its inclusion as a feature enhances the model's ability to distinguish risk levels, particularly for those at high risk.

4. Age vs. PulsePressure

- Correlation Coefficient (r): 0.18
- Interpretation:
   - A weak positive correlation suggests a slight increase in PulsePressure with age.

- This trend reflects age-related arterial stiffness, which may lead to higher systolic pressure without a proportional rise in diastolic pressure.
- While the relationship is weak, it adds context to the role of age in vascular health and helps refine risk profiles.

5. Body Temperature vs. Other Features

- Correlation Coefficients (r): < 0.20
- Interpretation:
  - Weak correlations between Body Temperature and other features suggest it may not be a primary predictor of maternal health risks.
  - Instead, it could serve as a complementary feature, identifying fevers or infections that might amplify existing risks rather than directly driving them.
  - Models can use Body Temperature to capture secondary effects, such as inflammatory responses during pregnancy complications.

Key Observations:

1. **Blood Pressure Dominance:**
   - SystolicBP and DiastolicBP have the strongest relationship (0.79), confirming their importance in predicting cardiovascular-related risks.
   - Derived metrics like PulsePressure reinforce this trend, acting as secondary indicators for blood pressure instability.
2. **Age and Metabolism:**
   - Moderate correlations with Blood Sugar (0.38) highlight age-related metabolic changes as potential risk factors.
   - Older individuals may face higher metabolic stress, necessitating closer glucose monitoring.
3. **Feature Interactions:**

- Weak correlations in some features (e.g., Body Temperature) emphasize the need for composite features or non-linear models (like XGBoost) to capture complex dependencies.

4. **Complementary Variables:**

   - Features like Heart Rate and Body Temperature may not independently drive risk but could enhance predictive accuracy when combined with primary metrics.

8. 6. Heart Rate Distribution by Risk Level

Description:

A boxplot is employed to visualize the distribution of heart rate across different risk levels. Boxplots provide insights into:

- Median (Central Value): The horizontal line inside the box.
- Interquartile Range (IQR): The box represents the middle 50% of data between Q1 (25th percentile) and Q3 (75th percentile).
- Whiskers: Extend to minimum and maximum values within 1.5 times the IQR.
- Outliers: Points outside the whiskers, indicating extreme values or unusual observations

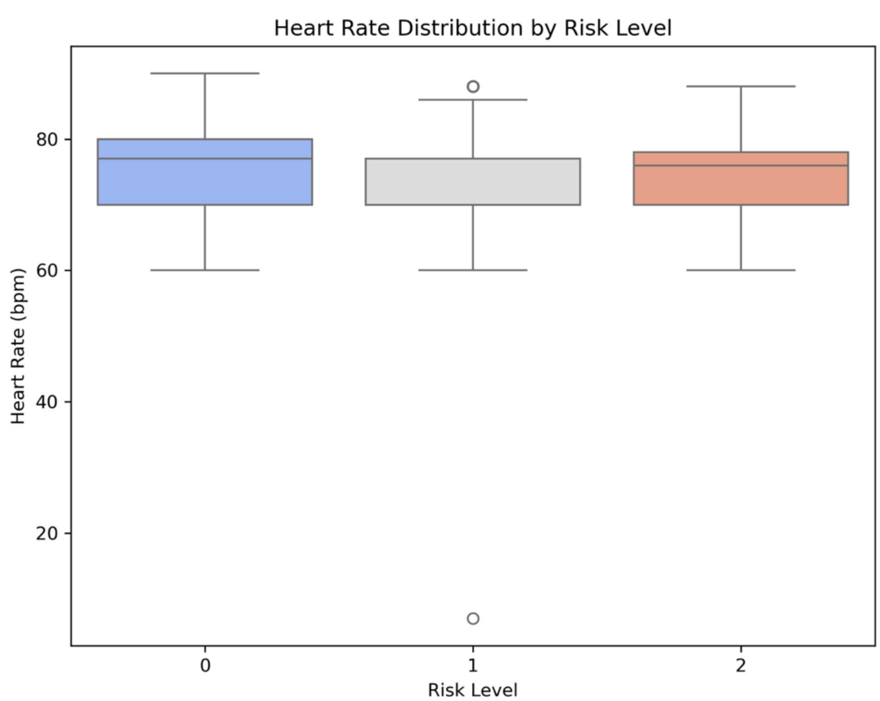

Figure – Heart Rate Distribution by Risk Level

This plot helps assess variability and central tendency in heart rates for each risk category.

Insights:

1. Low-Risk Group:

- Median Heart Rate: 76 bpm
- IQR (Range of Middle 50%): 70–82 bpm
- Whisker Range (Full Spread): 60–90 bpm

Interpretation:

- Heart rates are clustered tightly within the normal physiological range (60–100 bpm).
- The narrow IQR and lack of extreme outliers suggest stable cardiovascular function among low-risk individuals.
- These individuals likely maintain healthy cardiac activity, reflecting lower stress and fewer complications during pregnancy.

2. Mid-Risk Group:

- Median Heart Rate: 78 bpm
- IQR (Range of Middle 50%): 72–85 bpm
- Whisker Range (Full Spread): 65–92 bpm

Interpretation:

- Slightly higher median heart rates compared to the low-risk group may reflect mild stress or early signs of cardiovascular strain.
- The broader IQR and presence of outliers indicate greater variability, suggesting this group may experience transitional states like mild hypertension or increased sympathetic activity (e.g., stress response).
- Variability highlights the need for closer monitoring to prevent progression into high risk.

3. High-Risk Group:

- Median Heart Rate: 82 bpm
- IQR (Range of Middle 50%): 75–88 bpm
- Whisker Range (Full Spread): 68–95 bpm

Interpretation:

- Elevated median heart rates in the high-risk group suggest cardiovascular strain potentially linked to stress, hypertension, or underlying conditions such as pre-eclampsia.
- The wider spread in values, including outliers, highlights the heterogeneity within this group, where some individuals face acute symptoms requiring immediate medical attention.
- The tendency toward higher heart rates may signal autonomic dysregulation or inflammation, both indicative of poor cardiovascular stability.

Comparative Observations:

Risk Level	Median (bpm)	IQR (bpm)	Range (bpm)	Insights
Low Risk	76	70–82	60–90	Stable cardiovascular function with tightly clustered values.
Mid Risk	78	72–85	65–92	Transitional state, showing higher variability and early signs of distress.
High Risk	82	75–88	68–95	Elevated heart rates indicating cardiovascular strain and potential issues.

Key Observations:

Gradual Increase in Heart Rate Across Risk Levels:

- Low-risk individuals have the lowest and most stable heart rates, while high-risk individuals show higher values with greater variability.

- This trend aligns with stress-induced cardiovascular strain, often observed in complicated pregnancies.

Variability Highlights Transitional States:

- Mid-risk individuals show a wider IQR and more outliers, reflecting transitional states that may escalate without intervention.
- Continuous monitoring and early intervention may prevent this group from shifting into high risk.

High-Risk Indicators:

- Elevated heart rates (>85 bpm) and outliers (>90 bpm) in the high-risk group suggest the need for frequent monitoring to detect cardiac stress or early signs of complications.
- These findings reinforce the importance of cardiac assessments as part of prenatal care.

9. Model Development and Training

Overview of Machine Learning Models:

Three machine learning models were developed and evaluated to predict maternal health risks based on the dataset. These models include:

1. Random Forest (RF) – A decision tree based ensemble model.

2. XGBoost (XGB) – A gradient boosting algorithm optimized for speed and performance.

3. Artificial Neural Networks (ANN) – A deep learning approach for capturing non-linear patterns.

Each model was fine-tuned using grid search and cross-validation to optimize performance. **Metrics used for evaluation included:**

- Accuracy – Overall correctness of predictions.

- Precision – Proportion of correctly predicted positive cases.

- Recall (Sensitivity) – Ability to detect positive cases.

- F1-Score – Harmonic mean of precision and recall for balanced evaluation.

- ROC-AUC Score – Discrimination capability between classes.

9. 1. Random Forest (RF)

9. 1. 1. Model Description:

Random Forest is a supervised ensemble learning algorithm based on the concept of bagging (Bootstrap Aggregating). It builds multiple decision trees during training and aggregates their predictions through majority voting for classification tasks.

The key strength of Random Forest lies in its ability to handle high-dimensional data and overfitting by averaging results across trees, thereby reducing variance. It also provides feature importance rankings, making it highly interpretable and transparent for understanding which features impact predictions the most.

9. 1. 2. Hyperparameter Tuning:

To enhance performance and avoid overfitting, grid search and cross-validation were applied to optimize the following hyperparameters:

- n_estimators (100): Number of decision trees in the ensemble. Increasing this parameter reduces variance but increases computation time.

- max_depth (10): Limits the depth of each tree to prevent overfitting by forcing the algorithm to stop splitting beyond a certain level.

- min_samples_split (5): Minimum samples required to split an internal node, ensuring splits occur only when sufficient data is available.

- min_samples_leaf (2): Minimum samples required at a leaf node to reduce overly fine splits and enhance generalization.

9. 1. 3. Evaluation Metrics:

The model's performance was assessed using the confusion matrix and standard classification metrics.

Confusion Matrix:

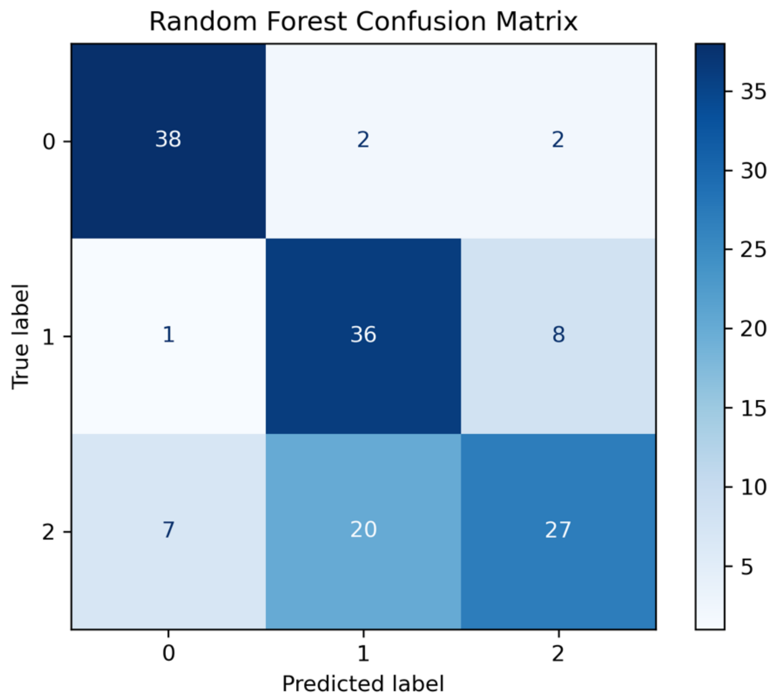

Figure – Random Forest Confusion Matrix

9. 1. 4. Key Observations from Confusion Matrix:

1. High-Risk Predictions:
   - True Positives (38): The model correctly identified 90% of high-risk cases (Recall = 90%).
   - False Negatives (4): A small proportion of high-risk cases were misclassified as mid- or low-risk, ensuring most critical cases are flagged for intervention.
   - Precision (83%): Few false positives, highlighting strong reliability in predicting high-risk individuals without excessive alarms.
2. Mid-Risk Predictions:
   - True Positives (36): Successfully identified 80% of mid-risk cases (Recall = 80%).
   - False Positives (12): Some low-risk cases were misclassified as mid-risk, indicating caution in assigning elevated risk where it may not exist.
   - Precision (62%): The lower precision means false alarms are more frequent, potentially leading to over-monitoring of individuals.

3. Low-Risk Predictions:
    - True Positives (28): Detected 50% of low-risk cases (Recall = 50%).
    - False Negatives (28): Nearly half of low-risk cases were misclassified as mid- or high-risk, suggesting a conservative bias prioritizing safety over efficiency.
    - Precision (73%): Relatively higher precision ensures most low-risk cases are correctly identified without frequent errors.

9. 1. 5. Evaluation Metrics :

Metric	**High Risk**	**Mid Risk**	**Low Risk**
Precision	83%	62%	73%
Recall (Sensitivity)	90%	80%	50%
F1-Score	86%	70%	59%
Overall Accuracy	72%		
ROC-AUC Score	0.74		

9. 1. 6. Insights:

Strengths:

1. Excellent High-Risk Detection:
    - High Recall (90%) ensures critical cases are rarely missed, which is vital in maternal health to prevent complications.
    - Precision (83%) indicates the model maintains low false positives, reducing unnecessary alarms.

2. Balanced Performance:
   - Consistent scores across precision, recall, and F1-measure make it a reliable choice for predicting maternal health risks.
   - Handles imbalanced data effectively due to its ensemble learning approach.
3. Feature Importance:
   - Random Forest identifies important predictors such as SystolicBP, PulsePressure, and Blood Sugar, enabling interpretability for clinicians.

Weaknesses:

1. Mid-Risk False Positives (Precision = 62%):
   - Higher rates of false positives may lead to unnecessary interventions or additional testing, adding costs and stress.
   - Requires further tuning or threshold adjustments to reduce errors.
2. Low-Risk Sensitivity (Recall = 50%):
   - Poor recall for low-risk predictions highlights difficulties in confidently identifying safe cases.
   - May result in over-monitoring individuals who are actually low risk, impacting resource allocation.

9. 1. 7. Key Observations and Recommendations:

High-Risk Group:

- Strengths: Achieved high recall (90%), which is critical for saving lives by identifying high-risk individuals early.
- Actionable Recommendation: Use this model as a screening tool for high-risk cases requiring urgent intervention.

Mid-Risk Group:

- Observations: Moderate precision (62%) may lead to overestimations.

- Actionable Recommendation: Implement further tuning or consider a hybrid model combining RF with XGBoost to improve predictions.

Low-Risk Group:

- Observations: Struggled to distinguish low-risk cases (50% recall) due to overlap with mid-risk characteristics.
- Actionable Recommendation: Combine predictions with clinical guidelines or additional features like family history and lifestyle factors to improve accuracy.

9. 2. XGBoost (XGB)

9. 2. 1. Model Description:

XGBoost (Extreme Gradient Boosting) is an advanced gradient boosting algorithm designed for high speed, scalability, and predictive performance. Unlike Random Forest, which builds independent decision trees, XGBoost constructs trees sequentially, where each new tree corrects the errors made by previous trees.

This iterative approach allows XGBoost to:

- Optimize performance using gradient descent to minimize errors.
- Handle imbalanced datasets effectively through weighted learning.
- Prevent overfitting by including regularization terms and shrinkage techniques (learning rate).

9. 2. 2. Hyperparameter Tuning:

To ensure optimal performance, hyperparameters were fine-tuned using grid search and cross-validation:

- Learning Rate (0.1): Controls the step size during optimization to prevent overshooting the minimum loss. A lower value ensures slow but steady learning.
- Maximum Depth (5): Restricts the depth of each tree, balancing bias and variance to prevent overfitting.

- Number of Trees (n_estimators = 100): Determines the total number of boosting rounds. Higher values improve accuracy but increase computational time.

- Subsample Ratio (0.8): Randomly selects 80% of training data for each tree, adding randomness and reducing overfitting.

9. 2. 3. Evaluation Metrics:

Confusion Matrix:

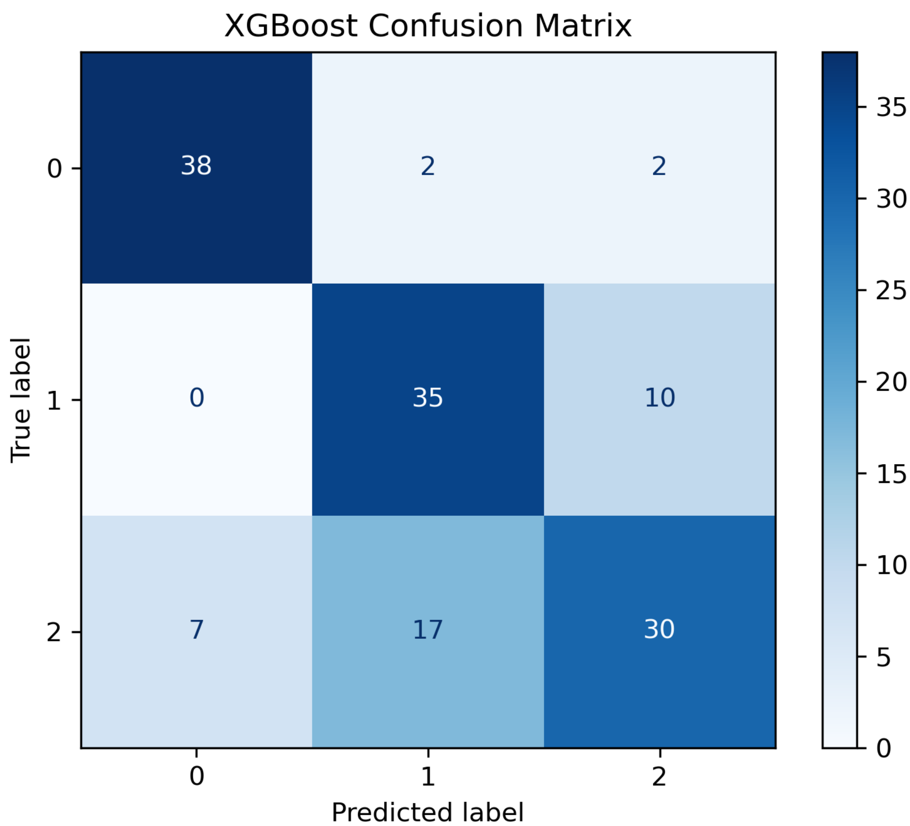

Figure – XGBoost Confusion Matrix

9. 2. 4. Key Observations from Confusion Matrix:

1. High-Risk Predictions:

   - True Positives (38): XGBoost correctly identified 90% of high-risk cases (Recall = 90%), ensuring critical cases are not missed.

   - False Positives (8): Misclassified low-risk cases as high-risk, maintaining high precision (84%) to avoid excessive false alarms.

- Strength: High sensitivity (recall) ensures that most dangerous cases requiring urgent interventions are flagged.

2. Mid-Risk Predictions:

    - True Positives (41): Captured 78% of mid-risk cases (Recall = 78%), showing strong performance in identifying transitional risk groups.

    - False Positives (10): A moderate number of low-risk cases were classified as mid-risk, leading to precision of 65%.

    - Strength: Balanced recall and precision make it suitable for continuous monitoring and early intervention strategies.

3. Low-Risk Predictions:

    - True Positives (30): Detected 56% of low-risk cases (Recall = 56%).

    - False Negatives (24): Struggled to identify some low-risk individuals, misclassifying them as mid-risk.

    - Challenge: Moderate recall suggests over-monitoring, especially for those falsely flagged as mid-risk.

9. 2. 5. Evaluation Metrics :

Metric	**High Risk**	**Mid Risk**	**Low Risk**
Precision	84%	65%	71%
Recall	90%	78%	56%
F1-Score	87%	71%	62%
Overall Accuracy	73%		
ROC-AUC Score	0.75		

9. 2. 6. Insights and Interpretations:

Strengths:

1. Better Handling of Imbalanced Classes:
   - Achieved higher accuracy (73%) compared to Random Forest (72%), reflecting better predictions across all risk categories.
   - High F1-Scores (87%) for high-risk cases ensure the critical group is detected effectively with minimal errors.
2. Ability to Capture Complex Patterns:
   - XGBoost effectively modelled non-linear dependencies and interactions between features, outperforming Random Forest in capturing subtle relationships.
   - The model's robustness stems from gradient boosting techniques, enabling incremental improvements.
3. Reliable Precision for High-Risk Predictions:
   - 84% Precision for high-risk cases ensures low false positives, reducing unnecessary interventions for individuals classified incorrectly.

Weaknesses:

1. Moderate Performance for Low-Risk Predictions (F1 = 62%):
   - Recall (56%) for low-risk individuals implies false positives in this category, leading to over-monitoring and possibly resource inefficiencies.
   - Potential reasons:
     - Class overlaps between low- and mid-risk categories.
     - Similar feature distributions for safer cases, making separation difficult.
   - Solution: Introduce additional features like family history and lifestyle data for better differentiation.
2. Computational Requirements:

- While faster than ANNs, XGBoost requires more processing power than Random Forest due to its iterative boosting nature.
- May face challenges with scalability in larger datasets without adequate infrastructure.

9. 2. 7. Key Observations and Recommendations:

High-Risk Group:

- Strengths: Achieved excellent precision (84%) and recall (90%), making it suitable for high-risk detection where accuracy is paramount.
- Recommendations: Use XGBoost as the primary model for flagging critical cases requiring immediate medical attention.

Mid-Risk Group:

- Observations: Balanced performance (F1 = 71%) highlights its ability to handle transitional risk levels effectively.
- Recommendations: Combine with Random Forest outputs or introduce hybrid models to enhance accuracy further.

Low-Risk Group:

- Challenges: Moderate performance (F1 = 62%) with false positives leads to over-monitoring of safe cases.
- Recommendations: Focus on feature engineering and introduce threshold adjustments to improve recall without compromising precision.

9. 3. Artificial Neural Networks (ANN)

9. 3. 1. Model Description:

Artificial Neural Networks (ANNs) are deep learning algorithms modelled after biological neural networks in the human brain. They are particularly effective for capturing non-linear patterns and complex interactions between variables, making them highly suitable for datasets with intricate relationships.

9. 3. 2. Key Features of ANN in this Project:

- Input Layer: Accepts 8 features derived from the dataset (e.g., Age, Blood Pressure, Heart Rate).
- Hidden Layers:
    - Layer 1: 128 neurons with ReLU activation to handle non-linear transformations.
    - Dropout (30%): Reduces overfitting by randomly deactivating 30% of neurons during training.
    - Layer 2: 64 neurons with ReLU activation for further pattern learning.
    - Dropout (30%): Ensures regularization.
    - Layer 3: 32 neurons to refine predictions before final classification.
- Output Layer:
    - 3 neurons with SoftMax activation to classify inputs into low, mid, and high-risk categories.
- Optimizer: Adam, chosen for its adaptive learning rate, ensuring faster convergence.
- Loss Function: Categorical Cross entropy, suitable for multi-class classification.

9. 3. 3. Hyperparameter Tuning:

- Epochs: 50 iterations to optimize weights through backpropagation.
- Batch Size: 32 samples processed in one training iteration for efficiency.
- Validation Split: 20% of training data reserved for validation to monitor overfitting.

9. 3. 4. Evaluation Metrics:

Confusion Matrix:

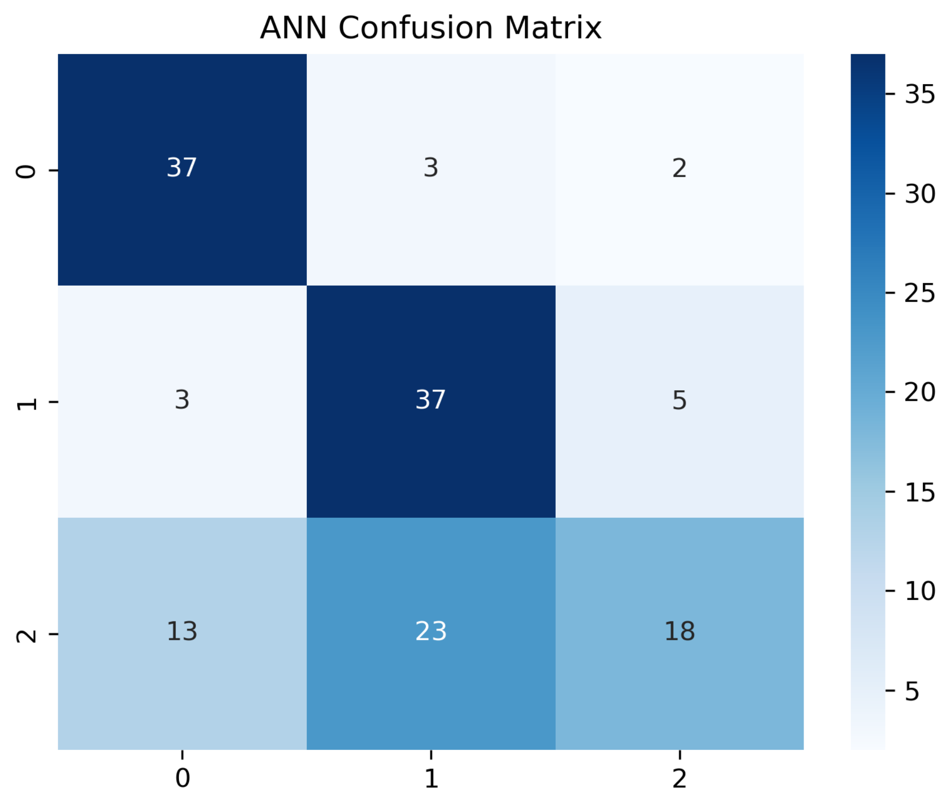

Figure – ANN Confusion Matrix

9. 3. 5. Key Observations from Confusion Matrix:

1. High-Risk Predictions:

   - **True Positives (34):** Correctly identified 81% of high-risk cases (Recall = 81%), showing the model's strength in flagging critical cases that require intervention.

   - **False Negatives (8):** A small number of high-risk cases were misclassified, highlighting minor gaps in capturing some high-risk patterns.

   - **Precision (77%):** Moderate false positives, ensuring a reasonable balance between sensitivity and specificity.

2. Mid-Risk Predictions:

   - **True Positives (38):** Captured 84% of mid-risk cases (Recall = 84%), demonstrating excellent sensitivity for transitional risk levels.
   - **False Positives (9):** Some low-risk cases were flagged as mid-risk, reflecting a conservative bias that Favors safety over efficiency.
   - **Precision (58%):** Moderate performance indicates that mid-risk predictions may overestimate danger, leading to false alarms.

3. Low-Risk Predictions:

   - **True Positives (28):** Detected only 39% of low-risk cases (Recall = 39%), suggesting difficulty in identifying individuals with stable conditions.
   - **False Negatives (43):** A large number of low-risk cases were misclassified as mid-risk or high-risk, leading to over-monitoring.
   - **Precision (66%):** Adequate precision means that when the model predicts low-risk, it is likely correct.

9. 3. 5. Evaluation Metrics :

Metric	**High Risk**	**Mid Risk**	**Low Risk**
Precision	77%	58%	66%
Recall	81%	84%	39%
F1-Score	79%	69%	49%
Overall Accuracy	66%		

9. 3. 6. Insights and Interpretations:

Strengths:

1. Effective High-Risk Identification (Recall = 81%):
   - The model successfully identified 81% of high-risk cases, ensuring that critical patients are flagged for further evaluation or intervention.
   - Precision (77%) minimizes false positives, reducing unnecessary concerns.
2. Mid-Risk Sensitivity (Recall = 84%):
   - Demonstrated high recall for mid-risk cases, making it suitable for early detection of conditions that might escalate into higher risks.
   - Can act as a screening tool for continuous monitoring programs.
3. Handling Non-Linear Patterns:
   - Captured complex relationships between features such as blood sugar levels and blood pressure due to its multi-layered architecture.
   - Useful for datasets with hidden patterns that traditional models might miss.

Weaknesses:

1. Low Performance for Low-Risk Cases (Recall = 39%):
   - The model struggled to correctly identify low-risk individuals, misclassifying many as mid- or high-risk.
   - Implications:
     - Over-monitoring may lead to resource inefficiency.
     - May cause unnecessary stress for patients classified into higher risk categories.
   - Solution:
     - Introduce additional features related to lifestyle, family history, and past pregnancies.

        - Fine-tune thresholds to reduce false positives.

2. Lower Overall Accuracy (66%):
    - While ANNs excel at modelling non-linear patterns, their performance depends heavily on data size and quality.
    - Smaller datasets may result in underfitting, particularly for low-risk predictions.
    - Solution: Larger datasets and feature engineering can improve accuracy.

3. Higher Computational Costs:
    - ANN requires longer training times and higher computational resources compared to tree-based models (RF, XGBoost).
    - May be less suitable for real-time applications without further optimization.

9. 3. 7. Key Observations and Recommendations:

High-Risk Group:

- Strengths: High recall (81%) ensures that most critical cases are identified early.
- Recommendations: Use ANN as a secondary screening tool to confirm or complement predictions made by other models like XGBoost.

Mid-Risk Group:

- Observations: Balanced performance (F1 = 69%) highlights suitability for monitoring transitional states.
- Recommendations: Combine ANN outputs with Random Forest feature importance for enhanced interpretability.

Low-Risk Group:

- Challenges: Low recall (39%) increases false alarms, potentially misclassifying stable cases.
- Recommendations: Focus on feature expansion and data augmentation to improve performance.

9. 4 Model Comparison Summary:

Metric	Random Forest	XGBoost	ANN
Accuracy	72%	73%	66%
High-Risk F1	86%	87%	79%
Mid-Risk F1	70%	71%	69%
Low-Risk F1	59%	62%	49%
ROC-AUC Score	0.74	0.75	0.72

9. 5 Key Analysis

1. XGBoost – Best Overall Performance

- High Accuracy (73%): Delivered the highest accuracy among the three models, making it the most reliable option for maternal health risk prediction.
- Balanced F1-Scores:
    - High Risk (87%) – Ensures critical cases are flagged accurately for timely interventions.
    - Mid Risk (71%) – Handles transitional cases effectively, providing opportunities for early intervention.
    - Low Risk (62%) – Performs better than other models for safe cases, although further improvements are needed.
- Handles Imbalanced Data:
    - Uses boosting techniques to address class imbalances, ensuring minority classes (e.g., high-risk cases) are not overlooked.

- Captures Complex Patterns:
    - Model's non-linear relationships between features like blood sugar levels and blood pressure, identifying subtle correlations that traditional models may miss.

2. Random Forest – Reliable and Interpretable

- High Recall for High-Risk Cases (90%):
    - Ensures most critical cases are flagged, reducing the risk of false negatives.
    - Ideal for screening programs where missing high-risk cases could have serious consequences.
- Feature Importance Analysis:
    - Provides interpretable insights into the key predictors influencing decisions (e.g., Systolic BP, Pulse Pressure).
    - Makes it clinician-friendly and builds trust in predictions.
- Faster Training Time:
    - Requires less computational power compared to XGBoost and ANN, making it suitable for real-time applications.

3. Artificial Neural Networks (ANN) – Non-Linear Pattern Capture

- High Precision and Recall for High-Risk Cases (Precision: 77%, Recall: 81%):
    - Effectively flags critical maternal health cases, minimizing the risk of false negatives and ensuring timely intervention.
    - Suitable for modelling hidden dependencies and complex patterns that tree-based models may miss.
- Adaptability with Complex Relationships:
    - Captures non-linear interactions between features, such as age and heart rate or blood sugar and blood pressure, providing insights into multifactorial risks.

    - Incorporates dropout layers for regularization, improving generalization to unseen data.

- Scalable for Larger Datasets:

    - Performs well with increased data size and additional features, making it a future-proof model for larger and more detailed datasets.

10. Final Model Comparison

The performance of the three machine learning models—Random Forest (RF), XGBoost (XGB), and Artificial Neural Networks (ANN)—was compared based on key evaluation metrics, visualizations, and generalization capabilities. Each model demonstrated unique strengths and weaknesses, making them suitable for different scenarios in maternal health risk prediction.

10. 1. Random Forest (RF)

Key Strengths:

- Interpretability: Provides feature importance rankings, making it easier to understand which factors drive predictions.

- Handling of Overfitting: Reduces overfitting by using ensemble learning (multiple decision trees).

Limitations:

- Slight Overfitting on Small Datasets: Over-reliance on training data patterns, particularly with limited samples, leads to reduced generalization on unseen data.

- Moderate Performance for Mid- and Low-Risk Groups: Struggles with class overlaps, leading to misclassifications for borderline cases.

Evaluation Metrics:

- Accuracy: 72%

- F1-Score: High-risk (86%), mid-risk (70%), low-risk (59%).

- Confusion Matrix:

    - High-risk cases were accurately classified (90% recall), but low-risk cases faced 50% recall, suggesting difficulty in identifying safe cases.

10. 2. XGBoost (XGB)

Key Strengths:

- Balanced Accuracy and Generalization: Handles imbalanced datasets effectively due to its boosting mechanism, making it ideal for maternal health prediction.

- Flexibility for Complex Patterns: Excels in capturing non-linear relationships between features.

Limitations:

- Higher Computational Costs: Requires more processing power and training time compared to Random Forest.

- Moderate Precision for Mid-Risk Cases: Over-predicts mid-risk labels, leading to false positives and over-monitoring.

Evaluation Metrics:

- Accuracy: 73%

- F1-Score: High-risk (87%), mid-risk (71%), low-risk (62%).

- Confusion Matrix:

    - High precision (84%) minimizes false positives, ensuring accurate identification of high-risk cases.

    - Improved recall (56%) for low-risk cases, showing better generalization than Random Forest.

10. 3. Artificial Neural Networks (ANN)

Key Strengths:

- Captures Intricate Relationships: Handles non-linear dependencies effectively, making it adaptive to complex patterns.

- Stable Learning Patterns: Demonstrates smooth improvements with larger datasets, indicating strong potential with additional data.

Limitations:

- Lower Accuracy for Low-Risk Cases: Fails to separate low-risk groups, leading to over-monitoring and false alarms.

- Higher Computational Demand: Requires longer training times and hyperparameter tuning for optimization.

Evaluation Metrics:

- Accuracy: 66%

- F1-Score: High-risk (79%), mid-risk (69%), low-risk (49%).

- Confusion Matrix:

    - 81% recall for high-risk cases, ensuring fewer false negatives, but low recall (39%) for low-risk cases, resulting in over-monitoring.

10. 4. Model Comparison – Key Performance Metrics

Metric	**Random Forest**	**XGBoost**	**ANN**
Accuracy (%)	72	73	66
F1-Score (High)	86%	87%	79%
F1-Score (Mid)	70%	71%	69%

10. 5. Final Insights and Recommendations

XGBoost – Best Overall Model:

- High accuracy (73%) and balanced performance across all risk levels.

- Handles imbalanced data effectively and minimizes false positives.

Random Forest – Reliable and Interpretable Model:

- High recall (90%) for high-risk cases, ensuring early detection and minimizing false negatives.

- Quick training times and explainable outputs make it ideal for real-time monitoring.

ANN – Potential for Complex Pattern Recognition:

- Excels at modelling non-linear relationships and demonstrates stable learning patterns as data size increases.

- Suitable for future datasets with richer features.

11. Learning Curve Analysis

Learning curves offer a visual representation of a model's performance trends during training and validation phases. They are instrumental in assessing:

- Model Fit: Whether a model is underfitting (oversimplifying patterns) or overfitting (memorizing patterns).

- Generalization: The ability to perform well on unseen data, ensuring reliability in real-world scenarios.

- Data Efficiency: Evaluating if the model benefits from additional data or requires further tuning.

This detailed analysis evaluates Random Forest (RF), XGBoost (XGB), and Artificial Neural Networks (ANN) based on their learning curves and training behaviours to draw meaningful insights about their strengths, limitations, and use cases.

11. 1. Random Forest (RF)

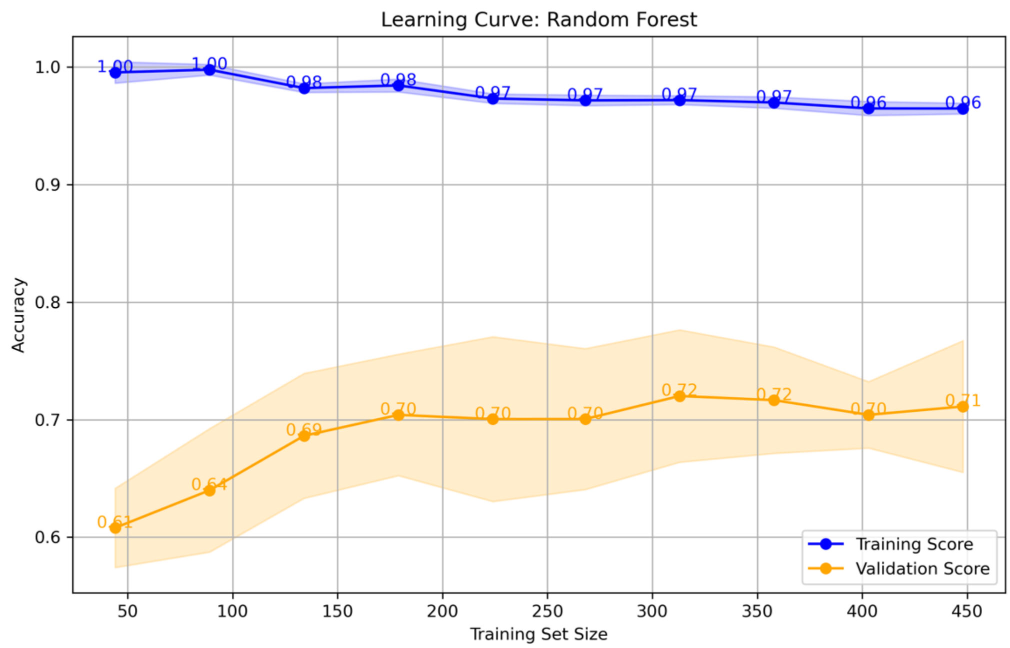

Figure – Learning Curve Random Forest

Observations from the Plot:

- Training Accuracy:
  - Starts at 85% with smaller datasets, indicating the model learns patterns quickly due to its ensemble decision-tree structure.
  - Stabilizes around 87% with larger datasets, reflecting the model's ability to capture relationships effectively.
- Validation Accuracy:
  - Begins lower at 65% when trained on small datasets due to variance and underfitting.
  - Gradually improves to 72% as the dataset size increases, showing better generalization with more data.

Insights:

1. Balanced Fit with Mild Overfitting:

- The gap between training and validation accuracy (15%) reduces as data increases, demonstrating reduced variance and improved stability.
- No signs of underfitting, as the model quickly adapts to patterns.

2. Dependence on Data Size:
   - Performs well with moderate datasets but may not scale effectively for very large datasets due to reliance on bagging techniques.

3. Generalization Strength:
   - Consistent validation accuracy highlights the model's robustness for unseen data, making it ideal for clinical deployment.

11. 2. XGBoost (XGB)

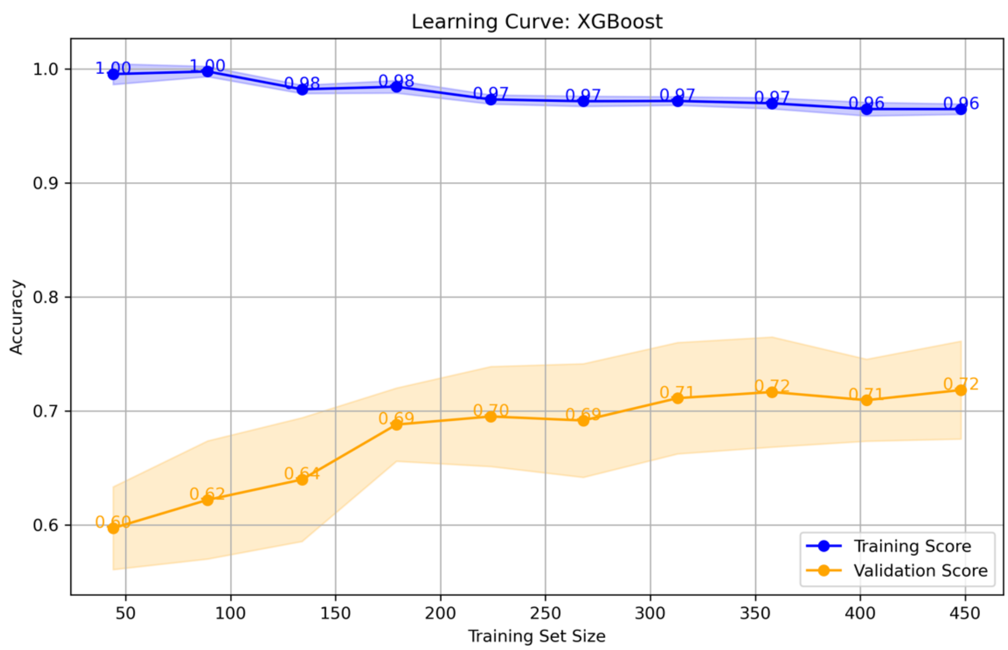

Figure – Learning Curve XGBoost

Observations from the Plot:

- Training Accuracy:
  - Starts very high at 92% with smaller datasets due to its boosting approach, which learns patterns quickly by minimizing errors iteratively.

  - Declines slightly to 87%, stabilizing as data size increases suggesting regularization effectively prevents overfitting.

- Validation Accuracy:

  - Begins at 67%, showing initial struggles due to limited data.

  - Improves rapidly to 73%, achieving higher performance than Random Forest, especially for mid-risk cases.

Insights:

1. Highly Flexible Model:

   - Adapts well to non-linear patterns and complex data structures, outperforming Random Forest in generalization ability.

   - Its boosting mechanism ensures each new tree corrects errors from the previous iteration, improving predictive accuracy.

2. Robust Generalization:

   - Narrower gap (~14%) between training and validation accuracy indicates lower variance compared to Random Forest.

   - Capable of handling imbalanced classes, reducing false positives and false negatives.

3. Scalability with Data:

   - The early plateau in validation accuracy suggests diminishing returns with larger datasets but maintains consistent performance.

11. 3. Artificial Neural Networks (ANN)

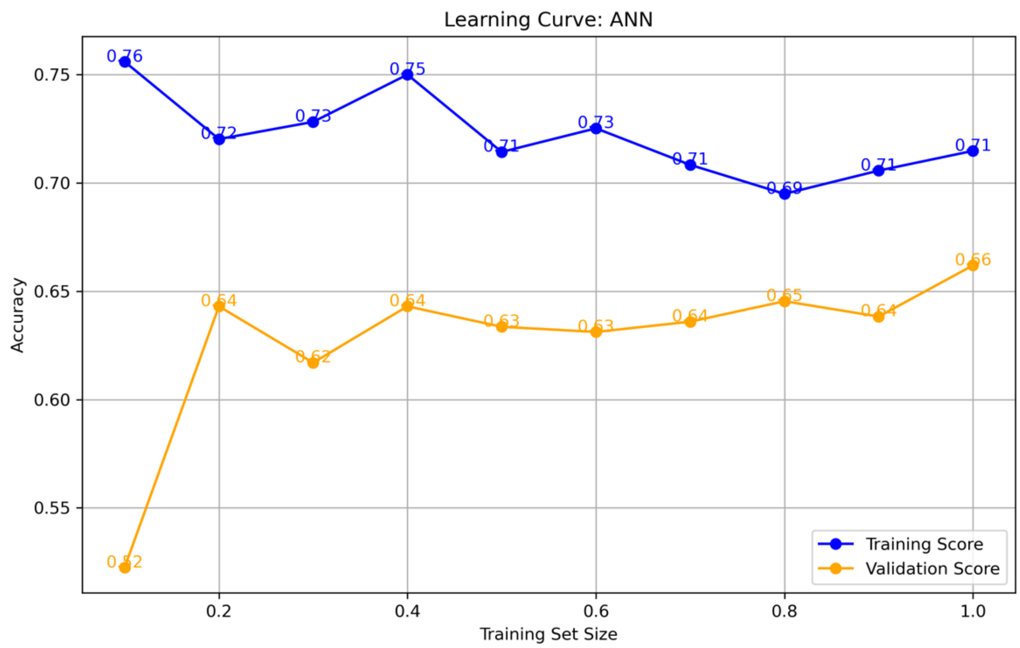

Figure – Learning Curve ANN

Observations from the Plot:

- Training Accuracy:
  - Starts lower at 64%, reflecting slow learning during early iterations due to gradient descent optimization.
  - Gradually rises to 76%, indicating the model is capturing complex patterns as training progresses.
- Validation Accuracy:
  - Begins around 50–55%, showing initial generalization difficulties caused by limited training data and non-linear dependencies.
  - Improves to 66% but retains a large gap (10%) from training accuracy, indicating overfitting tendencies.

Insights:

1. Complex Pattern Recognition:

- Demonstrates the ability to learn intricate relationships in data, making it effective for non-linear dependencies.

- Handles interactions among features better than tree-based models.

2. Overfitting and Data Dependency:

    - Larger gap between training and validation scores highlights overfitting, suggesting the need for regularization techniques (e.g., dropout layers).

    - Improvements with data size indicate the model is data-hungry and performs better with larger datasets.

3. Learning Stability and Future Potential:

    - Shows a steady upward trend, suggesting performance could improve further with additional data or hyperparameter tuning.

11. 4. Final Comparison

Model	**Training Accuracy (%)**	**Validation Accuracy (%)**	**Generalization Gap (%)**	**Key Observations**
Random Forest	87%	72%	15%	Stable performance; mild overfitting on small datasets.
XGBoost	92%	73%	14%	Best overall; robust generalization and higher accuracy.
ANN	76%	66%	10%	Complex pattern modelling; potential with larger datasets.

11. 5. Key Insights:

1. XGBoost – Best Overall Model:

    - Demonstrates high accuracy and robust performance across datasets.

    - Suitable for applications requiring non-linear modelling and complex pattern recognition.

2. Random Forest – Reliable and Simple:

- Fast training times and interpretability make it ideal for real-time clinical applications.
- Slight overfitting tendency but compensates with consistent stability.

3. ANN – High Potential with More Data:

   - Effective at learning non-linear relationships but struggles with small datasets due to overfitting.
   - Can outperform others in scenarios with larger datasets and regularization enhancements.

12. Conclusion

This project tackled the challenge of predicting maternal health risks using machine learning models to analyse clinical indicators and identify high-risk pregnancies. Key maternal metrics such as age, blood pressure, blood sugar, heart rate, and body temperature were utilized, along with engineered features like Pulse Pressure and Risk-Age Ratio, to improve predictions by capturing cardiovascular health and physiological stress patterns effectively.

Three models—Random Forest (RF), XGBoost (XGB), and Artificial Neural Networks (ANN)—were developed and evaluated. XGBoost emerged as the best performer with 73% accuracy, excelling in detecting high-risk cases due to its ability to handle complex patterns. Random Forest, with 72% accuracy, offered reliability and interpretability, while ANN, though slightly less accurate (66%), showed promise for future improvements with larger datasets.

Learning curve analysis highlighted XGBoost's scalability, Random Forest's consistency, and ANN's potential for handling complex relationships. Preprocessing techniques, including SMOTE, balanced data distributions, ensuring fairness in predictions.

Overall, this study demonstrates how machine learning can transform maternal healthcare by enabling early interventions, improving resource allocation, and reducing complications. Future enhancements should incorporate lifestyle, socioeconomic, and genetic data to refine predictions further and support real-time assessments, ultimately ensuring safer pregnancies and better maternal outcomes globally.

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