

**PREDICTION AND ANALYSIS OF POSTPARTUM DEPRESSION WITH
CHRONIC DISEASES AS RISK FACTORS**

by

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M.C.A., Cochin University of Science and Technology, 2014

THESIS SUBMITTED IN PARTIAL FULFILMENT OF
THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF SCIENCE
IN
COMPUTER SCIENCE

UNIVERSITY OF NORTHERN BRITISH COLUMBIA

March 2025

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Abstract

Postpartum Depression (PPD) is a mental health condition that is a leading cause of annually reported infanticide incidence. Many cases go underdiagnosed due to unawareness, and prolonged untreated conditions can lead to psychosis, causing harm to themselves and the infant. Hence, identifying the PPD risk has become crucial and has been widely studied in the context of traditional risk factors. Only limited research has been conducted addressing chronic diseases as the risk factor.

Predicting PPD by utilizing the power of Machine Learning (ML) algorithms can lead to timely intervention and management of the condition. Data obtained from the Center for Disease Control and Prevention – Pregnancy Risk Assessment Monitoring System (CDC-PRAMS) was used for this thesis to identify the risk factors and forecast the likelihood of depression for mothers who suffer from one or more chronic diseases using ML models. The performance evaluation of the selected machine learning models—Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), and Neural Network (NN) was assessed using accuracy and F1-score, which ranged from 76% and 77% for NN to 89% and 88% for LR. The impact of each key predictor identified in the SHAP analysis demonstrated close alignment across all models and highlighted the significance of chronic disease. The results also highlight how chronic diseases potentially interact with other common risk factors to increase the likelihood of PPD. An interactive dashboard is created to visualize and present preprocessed data using charts and graphs. Also, a diagnostic screening tool developed based on the trained models demonstrates the potential of ML as a screening tool to improve diagnostic precision and support personalized care for enhanced quality of life.

Table of Contents

Abstract	ii
Table of Contents	iii
List of Tables.....	vi
List of Figures	vii
List of Equations	ix
List of Abbreviations.....	x
Acknowledgment	xi
Chapter 1	1
Introduction.....	1
1.1 Utilizing ML in Healthcare: Addressing PPD.....	3
1.1.1 Postpartum Depression (PPD).....	4
1.1.2 Predictive Modeling for PPD Detection.....	6
1.1.3 PPD Screening Tools.....	8
1.2 Problem Statement	9
1.3 Research Methodology.....	10
1.4 Data Source	11
1.5 Contributions.....	13
1.6 Organization of Thesis	14
Chapter 2	15
Literature Review.....	15
2.1 PPD Predictive Analysis	15
2.1.1 PPD Risk Factors Analysis.....	21
2.1.2 Summary	29

2.2	Postpartum Depression Risk Factors: Chronic Illness	30
2.2.1	Summary	34
2.3	CDC-PRAMS Data PPD Analysis	34
2.3.1	Summary	38
2.4	PPD Tool	38
2.5	Summary	40
Chapter 3		42
Methodology		42
3.1	Data Collection.....	43
3.1.1	Ethics Approval.....	44
3.2	Data Preparation.....	44
3.2.1	Data Collection.....	45
3.2.2	Data Preprocessing.....	45
3.2.3	Feature Selection	49
3.2.4	Feature Engineering and Derived Variables.....	50
3.2.5	Data Encoding and Scaling	51
3.2.6	Challenges	52
3.3	SPSS Modeler	53
3.4	Predictive Model	54
3.4.1	Artificial Neural Network.....	56
3.4.2	Logistic Regression	58
3.4.3	Random Forest Tree	60
3.4.4	Support Vector Machine.....	62
3.5	Dashboard	63
3.6	Summary	64
Chapter 4.....		65

Experiment and Results.....	65
4.1 PPD Dashboard	65
4.1.1 Summary	70
4.2 Evaluation Metrics: Accuracy and F1 Score.....	71
4.3 Predictive Modeling: An Analysis of Four Models to Predict PPD.....	72
4.4 Model Comparison.....	73
4.4.1 Performance Metrics: Discussion.....	74
4.5 Post-Training Analysis: Identify Key Predictors	76
4.5.1 Summary: Post-Training Analysis	88
4.6 Identifying and Analyzing Interactions Among Key Predictors	90
4.7 Summary: Interaction Analysis.....	100
4.8 PD Screening Tool	102
4.9 Conclusion.....	104
Chapter 5	106
Conclusion and Future Work	106
5.1 Future Work	108

List of Tables

Table 1. Predictor Variables.....	12
Table 2. Precision, Recall, and F1 Score.....	73
Table 3. Key Features and Their Predictive Strength by Model	89
Table 4. Top Common Key Interactive Features Identified by the Selected Models	101

List of Figures

Figure 1. Projected Growth of the Global Mental Health Apps Market (2024-2029) [5].....	2
Figure 2. Spectrum of PPD [14].....	5
Figure 3. PPD Rate Trend in 2014 -2018 [46].	21
Figure 4. PPD and Pre-Existing Health Conditions [46].....	22
Figure 5. Proposed Research Model.	42
Figure 6. Data Preparation Process [70].....	45
Figure 7. a) ANN (b)Structure of ANN for a Neuron in a Hidden Layer with One Output [76].....	57
Figure 8. The Sigmoid Curve in LR [78]	59
Figure 9. RF: An Ensemble Learning Algorithm [80].	61
Figure 10. Linear SVM [82].....	62
Figure 11. PPD Dashboard.....	66
Figure 12. PPD Key Influencers	67
Figure 13. PPD and Maternal Age Group	68
Figure 14. PPD by Maternal Education Level and Marital Status (Married).....	68
Figure 15. PPD by Disease Factors.....	69
Figure 16. PPD by Prenatal Factors.	70
Figure 17. Model Comparison: Accuracy and F1 Score.	73
Figure 18. Feature Significance Using SHAP on NN Model.....	78
Figure 19. SHAP Summary: Visualizing Feature Impact and Distribution Using NN Model	79
Figure 20. Feature Significance Using SHAP on LR Model	80
Figure 21. SHAP Summary: Visualizing Feature Impact and Distribution Using LR Model	81
Figure 22. Feature Significance Using SHAP on RF Model	83
Figure 23. SHAP Summary: Visualizing Feature Impact and Distribution Using RF Model	84
Figure 24. Feature Significance Using SHAP on the SVM Model.....	86

Figure 25. SHAP Summary: Visualizing Feature Impact and Distribution Using SVM Model	87
Figure 26. SPSS Feature Selection Node	91
Figure 27. Feature Selection Results.....	92
Figure 28. Interaction Feature Significance Using SHAP on NN Model	94
Figure 29. Interaction Feature Significance Using SHAP on LR Model.....	96
Figure 30. Interaction Feature Significance Using SHAP on RF Model	98
Figure 31. Interaction Feature Significance Using SHAP on the SVM Model.....	99
Figure 32. PPD Screening Tool - Front End	103
Figure 33. PPD Screening Tool - Front End	103
Figure 34. PPD Screening Tool - Prediction.....	104

List of Equations

Equation 1. Output of the Neuron	57
Equation 2. Sigmoid Function.....	59
Equation 3. Accuracy by Percentage.....	71
Equation 4. F1 Score Formula.	71
Equation 5. Precision Formula.....	72
Equation 6. Recall Formula.....	72

List of Abbreviations

AUC	Area Under Curve
BI	Business Intelligence
CDC	Centre for Disease and Control
EHR	Electronic Health Record
GBM	Gradient Boosting Machine
LR	Logistic Regression
ML	Machine Learning
NN	Neural Network
OR	Odds Ratio
PPD	Postpartum Depression
PRAMS	Pregnancy Risk Assessment Monitoring System
RF	Random Forest
SVM	Support Vector Machine

Acknowledgment

I would like to begin by expressing my heartfelt gratitude to my family, especially my husband, Muhamed Rajeesh, our children, and our parents, whose unwavering love, support, and encouragement have been my greatest source of strength throughout this journey. Next, I acknowledge the traditional and unceded territory of Lheidli Teneh on which UNBC is located. I am grateful for the opportunity to learn, work, and conduct research on this land.

I extend my sincere thanks to my supervisor, Dr. Waqar Haque, for his invaluable guidance, motivation, and support. His guidance has been essential in shaping my research and academic growth. I would like to extend my deepest gratitude to my committee members, Dr. Fan Jiang and Dr. Kafui Monu, for their thoughtful feedback, constructive suggestions, and encouragement.

Special thanks to the PRAMS Working Group, which includes the PRAMS Team, Division of Reproductive Health, CDC, and the PRAMS sites for their role in conducting PRAMS surveillance and allowing the use of their data. I want to express my heartfelt gratitude to Dr. Rahul G.P. Sukumariamamma for his invaluable assistance in reviewing the data. I am also thankful for the support of my friends in Prince George and India. Additionally, I would like to extend special thanks to my colleagues at BIRG LAB for their ongoing encouragement and motivation throughout this journey.

Thank you all for being part of this significant chapter in my life.

Febina Muhamed Rajeesh

Chapter 1

Introduction

Processing large volumes of complex health data with traditional analytics methods often takes too long to reveal valuable insights. As a branch of Artificial Intelligence (AI), Machine Learning (ML) techniques like Deep Neural Network (DNN) models have gained increased attention in extracting hidden patterns, finding relationships within datasets, and other valuable information from the massive quantity of health data. ML can enhance focused patient care by learning from the patterns and making predictions to improve speed and precision [1]. In addition to healthcare, it provides valuable benefits to other industries, such as finance, to improve trading strategies and various other sectors to adopt automated systems [2].

The significance of AI in the medical field has grown as ML techniques are increasingly used to diagnose, forecast, and treat various health conditions, including mental illnesses [3]. With the help of vast patient datasets, these systems can aid clinicians in making more accurate assessments and individualized treatment plans, thereby improving the overall quality of mental healthcare delivery [4]. While prior ML research has focused on the benefits of improving mental health conditions such as depression, Alzheimer's, and schizophrenia, the current research in this area is proving to be increasingly vital in advancing broader mental health care and showcasing its impact in the field. Therefore, the impact of ML and big data applications is invaluable in mental health care and management advancements for improving treatment options and patient support, thus contributing to public health initiatives.

Figure 1 presents the global market for mental health apps, expected to grow from \$7.03 billion in 2024 to \$15.95 billion by 2029, with a compound annual growth rate (CAGR) of 18.7% [5]. This increase reflects the growing role of ML and digital technologies in mental health, enabling more personalized care, enhanced support, and improved accessibility through relevant applications. Together, these areas showcase the potential of ML to enhance mental health care and address critical challenges in this field, such as identifying risk factors and developing individualized treatment plans.

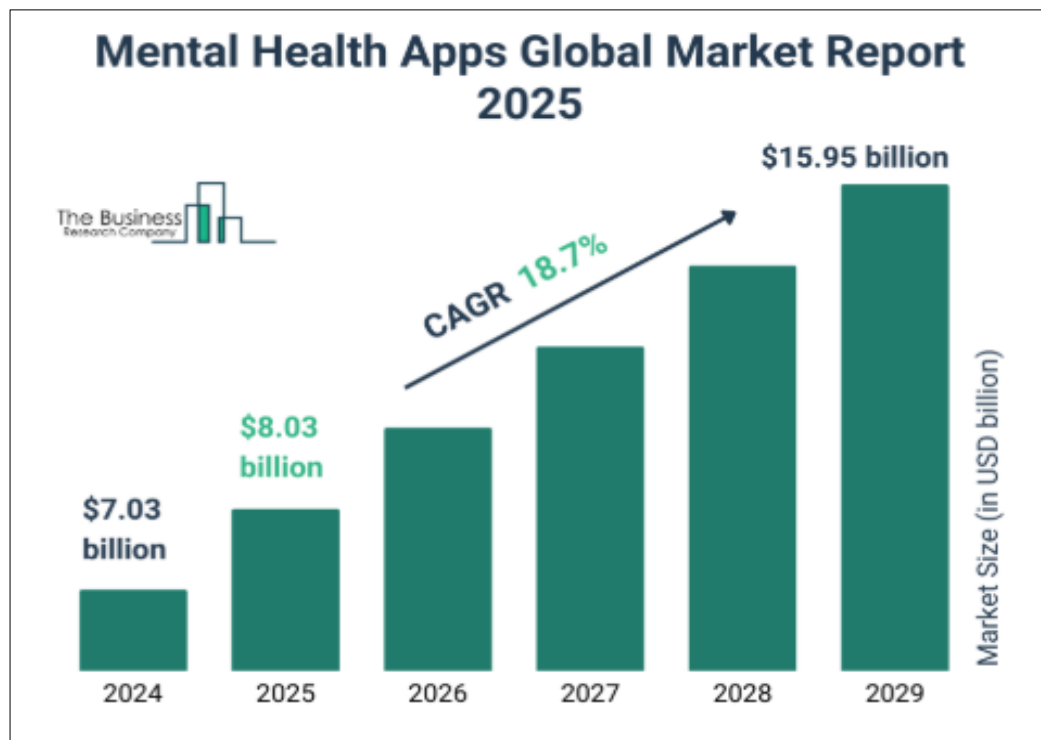


Figure 1. Projected Growth of the Global Mental Health Apps Market (2024-2029) [5].

Maternal mental health poses a considerable global challenge. Nearly one in five women will encounter a mental health condition during pregnancy or within the year following childbirth; of those with perinatal mental health conditions, 20% will also be grappling with suicidal thoughts or engaging in acts of self-harm [6]. Postpartum psychiatric disorders typically fall

into three categories: baby blues or postpartum blues, postpartum depression (PPD also known as postnatal depression), and postpartum psychosis. Unfortunately, these conditions are often disregarded and left untreated. Mothers grappling with mental health challenges may also experience exacerbated physical health issues, which could potentially impact the well-being of their infants. The formation of attachment between mother and infant may be affected by the cognitive and emotional challenges faced by mothers with PPD [7]. Timely intervention is important to prevent complications.

Numerous studies have investigated the use of ML techniques for predicting PPD and effectively contributing to mental healthcare practices [8], [9], [10]. As machine and deep learning methods gain popularity, analyzing existing work to better guide future research becomes necessary. A comprehensive literature review is provided in Chapter 2.

1.1 Utilizing ML in Healthcare: Addressing PPD

ML has been applied to various areas of mental health, including clinical psychology and psychiatry, enhancing research methods, treatments, public health studies, and analysis of support community behaviors. It aids in offering automated solutions to enhance predictive accuracy and reveal complex patterns in data. The ability of ML to process diverse data types, including clinical records, has made it a powerful tool in mental health research. Analyzing complex data, predicting risk factors, providing patient-specific treatment approaches, and monitoring symptoms enhance the quality of mental health care. Early intervention and targeted support could be facilitated for at-risk mothers by this predictive model for PPD, potentially resulting in improved outcomes for both mothers and their infants. Overall, ML

demonstrates the potential to improve the efficiency of clinical and research processes and generate new insights into maternal mental health and well-being.

1.1.1 Postpartum Depression (PPD)

PPD is characterized by symptoms such as profound sadness, fatigue, anxiety, frequent crying, irritability, and alterations in sleeping or eating habits [11] and is highly prevalent among women in the first year of delivery. It is influenced by environmental and genetic factors, making it a complex, multifaceted condition. While its exact cause remains unknown, it is believed to result from physical, emotional, genetic, and social factors. It is also the most underdiagnosed obstetric complication globally, including in the United States [12]. Although the feelings associated with PPD are often temporary and seen as mild conditions by health professionals, they highlight the crucial need for support during the postpartum period to manage emotional challenges and maintain well-being. PPD does not go away on its own, and it is one of the leading causes of the annually reported infanticide incidence [11].

Figure 2 illustrates the spectrum of postpartum mood disorders, highlighting postpartum blues, PPD, and postpartum psychosis, with their prevalence rates, key symptoms, and severity levels. Timely diagnosis and proper identification are expected to largely cure this condition. A very different disorder with psychotic symptoms associated with the postpartum period is postpartum psychosis. Unknown and untreated diseases lead to prolonged psychosis in severe cases. Approximately 1-2 cases per 1000 births result in postpartum psychosis, requiring emergency medical attention. As a severe condition, there is an increased risk of suicide and

risk of harm to the baby [13]. Hospitalization, psychotherapy, and medication are the usual treatments.

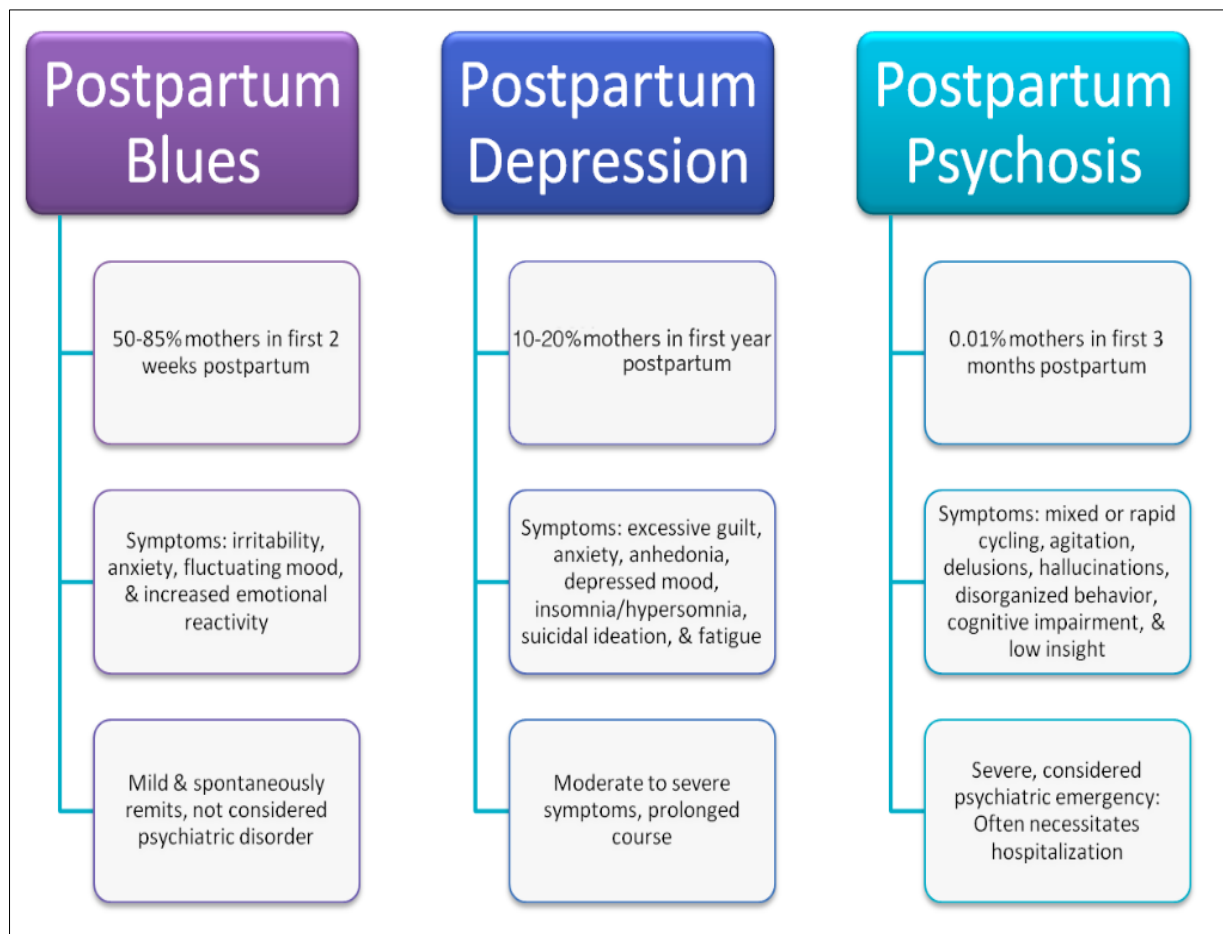


Figure 2. Spectrum of PPD [14].

Biological elements like reproductive hormones, stress hormones, and thyroid hormones, in conjunction with psychological factors, significantly contribute to the onset of PP. Recognizing key risk factors enables healthcare providers to identify women who may be at high risk of developing PPD, ensuring they receive medical interventions to lower the persistence during motherhood [15].

Common risk factors for PPD [11] are:

- A change in hormone levels after childbirth.
- Previous experience with depression or anxiety.
- Family or personal history of depression or mental illness.
- Stresses due to caring for a newborn and managing new life changes.
- Having a challenging baby who cries more than usual is hard to comfort or whose sleep and hunger needs are irregular and hard to predict.
- Having a baby with special needs (premature birth, medical complications, illness).
- First-time motherhood, very young motherhood, or older motherhood.
- Other emotional stressors or stress events, such as the death of a loved one or family problems.
- Financial or employment problems.
- Isolation and lack of social support.

Clinical organizations can identify trends and patterns and support personalized interventions using data mining, predictive analytics, and ML techniques such as Microsoft Power BI and IBM SPSS Modeller. Business Intelligence (BI) platforms provide tools for analysis and visualization, transforming data into strategic information to answer specific queries and guide decisions and planning [16].

1.1.2 Predictive Modeling for PPD Detection

Predictive modeling anticipates future outcomes by utilizing historical and current data and applying advanced statistical techniques and ML algorithms to generate accurate forecasts and

practical recommendations. It identifies patterns and relationships between independent and predicted variables and provides meaningful insights into data [17]. Prediction models play an important role in clinical decision-making, helping to improve personalized and targeted treatments [18].

ML models, such as neural networks (NN), logistic regression (LR), and decision trees, are widely used for predictive analysis in mental health, especially for screening and diagnosing depression. It has also been proven as an effective approach to analyzing PPD, focusing on prediction, optimizing risk assessment, and improving clinical outcomes [19], [20]. These models use factors such as demographics, medical history, and psychosocial variables to improve PPD management [9], [21]. A recent review evaluated the risk of bias and applicability of PPD prediction models commonly used in screening and diagnosis [21]. An innovative model using deep reinforcement learning to improve the process of identifying PPD was proposed in [22]. A scoping review [23] on ML methods for predicting PPD highlights the need for further clinical research to fine-tune ML algorithms for improved prediction and treatment outcomes.

The work presented in this thesis examines the relationship between independent variables, including chronic disease features, and the target variable PPD using Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), and Neural Network (NN) models. This approach has proven to be very effective for analyzing PPD by focusing on prediction, optimizing risk assessment, and improving clinical decision-making [8], [20], [24], [25].

1.1.3 PPD Screening Tools

Primary screening tools widely used for assessing depressive symptoms postpartum include the Postpartum Depression Screening Scale (PDSS) and the Edinburgh Postnatal Depression Scale (EPDS). EPDS [26] is a 10-item self-reporting questionnaire designed to screen for PPD. Among other variables, it assesses mood, anxiety, and anhedonia experienced by mothers in the postpartum period. Each item is scored on a point scale, resulting in a total score ranging from 0 to 30. A cut-off score of ≥ 13 is commonly used to indicate the need for further evaluation, while some guidelines recommend ≥ 10 in primary care settings for broader assessment. Likewise, the PDSS [27] is a 35-item self-reporting tool specifically developed to identify PPD and assess its severity across seven dimensions: anxiety/insecurity, emotional lability, cognitive impairment, loss of self, guilt/shame, sleep/appetite changes, and suicidal thoughts. A PDSS cut-off score of ≥ 9 suggests the need for a formal diagnostic assessment. There are web-based tools that utilize screening scales such as EPDS and PDSS. These tools allow users to complete the questionnaire digitally, providing immediate scoring and feedback to support early detection and further evaluation by healthcare providers.

The BabyCenter [28] postpartum depression quiz is an online screening tool based on the EPDS, featuring 10 multiple-choice questions to assess emotional well-being, mood, and anxiety over the past week. Healthy Mom [29] offers a similar online platform with a test based on validated tools like the EPDS, allowing new mothers to complete screenings digitally with immediate results and guidance. Mental Health America (MHA) [29] provides another online test using similar tools to assess PPD risk. This includes questions on general health conditions, such as heart disease, reproductive health concerns (e.g., PCOS, endometriosis), diabetes,

asthma, and neurological conditions. These screenings combine standard scale-based items with contextual questions about health and life factors, providing a score out of 30. These tools raise awareness about postpartum mental health, provide quick insights, and encourage users to seek professional help if the results indicate potential concerns. Besides EPDS and PDSS, a few other innovative tools are explained in Section 2.4.

1.2 Problem Statement

PPD is a complex and prevalent mental health condition, often challenging to diagnose and treat effectively. Traditional methods in healthcare often fall short of efficiently analyzing complex data related to mental health [30], leading to delayed detection. Without detection tools and personalized treatment plans, individuals with depression face prolonged struggles, affecting their quality of life.

In 2019, almost one-quarter (23%) of mothers who recently gave birth in Canada reported conditions consistent with either PPD or an anxiety disorder [31]. Although the risk factors for PPD have been studied, many potentially critical clinical variables remain unexplored [32]. Previous research on mental illness has demonstrated that depression frequently co-occurs with chronic diseases [33], [34]. Another study highlighted chronic physical illness as a significant predictor of PPD but examined it broadly without focusing on specific types or conditions [35]. Further evidence suggests that women with chronic conditions such as diabetes, hypertension, heart disease, migraines, and other neurological disorders are at an increased risk for peripartum mental illness [36]. Chronic illness may also reduce appetite, leading to amino acid deficiencies that hinder serotonin production, a critical factor in depression [35]. Overall,

studies specifically investigating the relationship between chronic diseases and PPD are limited.

Following the above insights, the current study presumes that chronic diseases serve as a potential risk factor for PPD, warranting further exploration. This research hypothesizes that chronic diseases are significant risk factors for PPD and attempts to find evidence for this hypothesis using ML models. Further, when chronic disease is identified as a risk factor, it is important to know the specific disease that increases the likelihood of PPD.

1.3 Research Methodology

A comprehensive literature review established the foundation for this research. The research progressed by determining relevant data sources, suitable tools, and modeling techniques to ensure compatibility with the dataset and research objectives.

The ML-based classification was used to build predictive models. This approach helps find correlations among variables to analyze the PPD risk factors to aid healthcare providers working with chronic disease patient groups. The source data was integrated into a database using SQL Server Management Studio (SSMS) 16.0, and relevant variables were selected using SPSS Modeler 18.4 in consultation with medical personnel. The preprocessed data was used to develop the models and generate results in Python 3.11.11 [37]. The models underwent training, testing, and validation stages to ensure their accuracy and reliability in predicting outcomes related to the research objectives.

Furthermore, an interactive dashboard was developed using Power BI [38] to visually present valuable insights in a user-friendly dashboard. Flask 2.3.3 [39] integrated a backend framework into the dashboard to offer personalized risk assessment based on user input. Chapter 3 provides a detailed description of the research methodology.

1.4 Data Source

The primary data source for this research is the Centre for Disease Control and Prevention – Pregnancy Risk Assessment Monitoring System (CDC-PRAMS) [40], a population-based surveillance system that gathers data on maternal experiences surrounding pregnancy to improve maternal and infant health. Sampling from birth certificate registries, PRAMS surveys new mothers monthly, providing valuable data for research purposes. This research uses data from 202,745 mothers surveyed across all states from 2016 to 2020. The categories of predictor variables used by this study are summarized in Table 1.

Table 1. Predictor Variables

Indicator	Variable
Demographic Variables	Age, gender, race/ethnicity, marital status, education level, and income.
Disease Variables	Medical history and family history of mental health conditions.
Pregnancy and Childbirth Factors	Gestational age, delivery mode, prenatal care utilization, and complications during pregnancy and childbirth.
Psychosocial Variables	Stress levels during pregnancy and postpartum, as well as social support networks and relationship status.
Lifestyle and Behavioral Factors	Substance use (e.g., smoking) and physical activity during pregnancy.
Postpartum Factors	Breastfeeding, sleep patterns, and infant care.
Geographic Factors	Geographic factors, such as regional variations.
Income and Socioeconomic Status	Income levels and socioeconomic status.
Infant Health and Development	Infant health and development, such as birth weight, immunizations, and infant feeding practices.
Parenting and Infant Care Practices	Parenting practices, infant sleep routines, and childcare arrangements.
Healthcare Utilization	Healthcare utilization during pregnancy and the postpartum period, including the number of prenatal care visits, healthcare-provider interactions, and access to healthcare services
Social Determinants of Health, Communities, and Neighborhood Characteristics	Social determinants of health, such as housing stability, food security, and access to transportation.

1.5 Contributions

This research focuses on enhancing PPD care for mothers by developing predictive models, creating a diagnostic screening tool, and designing a multi-level dashboard. First, developing ML models to forecast the likelihood of depression incorporating multiple risk factors, including chronic diseases, provides the following contributions:

- Detection of key risk factors of PPD to help identify high-risk individuals, enabling early interventions, tailored treatment strategies, and improved preventive care.
- Identification of specific chronic diseases and their interaction with other risk factors that impact the onset of PPD in vulnerable populations.

Second, the developed dashboard visually highlights relationships and patterns in the data, which offers the following contributions:

- Insights into PPD statistics, including prevalence, correlations, and trends.
- Helps identify gaps in PPD care, enabling experts to create targeted care plans and improve support for vulnerable postpartum populations.

Third, developing a diagnostic screening tool integrating predictive models into an ensemble framework to estimate depression probability based on user input demonstrates the potential of ML for effective PPD management, timely identification, and customized preventive care.

1.6 Organization of Thesis

This thesis focuses on PPD risk factor identification and prediction, comprising five chapters focusing on prediction through various ML methodologies. The first chapter introduces PPD and its connection with chronic diseases and explains why this research is important. Chapter two reviews existing studies on PPD. Chapter three explains the design of the prediction models. Chapter four describes the experimental setup and presents the findings and results of the models. Finally, Chapter five provides insights and recommendations for future research.

Chapter 2

Literature Review

The consequences of untreated or late-detected PPD can be severe, potentially leading to severe issues and effects on both the mother and the child or may escalate to postpartum psychosis. Thus, prior studies in the field of PPD were primarily aimed at identifying risk factors and developing predictive models to facilitate timely intervention and effective management of PPD. However, the research on the impact of chronic diseases on PPD is limited. This chapter provides an overview of the current knowledge, gaps, and advancements in predicting PPD, highlighting the significance of identifying at-risk individuals.

2.1 PPD Predictive Analysis

Statistical algorithms and ML techniques have been used in predictive analytics to reveal complex patterns and predict future trends based on historical information. This approach is especially important in the context of PPD where developing predictive models can assist healthcare professionals to identify individuals who are at heightened risk of developing this condition and enable proactive measures to be taken. A brief literature review on PPD predictive analysis is provided in this section.

A two-year longitudinal study [41] was conducted with 301 pregnant participants to validate the Postpartum Depression Predictors Inventory-Revised (PDPI-R) tool in Turkish women and assess its predictive validity for PPD using two standards: the EPDS and the Structured Clinical

Interview. Eligible participants for the study were over 18, in gestational weeks 28-32, carrying a single fetus, and without psychiatric disorders or medical complications for the baby. Statistical analyses conducted in SPSS confirmed the predictive validity of both versions with specific cut-off points established for accurate prediction of PPD using EPDS. The study identified various predictors of PPD, which included unwanted pregnancy, previous history of depression, life stress, self-esteem, social support, and marital satisfaction. The tool examined both prenatal and postnatal versions, with accuracies ranging from 64% to 81%. While the findings support routine screening with the tool to assess women's susceptibility to PPD, limitations in generalizability and interpretation should be addressed through additional research.

A study aimed to utilize ML to develop a predictive model for identifying women at a higher risk of PPD [42]. Data from 686 mothers in Sri Lanka collected within six months of childbirth was used, and the risk levels for PPD were assessed using the Sri Lankan version of EPDS. The questionnaire included multiple factors such as physical disabilities, drug abuse history, life stressors, social support, socioeconomic status, family problems, marital status, baby-related issues, education level, and number of children. The EPDS scores were categorized into mild, moderate, severe, and profound PPD. Exploratory data analysis and Spearman correlation were performed to identify relevant features for predicting PPD. Four models were built using an Adaptive Neuro Fuzzy Inference System with Genetic Algorithm (ANFIS-GA), ANFIS, and Feed Forward Artificial Neural Network (FFANN), SVM, and RF. Among these models, FFANN with 25 epochs exhibited superior performance compared to other models, achieving high accuracy in testing, training, and validating datasets. Researchers identified ANFIS-GA performance in running the Genetic Algorithm (GA) for five hundred generations,

resulting in the lowest loss and optimal parameters. Despite the promising findings, the study did not provide a detailed discussion on the selected features for the predictive models and present any identified risk factors for PPD, which could have provided valuable insights into the underlying causes of PPD.

A study in 2021 employed data mining algorithms, specifically J48, Random Tree, RF, and Reduce Error Pruning (REP) Tree, in combination with ensemble techniques such as Adaptive Boosting and Bagging considering social and demographic factors and identifying common symptoms, utilizing non-clinical information and observations [43]. The analysis aim was to identify the conditions under which women are more likely to experience PPD by surveying ninety-six participants and implementing the algorithms to analyze and predict the risk level of PPD. The study examined women who had given birth within the past year, irrespective of their depression history, and considered both urban and rural areas to assess the influence of quality of life on PPD probability. The collected information focused on social, mental, and quality of life aspects as well as 31 attributes of EPDS score to assess different levels of risk. The models achieved accuracy in the range of 84 - 94%. The findings highlighted associations between unplanned pregnancy, spousal support, delivery method (Caesarean vs. vaginal), and urban residence with PPD risk. The study revealed a concerning trend where most women facing PPD go unnoticed or undiagnosed. Also, women living in rural areas have had a lower prevalence of PPD, indicating a positive impact on lifestyle and living conditions. The limitations of this work include a small participant pool and a limited sampling area. This was also acknowledged by the authors.

A regional study conducted in five Arab countries (Jordan, Palestine, Lebanon, Saudi Arabia, and Bahrain) during the COVID-19 pandemic aimed to develop ML models for predicting maternal depression and anxiety among pregnant and postpartum women [25]. The data was collected through a web-based questionnaire. The dataset included 3569 pregnant women over 18 who had normal pregnancies during the COVID-19 pandemic. Exclusions applied to those conceiving during the pandemic and those with risk factors like miscarriage and chronic health issues. ANOVA test was implemented to assess risk factor distributions and the ML models, including Gradient Boosting (GB), Random Forest (RF), Extreme Randomized Forest (XRT), Naïve Bayes (NB), Support Vector Machine (SVM), Multilayer Neural Network (MNN), and Decision Tree (DT) were evaluated for their ability to predict mental health outcomes. Higher depression rates were associated with factors such as family problems, inadequate sleep, psychological issues, financial challenges, and a COVID-19 diagnosis. Women, with an average age of 28.5 years, experienced varying levels of depression and anxiety influenced by various factors. The Gradient Boosting and RF models accurately predicted depression and anxiety symptoms. In general, all models performed similarly in terms of accuracy.

PPD risk prediction models were developed using electronic health record (EHR) datasets from single and multiple sites [44]. Data from Weill Cornell Medicine and New York-Presbyterian Hospital in New York City, USA, focusing on individuals aged 18 to 45, was utilized to develop the models. An end-to-end framework was developed to extract features and process the data, which included demographics, clinical diagnoses, medication prescriptions, laboratory results, and unstructured clinical notes. A PPD diagnosis was defined as using an antidepressant within one year after childbirth, based on the Systematized Nomenclature of Medicine. ML models, including RF, Decision Trees, Extreme Gradient boosting, Regularized

Logistic Regression, and Multilayer Perceptron, were used to train and optimize the model using Sequential forward selection separately for women with or without a mental disorder history. In the PPD group, higher emergency room visit rates, Caesarean delivery, medication prescriptions, past or current mental health conditions, being a single parent, and pregnancy complications (e.g., palpitation, diarrhea, vomiting, abdominal pain) were associated with increased risk of PPD. While this study incorporated clinical diagnoses, medication prescriptions, and laboratory results, it did not consider pre-pregnancy health conditions.

The need for a more reliable comprehensive tool for identifying mothers at risk of PPD was recognized and implemented in a study by Elday Hochman et al. [19]. Longitudinal EHR data over a period of eight years from Clalit Health Services (CHS) was utilized to develop a PPD risk prediction model. The data excluded non-singleton births, stillbirths, and births ending with infant death. After primary and secondary exclusions, the final cohort consisted of 214,359 individuals, from which the training and validation sets were derived. Out of the initial 156 (sociodemographic, clinical, and obstetric) potential predictor features in the model development, 65 features were identified as having a significant impact on model performance due to their nonzero SHAP values. The model was built using XGBoost using the SHAP mean absolute values to measure how each feature contributed to predicting PPD. A calibration plot showed consistency between predicted and observed risks across different risk scores. The model's accuracy was measured using AUROC, and 95% confidence intervals were calculated using bootstrapping. The model consistently performed well for age and first-time births but less accurately for women without a psychiatric history. Additionally, the birth cohort was categorized into "low-risk" and "high-risk" based on PPD risk scores, with the "high-risk" group characterized by factors such as prior psychiatric disorders, increased third-trimester

healthcare visits, higher BMI, smoking, lower birthweight, and gestational age. This group also experienced more pregnancy complications and showed distinct blood test patterns, more tests during pregnancy, and earlier gestational tests compared to the "low risk" group. The study suggests using symptoms and predictive modeling together makes it more accurate at spotting those at risk of or experiencing PPD.

A PPD detection and prevention study in expectant mothers suggested perinatal (or peripartum) interventions [45]. This pilot study used six ML algorithms featuring longitudinal clinical information and patients' socio-demographic characteristics. The statistically significant variables associated with PPD were selected (71 variables were diagnoses, and 22 were medications). This study evaluated each model's performance using the area under the receiver-operator curve in 10-fold cross-validation by differentiating variables into demographic, diagnoses, and medication variables. The SVM model showed the highest AUC whereas Decision Tree with least AUC. Race, threatened abortion, prior or prenatal depression disorder, anxiety, backache in the 3rd trimester, and muscle pain in the 2nd trimester were significant associated factors. Also, antidepressant use across three trimesters was found to be a strong predictor of PPD, consistent with previous studies. Though medication variables were included in the research, none of the chronic illnesses were included.

A study was done to diagnose PPD in women and develop appropriate treatment plans using demographic, depression, and pregnancy survey data [24]. The ML-based algorithm, including decision trees, Naive Bayes, and SVM, and a functional-gradient boosting algorithm were implemented to predict PPD. A final classification tree was made, including factors like being a first-time mother, finances, age, education, other illnesses, sleeping trouble, and

relationships. As this study focused on survey data, the clinical variables were not used in predicting PPD. This research examined several stressors before pregnancy and found that women with depression before getting pregnant were four times more likely to have PPD. Furthermore, the highest prevalence of PPD was observed in women who were younger, unmarried, had a lower income, had low education, or had a baby born less than 37 weeks.

2.1.1 PPD Risk Factors Analysis

Risk factors refer to identifiable characteristics or conditions that research has shown to elevate the chances of experiencing PPD. It is crucial to identify the factors associated with PPD. It has been identified that women within the age range of 18-24 and those with pre-existing anxiety health conditions are particularly susceptible to receiving PPD diagnoses (Figure 3 and Figure 4) [46]. A literature review of studies focusing on identifying risk factors for predicting PPD is provided in this section.

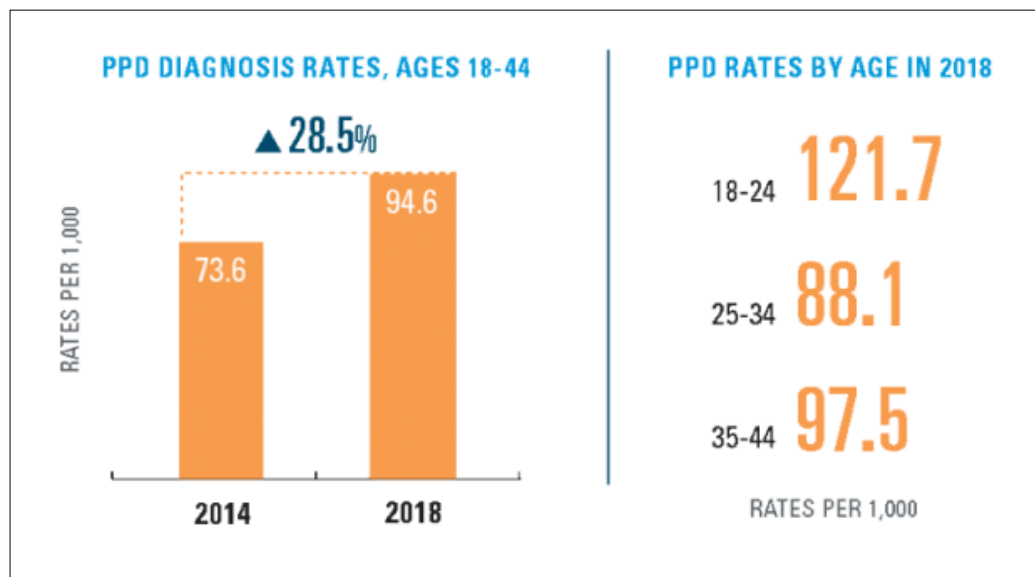


Figure 3. PPD Rate Trend in 2014 -2018 [46].

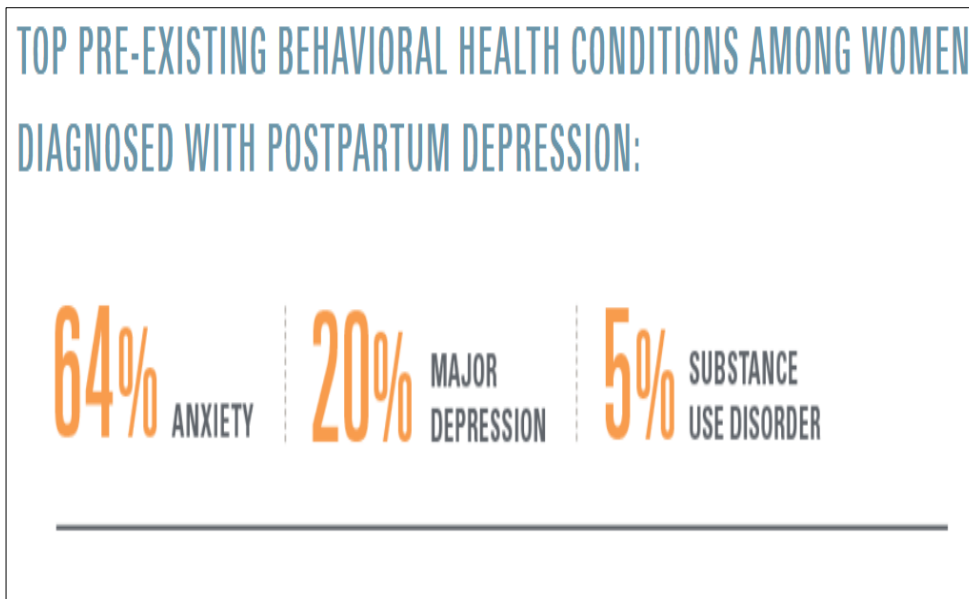


Figure 4. PPD and Pre-Existing Health Conditions [46].

A randomized controlled trial (RCT) examining the effectiveness of tranexamic acid in preventing postpartum hemorrhage (PPH) after vaginal delivery was conducted as part of the Tranexamic Acid for Preventing Postpartum Hemorrhage After Vaginal Delivery (TRAAP) [47]. The study was carried out in 15 maternity units in France and included women who were 18 years or older and planning to give birth vaginally to a single live fetus at 35 or more weeks of gestation. Three types of exposure variables were investigated: pre-pregnancy characteristics (including psychiatric history), pregnancy and delivery factors, and postpartum variables (like neonatal complications and childbirth memories). Factors such as age, psychiatric history, and experiences during labor and delivery were found to be linked to PPD. PPD was found to be associated with negative childbirth memories, as well as induced labor and operative vaginal delivery, with the latter two being significant risk factors. Pre-pregnancy characteristics and obstetric events, emphasizing the need for targeted screening and intervention strategies, were identified as risk factors. Although the findings provide valuable

insights into postpartum care, potential limitations are underestimation and reliance on self-reported screening.

The effects of different factors on PPD and post-traumatic stress disorder (PTSD) among women in Slovakia who experienced traumatic childbirth were determined in [48]. A multi-step approach was employed to investigate the impact of sociodemographic factors, maternal and child health complications, and childbirth experiences on postpartum well-being. The study investigated the postpartum experiences of 437 females, including childbirth satisfaction, maternal and child health complications, and overall preparedness. Standardized questionnaires assessed PTSD symptoms, PPD risk, birth satisfaction, and perceptions of trauma and respect during childbirth. This study found an association between primiparity, maternal and child health issues, previous trauma, and PPD/PTSD, with lower birth satisfaction levels correlating with higher depression and PTSD symptoms, emphasizing the significance of subjective birth trauma perception and perceived birth respect as contributors. The study acknowledged limitations in sample representation and the complexity of understanding the factors involved while highlighting the high reliability of data collection and analysis which enhanced the validity of the research findings.

In 2021, an online survey involving [49] 3,523 postpartum women in Brazil, South Korea, Taiwan, Thailand, and the United Kingdom was conducted to investigate factors related to PPD symptoms during the COVID-19 pandemic. The criteria for this study included individuals aged 18 to 49 who are within the first six months postpartum. Descriptive statistics were performed, including calculating frequencies and percentages for categorical variables and means and standard deviations for continuous variables. Chi-square tests and t-

tests were used to detect associations with PPD symptoms, where PPD was defined as an EPDS score exceeding 13. A binary logistic regression model was employed to pinpoint the factors explaining the association with PPD. This included calculating crude and adjusted odds ratios (OR and AOR) and their corresponding 95% confidence intervals. The independent variables that exhibited a p-value below 0.05 in the simple linear regression analysis were utilized in the multiple linear regression model. Results indicate that both Taiwan and Thailand exhibited a reduced risk of experiencing PPD symptoms compared to individuals in Brazil. Furthermore, 29.3% of women exhibited PPD symptoms linked to younger age. High-risk factors for PPD include younger women experiencing health problems during pregnancy, delivery, or postpartum, no improvement or worsening of food security during COVID-19, feeding babies with expressed human milk or complementary food, receiving low or medium support, and having low social support. However, this research identified health problems as a contributing factor to PPD but did not delve into specific details regarding the types or nature of these health problems.

Several factors were examined, including socio-demographics (age, education, occupation), substance use, reproductive characteristics (pregnancy index, inter-delivery interval, live children), and maternal social factors (violence, support, gender satisfaction, decision-making) in a study conducted in Ethiopia [50]. This study included 479 postpartum mothers, all within the first year after childbirth and aged at least 18 years old. Both bivariate and multivariable analyses were conducted using a binary logistic regression model. Variables with $p < 0.25$ in the initial analysis were included in a multivariable model to control for confounding, and those with $p < 0.05$ were considered statistically significant. In the results, a prevalence of 23% was observed for late PPD, alongside factors such as husband's Khat use, partner dissatisfaction

with the baby's gender, difficulty in meeting the husband's sexual needs, postpartum intimate partner violence, and low social support. It is noted that being cross-sectional does not necessarily establish cause-and-effect relationships.

A cross-sectional study was conducted involving 1028 women aiming to investigate the link between dietary patterns and elevated PPD symptoms among participants in the initial phase of the Maternal and Child Health cohort study [51]. The study employed the Food Frequency Questionnaire (FFQ) to collect dietary data. Four distinct dietary patterns—prudent, sweet and dessert, junk food, and western—were identified using exploratory factor analysis (EFA) and EPDS. Data analysis involved various statistical tests, including the chi-square test, Fisher's exact test, independent sample t-test, and multiple logistic regression (MLR). The study utilized a multiple logistic regression model to examine how high PPD symptoms relate to dietary patterns. The study found that 24% of participants experienced high PPD symptoms. Compared with the Prudent dietary pattern, high adherence to the Western dietary pattern was linked to an increased risk of PPD symptoms. However, no significant association was observed between sweet, dessert, or junk food patterns and high PPD symptoms. When comparing the two groups based on income, smoking, history of chronic disease, gestational diabetes, dietary supplement uses during pregnancy, types of childbirth, and the gender of the baby, no significant differences were found. A limitation of this study is that it excluded women with prior mental illness or depression, epilepsy, nephropathy, or cancer, and abnormal pregnancies.

In 2019, Smorti et al. [52] analyzed PPD in 161 Italian nulliparous low-risk women to investigate multiple risk factors and relate them to labor and birth experience. Socio-

demographic and clinical measures included age, educational level, work status, marital status, information about the number of years of their relationship, and information about a planned or unplanned pregnancy. Psychological measures included levels of depression and anxiety during pregnancy. Relational measures included the relationship with the mother, father, and partner, as well as prenatal attachment to the child. In addition, labor measures and mode of delivery were also included. Age, induced labor, prenatal anxiety, and depression were found to be significant risk factors for PPD. On the other hand, the length of the relationship with the partner, level of education, employment status, and planned pregnancy were not significant. The study's limitation lies in its inclusion criteria, as it only encompassed nulliparous women aged between 18 and 42 with no risk during pregnancy, excluding those with twins, previous miscarriage, or abortion experiences.

In 2017, G. Palumbo et al. [53] established screening procedures in Italy to identify women at risk of PPD as part of the "Prevention and Early Intervention for Risk of PPD" project. A total of 1,558 women were screened, with an average age of 32.5 years. The Italian version of the EPDS was used to assess symptoms of depression. Information collected included delivery, maternal health problems, pre-delivery and pregnancy details, stressful events in the past year, mental health conditions before pregnancy, perceived family, and sociodemographic variables. Using SPSS, the sociodemographic and psychosocial characteristics of women with and without current PPD symptoms were summarized. LR was used to identify the PPD. A significant proportion of women (7.1%) in the study tested positive for PPD, and those with positive scores showed higher rates of self-harm thoughts, recent stressful events, depressive and anxiety symptoms, psychotropic drug use, lower social support, and relationship dissatisfaction. The analysis revealed that loss of interest during pregnancy and lack of

psychological support from family and friends were the most significant predictors of PPD symptoms. Other significant predictors included anxiety or depressive symptoms during pregnancy, job loss or change, personal health problems after childbirth, sleep disorders, difficult infant temperament, and history of a mental health condition. The study acknowledges certain limitations, including using a non-random sample, and it may introduce bias and limit the generalizability of the findings, as this group might have had experiences different from the broader population.

A web-based survey using a cross-sectional design analyzed PPD risk factors in U.S. women who gave birth to a live infant after COVID-19 was declared a public health emergency [54]. Out of the 670 postpartum patients in the study, one in three screened positive for PPD, and one in five showed major depressive symptoms. Formula-feeding was associated with a 92% higher likelihood of PPD and a 73% higher likelihood of major depressive symptoms compared to breastfeeding. In addition, PPD risk increased by 74% with infant NICU admission, 4% per postpartum week, and 71% due to COVID-19-related worry. Due to reduced healthcare access, changes in peripartum care, and limited early telehealth options, infection concerns for themselves or their infants during the COVID-19 pandemic also increased the likelihood of screening positive for PPD. This study has limitations due to its reliance on a social media-based convenience sample, which may not fully reflect the diversity of the postpartum population, and it did not consider all potential PPD factors or regional infection rate differences.

A study assessed the probability and the prevalence of diagnosed PPD occurrence among first-time mothers (primiparous women) and examined how maternal factors associated with PPD

differ between adolescent mothers (ages 12–19) and adult mothers (ages 20 and older) [55]. An observational design was utilized to analyze data from 61,226 first-time mothers who had at least one non-emergency visit within ten years prior to their first live birth. Data were obtained from three sources: (1) electronic health records (EHR) from Intermountain Healthcare, (2) electronic health records (EHR) from the University of Utah Health, and (3) the Utah Population Database (UPDB), which encompassed a wide range of socioeconomic, demographic, psychological, and clinical factors. Using multivariable logistic regression, the study found that a history of depression or anxiety is a significant factor. A higher rate of PPD was diagnosed among adolescents (6.1%) compared to adults (3.8%), and maternal demographic factors associated with PPD were more prevalent among adolescents. Adolescents also had a more considerable proportion of potential PPD risk factors, such as non-White race, Hispanic ethnicity, and various health and lifestyle factors. Moreover, adolescent mothers exhibited a greater tendency to postpone prenatal care, with a higher occurrence of inadequate prenatal care and a prevalence of tobacco use and infections in comparison to adult mothers. It was found that the youngest and oldest individuals among the participants had a higher risk. The limitation of the study included a potential misclassification of PPD and associated maternal factors due to reliance on diagnostic codes, which may underestimate mild PPD cases and the unavailability of clinical records from outside the study's health systems.

A cohort study of all women with singleton births over 11 years in Sweden found that the risk of PPD increased with a history of depression, advanced maternal age, and gestational diabetes [56]. Poisson regression models estimated the relative risk of PPD using incidence rate ratios. Women with a history of depression have a 20-fold higher risk of PPD compared to those with

no prior depression. For women with a history of depression, higher PPD risk was associated with advanced maternal age (>30 years) and pregestational diabetes. In contrast, among women without a history of depression, PPD risk increased with young age (<24 years), older age (>35 years), and Caesarean or instrument-assisted delivery. Also, moderate preterm delivery (32–36 weeks) increased PPD risk regardless of depression history. Gestational diabetes raised PPD risk for all women, while pregestational diabetes posed an additional risk only for women with a history of depression. A shorter gestational age increases PPD risk, particularly for preterm births. Although 11 years of data were analyzed, the predictors were limited to obstetric, gestational, psychiatric, and demographic factors, excluding other disease factors.

2.1.2 Summary

Research analyzing the risk factors for PPD has found that a person's history of depressive disorders, such as depression or anxiety, is a significant predictor [4], [53], [55]. Previous studies have primarily looked at factors related to maternal and paternal demographics when considering potential predictors. Other key factors associated with PPD include health problems during pregnancy [49], lack of social support, experiences of violence after giving birth, and dissatisfaction in the partner relationship [50]. Some studies have considered gestational diabetes as a separate factor, but there is no statistical evidence to confirm a significant link [51]. Age is a unique risk factor, with younger age being associated with a higher risk [56] and its impact on predicting PPD can vary depending on different combinations of factors.

In PPD research, statistical methods and ML techniques have been employed to forecast future outcomes. By examining historical data, the research seeks to reveal concealed patterns and comprehend the factors influencing the onset and severity of PPD. This approach enables early detection and precise intervention, enhancing the welfare of postpartum individuals and their families. With the utilization of predictive analytics, researchers are refining their capacity to identify PPD risk factors and tailor treatments to individual needs. It was found that psychiatric history, stress, gestation, and demographic-related variables are reliable predictors of PPD [19], [24].

2.2 Postpartum Depression Risk Factors: Chronic Illness

People with chronic illnesses often have a higher prevalence of depression and anxiety [57]. This section presents a concise overview of the literature on the relationship between chronic diseases and PPD.

R. D. Björvang et al. [58] aimed to address existing gaps in the literature concerning the relationship between Diabetes Mellitus in Pregnancy (DMP) and perinatal depression, specifically examining antepartum and PPD separately. They conducted a longitudinal investigation within a large prospective cohort study. By including multiple assessment methods for depression and adjusting for relevant confounders, the study provided a comprehensive understanding of the association between DMP and perinatal depression. The findings revealed a significant positive association between DMP and PPD. However, the study did not find a statistically significant association between DMP and antepartum depression once confounders were considered. Sub-analyses examined specific types of Diabetes Mellitus

(pre-gestational, gestational, and unspecified) and found varying associations with perinatal depressive symptoms. The study highlights the complexities of metabolic factors, hormonal changes, and psychological well-being during this period. The acknowledged limitations were low prevalence of DMP which may impact generalizability, and possible biases due to sample characteristics such as higher education levels. Also, future research is suggested to investigate how different types of DMP are related to depression over time and explore underlying biological pathways.

A systematic review and meta-analysis [59] of longitudinal studies investigated the association between thyroid autoimmunity during pregnancy and the weeks after childbirth and the risk of developing PPD. Women with and without anti-thioperoxides antibody-Thyroid Peroxidase Antibodies (TPOAb) positivity were specifically focused. The analysis involved five studies, encompassing data from 449 TPOAb-positive women and 2483 TPOAb-negative women. It revealed a significantly higher risk of developing PPD in the TPOAb-positive group, although there was some heterogeneity. The study indicates that thyroid autoimmunity during pregnancy and postpartum is linked to a higher risk of PPD. However, more rigorously designed studies are needed to verify this association and to better understand the underlying pathophysiological mechanisms, which was a limitation of this research. Additionally, only one specific disease was explored in this study.

A multinational study was conducted during the COVID-19 pandemic [60] aimed to assess the mental health of pregnant and breastfeeding women (9041) in Ireland, Norway, Switzerland, the Netherlands, and the UK. Descriptive statistics were used to analyze women's characteristics and mental health scores. Associations between depressive symptoms, anxiety,

and stress were assessed using logistic and linear regression models, with significant covariates retained in the final adjusted model, including country, maternal age, professional status, smoking, chronic somatic and mental illness, planned pregnancy, and breastfeeding status. Among the pregnant women, 15% exhibited major depressive symptoms, while 11% had moderate to severe generalized anxiety symptoms. In the breastfeeding cohort, 13% had major depressive symptoms, and 10% experienced significant generalized anxiety. Pregnant and breastfeeding women who reported chronic mental illness, smoked, or lived in the UK or Ireland were likelier to experience major depressive symptoms. These symptoms were also linked to not breastfeeding, having an unplanned pregnancy, and having a chronic physical illness after childbirth. This study has a limitation related to potential selection bias, as the survey was distributed via social media and did not assess whether depressive symptoms were linked to postpartum status.

The prevalence of PPD was high in an institutional-based cross-sectional study conducted in Ethiopia [61]. All mothers who had delivered within the last 12 months and followed up for PPD were selected for this study. The PPD outcome variable was measured by using the EPDS. This study uses the SPSS statistical package, and bivariate analysis was done to find the association between the independent and dependent variables. Among the 408 participants, 7.4% had chronic medical illnesses. The result demonstrated that about 33.82% had PPD, and those who had other chronic physical illnesses were 7.7 times more likely to develop PPD. In addition, unstable marital status, infant death incident, unplanned pregnancy, and age greater than 30 had increased probability for PPD. Even though this research explored chronic physical illnesses, the prediction of specific chronic illnesses was not determined.

A review examined the prevalence of PPD in three populations: women who use substances, women with current or experience of abuse, and women with chronic illness [62]. No matter the direct or indirect effect, this review found that PPD increased among women with substance use and those who experienced abuse, and these women are more likely to seek treatment. Additionally, this review found an increased risk of PPD in only one of the four reviewed studies involving women with chronic illness. The combined effect of multiple chronic health problems over a single or specific chronic illness increases the risk of developing PPD. The main limitation acknowledged in this review was the failure to confound depression in pregnancy in most of the studies.

A study in Lebanon analyzed the determinants and prevalence of PPD [63] in 369 women from two locations, Beirut and Bekaa Valley. The chosen women were screened using EPDS, and scores above a threshold of 12/13 were considered as PPD. Bivariate analyses were performed using chi-square tests and identified covariates were adjusted to predict the PPD using multiple LR analyses. In both areas, the study determined the significant factors of PPD as the lack of support and prenatal depression. Also, women with prenatal depression and multiple chronic health problems were more likely to develop PPD. The prevalence of PPD was significantly higher in Bekaa Valley (21%) than in others. At the same time, the pattern of having more than one chronic illness was seen as a significant predictor for PPD in both regions. However, this study did not reveal or classify the chronic diseases that act as risk factors for PPD. In addition, the limitation mentioned in this study was that rather than psychiatric evaluation or other objective measures the potential risk factors were based on self-reports and retrospective information.

2.2.1 Summary

Considering chronic diseases as the risk factor for developing PPD, only limited studies have been conducted. Among those, researchers found out that women with chronic illnesses had a higher chance of having PPD, and those having more than one chronic physical illness had an increased risk for PPD. In addition, the data used in those studies was on a minimal population or a concise period. Moreover, none of the studies had determined the specific chronic illnesses impacting PPD.

2.3 CDC-PRAMS Data PPD Analysis

Researchers have previously utilized the PRAMS dataset for studies exploring various aspects of PPD, including its prevalence, significant risk factors, and the impact of health, maternal behaviors, and experiences on postpartum mental health. Below is a brief overview of selected research articles that have utilized PRAMS data to analyze PPD, shedding light on significant findings and their implications for maternal and infant health.

A. Paul et al. [8] used 28,755 records of PRAMS data and utilized different ML algorithms, including RF and SVM, to predict PPD using metrics such as AUC values, accuracy, precision, recall, F1 score, specificity, and sensitivity. Health factors such as pre-pregnancy BMI, nutrition status, and health problems while ignoring demographic and socioeconomic factors were considered. The analysis of different models revealed that SVM performed the best overall, achieving an accuracy of 74% and highest precision and F1 score. TabNet showed the highest AUC value, while the Gradient Boosting Machine (GBM) had the highest specificity,

and KNN had the highest sensitivity. While integrating ML models into remote monitoring systems for early detection of PPD was suggested, the dataset's state-specific nature and limited diversity may pose challenges to maintaining accuracy across varied populations. Also, no risk factors were analyzed since this research focuses on the ML model evaluation.

PPD risk factors and prevalence were assessed using general-purpose statistical software (STATA) on PRAMS data [64]. This study highlighted the need for evaluating the epidemiology of PPD detection, prevention, and control strategies. A Chi-square test was conducted to assess the difference between the PPD and non-PPD groups, and LR models were created to analyze the risk factors. The evaluation showed that 12% of the 4,022 mothers had PPD, with prevalence fluctuating over the years. PPD was also common among unmarried mothers, those with lower education, low income, preterm births, low birth weight babies, and those receiving WIC during pregnancy. Additionally, mothers with prior depression or hypertension had the highest prevalence, while no significant differences were observed based on delivery type. Sociodemographic factors such as younger age, being Black, unmarried, or having a lower income were associated with higher odds of PPD. Depression before pregnancy, abuse before or during pregnancy, job loss, extended time away from husband/partner due to work-related travel, husband/partner not wanting the pregnancy, or arguing more than usual with a husband/partner were the key risk factors determined. Clinical factors like hypertension, unintended pregnancies, preterm births, and low birth weight babies also increased the risk. Additional stressors, such as divorce, homelessness, financial difficulties, substance abuse in someone close, and the death of a loved one, further elevated the risk of PPD. The sample data for this study was limited in size and was chosen only from a single state.

In 2014, Sundaram S et al. [65] investigated the relationship between maternal health issues and PPD using PRAMS data. A Hierarchical Linear Modeling (HLM) approach was used to explore various maternal morbidities and their potential association with PPD. A total of 13 medical and obstetric issues were examined that can occur during pregnancy within two distinct samples: women from all states and women specifically from Alaska and Maine. Approximately 13.8% of participants showed symptoms of PPD, while 7.6% had a formal diagnosis of PPD. Five statistically strong significant maternal morbidities identified with both PPD symptoms and PPD diagnosis are vaginal bleeding, kidney/bladder infection, nausea, preterm labor, and bed rest. Hypertension and blood transfusion emerged as strong predictors for the diagnosis of PPD. The main findings reveal that both PPD symptoms and diagnosis are associated with preterm labor and nausea in Alaska and Maine. Additionally, vaginal bleeding, kidney/bladder infection, blood transfusion, and bed rest were associated with PPD symptoms only, whereas pre-existing diabetes was associated with PPD diagnosis only. The study acknowledges several limitations, including the potential for recall bias and underreporting of PPD symptoms due to the self-reported nature of PRAMS data. Discrepancies between self-reported symptoms and PPD diagnosed by a healthcare provider were also noted. Limited generalizability was highlighted due to the state-specific nature of the data. Furthermore, the study points out the potential for bias due to uncontrolled variables and the exclusion of observations with missing data.

The prevalence of PPD using PRAMS data was analyzed considering the effects of different stressful life events [66]. The overall prevalence of self-reported PPD was 14.8%, which was higher in teen mothers, unmarried mothers, and low-income mothers, lower in mothers with graduate degrees, and among those with stressful life events. There was no significant

difference in prevalence by race or parity. This study conducted Chi-square tests, t-tests, and logistic regression analysis by categorizing 13 stressors into four groups: financial, relational, trauma-related, and emotional. The results found the highest probability of PPD in mothers who experienced severe relationship problems with low financial and high trauma-related stresses. Interaction effects showed the highest PPD likelihood with high relational and trauma stresses but low financial stress. Married teens were also more likely to experience PPD than married mothers aged 30 or older. The limitations highlighted include the inability to establish causal inference due to the cross-sectional design and potential biases from the self-reported nature of the data. The generalizability of the findings was restricted to states with similar demographics, such as higher proportions of low-income, less educated, and unmarried mothers. Additionally, key factors like pregnancy complications, birth outcomes, stress perception, past depression history, biological factors, and paternal support were not examined.

Shin et al. [20] developed predictive models utilizing the PRAMS 2012-2013 dataset. Nine ML algorithms, including k-nearest neighbor (kNN), recursive partitioning (RPART; a decision tree-based method), support vector machine (SVM), stochastic GBM, Random Forest (RF), Neural Network (NN), Naïve Bayes (NB), Logistic Regression (LR), and AdaBoost were used in this study. The study revealed that among those tested, RF emerged as the most effective in predicting PPD, followed by SVM. Random Down-Sampling and The Synthetic Minority Over-Sampling Technique (SMOTE) were used to address the imbalance, and a 10-fold cross-validation strategy was used to evaluate the classification models and the area AUC as the performance metrics. The study results showed that women of younger age, lower education, small-for-gestational-age infants, smoking reduction during pregnancy, and unmarried status are more likely to have PPD. Other important key predictors were stress

during pregnancy, prior depression, weeks of breastfeeding, income, dental hygiene, and infant gender. Self-reporting bias and the likelihood of limiting generalizability due to missing data were recognized as limitations.

2.3.1 Summary

The research on CDC-PRAMS data primarily focused on maternal, relationship, and psychiatric variables to predict PPD and its risk factors. However, current studies in this field often rely on data from specific locations (states) or limited time periods. Additionally, no comprehensive study has considered chronic illnesses as potential predictors of PPD. SVM was identified as a high-performing model [8], [20]. Key factors consistently identified across studies include a history of depression [20], [64], [67], younger age [20], [64], [66] and stress [20], [64], [66]. The predictors identified in these studies were consistent with findings from other research using different datasets.

2.4 PPD Tool

Section 1.1.3 discussed standard PPD screening tools, including EPDS and PDSS. Advancements in PPD screening have introduced new tools that assess a broader range of factors, such as psychosocial and cognitive risks. Details of these tools are outlined below.

AJ Bjertrup et al. [68] examine how negative thinking about infant distress during pregnancy relates to PPD and provide a proof of concept to test the practicality of measuring negative neurocognitive bias using an online risk screening tool, REDCap. Eighty-seven participants in

their second or third trimester completed the online screening via a webpage on infant distress reactivity and psychosocial risk questionnaires. Bivariate associations were analyzed, followed by LR and multiple LR for PPD and post-birth depressive symptoms as outcome variables. The predictor variables included Affective Neurocognitive Processing of Infant Stimuli (emotional reaction to an infant distress video) and psychosocial factors. Other factors included age, depressive symptoms during pregnancy, education level, pregnancy week, parental bonding, attachment to the unborn child, job status, financial worries, income level, social support, family history of psychiatric disorders, personal history of psychological illness, loss of a parent, and childhood trauma. Key findings showed that negative emotional reactivity to an infant distress video and negative interpretations of infant cries during pregnancy led to PPD and symptom severity. The practicality of the online screening tool was less than ideal. The low response rate suggests the need for a shorter, more optimized screening tool. As mentioned in the paper, the key limitation indicated that the tool is not feasible in its current form, and validation is required on large-scale data.

In 2012 McDonald S et al. [69] developed and validated a prenatal screening tool to identify women at risk of postpartum distress. A longitudinal cohort data from the All Our Babies (AOB) study was used to develop the tool based on regression coefficients. The independent variables selected to derive the screening tool are depression in late pregnancy/4 months postpartum, anxiety in late pregnancy/4 months postpartum, stress in late pregnancy, history of depression, history of abuse, and social support in late pregnancy, and relationship tension. The tool demonstrated higher sensitivity and broader focus compared to the EPDS, effectively identifying women at risk of both depression and anxiety. However, it showed lower specificity and performed better in women with middle to high socioeconomic status groups. Limitations

include reliance on self-reported measures instead of standard psychiatric diagnoses, missing data, and underrepresentation of ethnic minorities and low-income households. Despite these challenges, the tool provides a comprehensive approach to psychosocial risk assessment during pregnancy.

In summary, beyond traditional scales like the EPDS, innovative tools provide a broader perspective by incorporating emotional reactivity, psychosocial variables, and personal histories. While these tools show promise, low response rates and limited generalizability highlight the need for optimization to create more reliable and effective solutions. Additionally, there are limited studies focused on developing new tools for screening or calculating the likelihood of PPD, emphasizing the need for further research in this area.

2.5 Summary

In the field of developing predictive models for PPD, research commonly considers a range of variables related to mental health, such as psychiatric history (during pregnancy, before pregnancy, history of PPD, other depression or psychiatric illnesses, and family history of depression). Furthermore, identified risk factors for PPD encompass financial aspects (such as low income), age, mode of delivery, gestational medical conditions or illnesses (including gestational diabetes), unplanned pregnancies, preterm births, and lower levels of education. These models also incorporate factors associated with the gestational period, maternal factors, and variables related to the family environment. However, it is essential to acknowledge that there has been a relatively limited focus on investigating the potential impact of pre-gestational health, disease, and specific conditions as predictive factors for PPD in the current literature.

While research has shed some light on the relationship between chronic illnesses and PPD, it remains a relatively understudied area. Significantly, the existing literature has not identified specific diseases that can be definitively classified as predictors for the onset of PPD. It has been identified depression as a potential risk factor for developing chronic diseases, particularly cardiovascular disease [12]. Also, Thyroid autoimmunity during pregnancy was identified as a risk factor for PPD [59]. Further exploration and investigation are needed to better understand the potential role of these diseases in predicting PPD. It is crucial to emphasize that the understanding of predictive models integrating chronic diseases as potential risk factors for PPD prediction is still in its early stages and lacks comprehensive insight.

Chapter 3

Methodology

This chapter provides a comprehensive overview of the research methodology. The proposed framework includes analytical methods for predicting PPD and identifying risk factors, a dashboard for enabling data exploration, and a web-based tool to find the likelihood of PPD based on user input. The research methodology comprises several components ranging from data collection to the visualization and final web-based tool (Figure 5). These components are explained in this section.

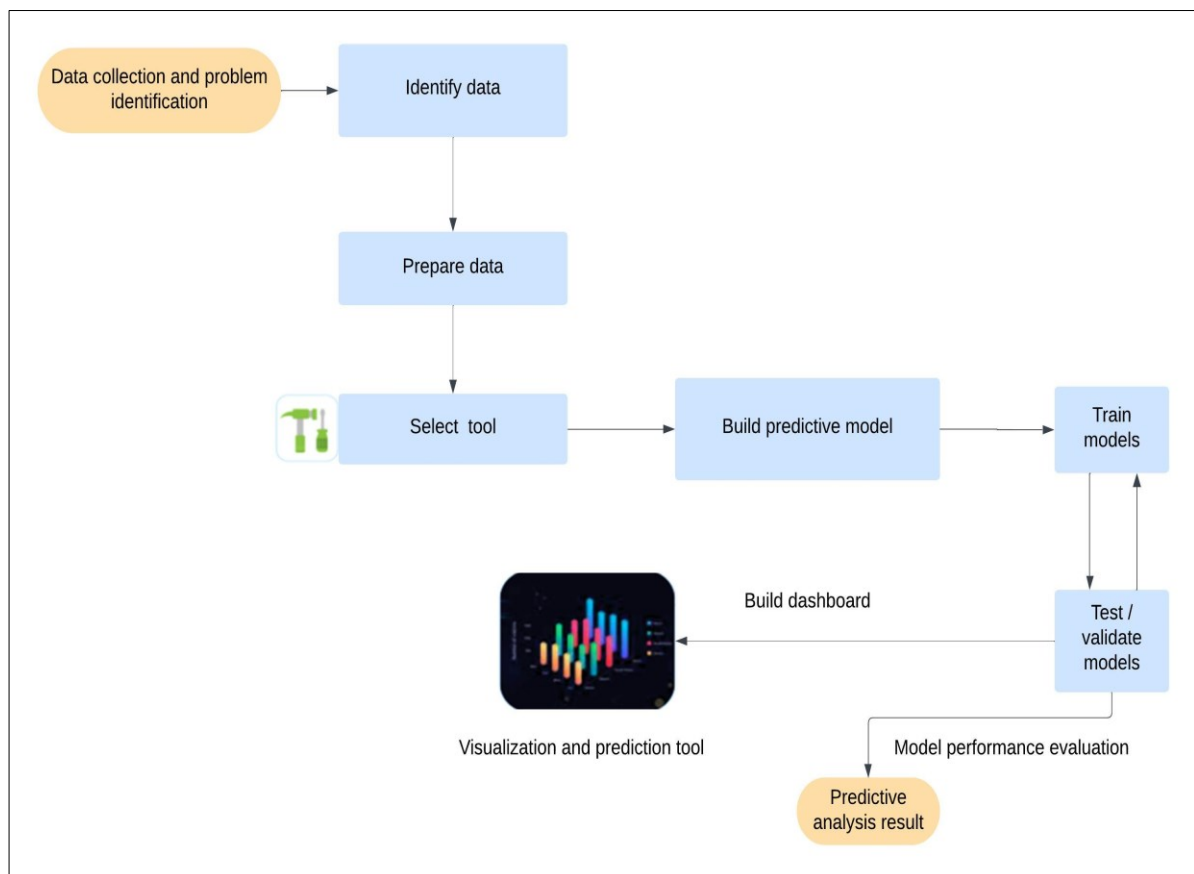


Figure 5. Proposed Research Model.

3.1 Data Collection

The primary data source, PRAMS has undergone several phases of questionnaires, starting from Phase 1 (1988–1989) and continuing to Phase 9 (2023–present). The questionnaire is periodically updated and includes three parts:

- Core questions: Used by all sites, covering topics like maternal pre-pregnancy status, prenatal care, smoking, and alcohol use.
- Standardized questions: Optional questions for sites to choose from.
- Site-developed questions: Unique questions used by individual sites.

The PRAMS contains a standard set of variables in five categories, as given below [40]:

- Birth Certificate: Provides information primarily on maternal and infant demographics.
- Operational Variables: Indicate the mode used to complete the questionnaire, such as by mail or phone.
- Weighting Variables: Account for the PRAMS survey design and ensure statistical data weighting.
- Questionnaire Data: Represents the responses collected from the PRAMS survey.
- Analytic Variables: Pre-calculated variables derived by combining different variables within the dataset.

The anonymized dataset obtained for this study comprised 950 fields which includes maternal and paternal demographics, infant- and family-related factors, chronic diseases, postpartum,

gestational, and obstetric variables. The collected records had a valid PPD symptom variable ‘PP_DEPRESS¹’ with values 1 and 2 (False and True). The data was provided as a SAS file containing detailed records, which was then exported to an SSMS database for processing. SSMS was chosen for its robust data management capabilities.

3.1.1 Ethics Approval

The Research Ethics Board (REB) of the University of Northern British Columbia (UNBC) reviewed the ethics approval application and determined that REB approval was not required.

3.2 Data Preparation

Data preparation (Figure 6) is a critical step in the data analysis process, involving procedures that make raw data suitable for consumption by ML models [70]. These procedures include cleaning, transforming, and organizing data. Adequate data preparation ensures optimal outcomes by enhancing the efficiency and reliability of ML models.

¹ PP_DEPRESS refers to the target variable "Post-Partum Depression," which was used to predict the likelihood of post-partum depression in mothers.

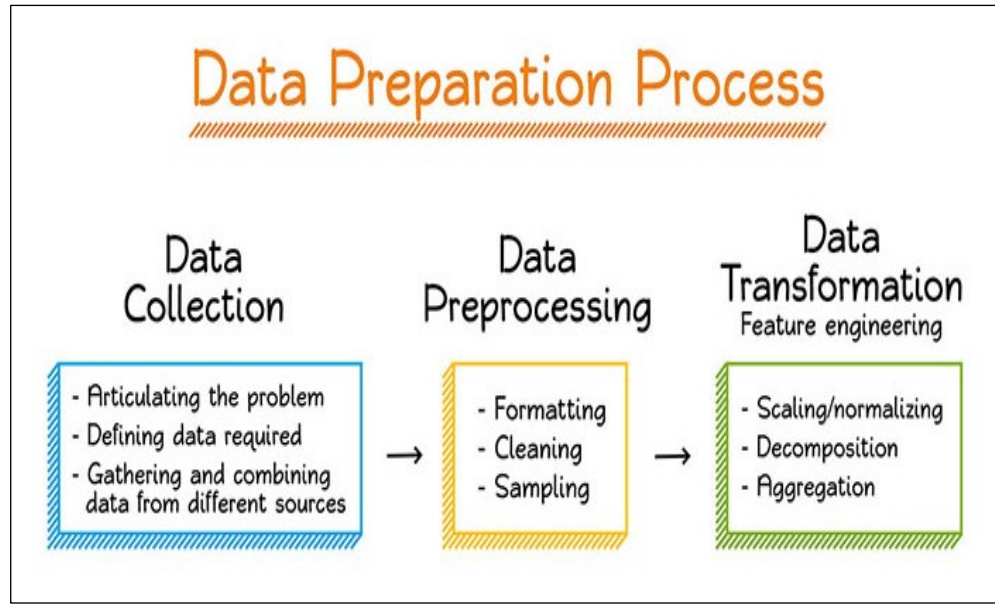


Figure 6. Data Preparation Process [70].

3.2.1 Data Collection

The primary focus of this research was to identify potential high-risk chronic diseases contributing to PPD. So, in addition to the risk factors described in Section 1.1.1, disease-related variables were included in the input features. Specifically, variables such as diabetes and asthma were added to address the research question.

3.2.2 Data Preprocessing

Data preprocessing involves broader tasks such as handling missing values, feature engineering, and handling imbalances in labeled data to improve data quality and relevance, making the analysis more effective and valuable [71]. Proper execution of these tasks ensures reliable results from predictive models.

Identifying the relevant variables that affect the outcome of interest poses many challenges. Sometimes, unrelated variables indirectly influence the outcome, making it crucial to consider all potential variables carefully. The initial dataset obtained was overly complex, leading to model overfitting. This required extensive preprocessing to make the data suitable for analysis. Identifying and handling issues in the dataset includes several tasks, which are explained below.

Missing value treatment

Handling missing values is vital to reduce the impact of poor data quality on the model's performance. Issues such as biased predictions, reduced model reliability, and compromised decision-making often stem from unclean data [71]. Dealing with missing data primarily involves two major methods: imputation and row deletion. The underlying factors for missing values in PRAMS data include item-non-response (explained in Section 3.2.6) and skipping patterns. Item non-response occurs when individuals choose not to answer certain questions. It significantly increases the risk of developing bias, leading to inaccurate or unreliable predictions. Since PRAMS data is survey-based, records with missing data were removed to address item non-response bias. Imputation was applied in cases involving skip patterns. For example, in PRAMS' Phase 5 survey, if a mother reported that her infant was still in the hospital, she was instructed to skip the question about whether her infant was alive. It is reflected in the variable INFLIVE5, where responses were coded as missing for mothers whose infants were still hospitalized. Missing values for INFLIVE5 were imputed by referencing the variable LTH_HOSP, where a response of "7" indicated that the baby was still in the hospital.

Challenges arose when analyzing subgroups within the PRAMS dataset. The primary issue was sample size constraints, with limited entries for certain features in specific states. Additionally, when state-specific features were excluded from surveys, the results became skewed, reducing the reliability of specific analyses.

Irrelevant and redundant information

Knowledge discovery becomes more complicated when there are a lot of irrelevant and duplicative details or noisy and unreliable data. This difficulty arises for the following reasons:

- Multifaceted questioning: The survey may ask similar or nearly identical questions in different sections. It can lead to repeated or conflicting information if participants answer these questions again.
- Incomplete updates: Updating the survey may change or remove questions, but their old versions might remain. It can result in redundant questions in the survey.

For instance, the dataset comprised MH_PPDPR, MH_PPINT (these questions are adapted from PHQ-2 - Phase 2 Questionnaire), and PP_DEPRESS variables which are defined as follows:

MH_PPDPR: Since your new baby was born, how often have you felt down, depressed, or hopeless?

MH_PPINT: Since your new baby was born, how often have you had little interest or pleasure in doing things you usually enjoy?

PP_DEPRESS: Coded as “yes” for PPD symptoms if mother responded “always or often” to MH_PPDPR or MH_PPINT and coded as “no” if mother responded “sometimes, rarely, or never” for MH_PPDPR and MH_PPINT.

The PP_DEPRESS is an analytic variable composite of two variables, MH_PPDPR and MH_PPINT. In the context of composite target variable PP_DEPRESS, MH_PPDPR and MH_PPINT primarily serve as building blocks and there was no specific need to analyze them separately. Here, removing the variables MH_PPDPR and MH_PPINT was considered. Similarly, instances of redundancy can arise, such as the features INFQ_AGE and INFQ_AGE_MOD, both representing infant age in days whereas the latter was identified as being the cleaned version.

In addition, capturing different phases of the questionnaire in varying formats may lead to similar variables. For example, starting from Phase 5, the INFLIVE5 variable reflects a change in the survey skip pattern, where mothers with infants still in the hospital were instructed to skip the question, "Is your baby alive now?" This case is coded as missing in INFLIVE5. In earlier phases (Phase 4 or before), mothers were required to respond to this question, and their responses were recorded in the INF_LIVE variable for comparability. While both variables record the same frequencies for deceased infants, INFLIVE5 has fewer entries for alive infants due to the enforced skip pattern. Additionally, the INFLIVE5_RAW variable captures responses from mothers who did not follow the skip instructions and answered the infant alive question. This response was coded as missing in INFLIVE5 to align with the enforced skip pattern. Since this research focuses on Phase 5 to Phase 8 survey data, INFLIVE5 is selected,

and other similar variables, such as INF_LIVE and INFLIVE5_RAW, are removed during preprocessing.

3.2.3 Feature Selection

Feature selection is necessary to choose the most relevant features (input variables) from the original set of features for building a predictive model. Its purpose is to boost the performance of the model, mitigate overfitting, and enhance the interpretability of the model [72].

Variable inclusion and exclusion

Input variables in predictive models were carefully selected to include only relevant factors, ensuring model simplicity and improved accuracy. All the chronic diseases and health-related variables available in the dataset were added to the input features to address the research question. Variables deemed irrelevant to the predictive goals were removed to minimize errors caused by unnecessary information. For instance, the variable "PRE_STI," which captures discussions about sexually transmitted infections (STIs) such as chlamydia, gonorrhea, or syphilis occurring before pregnancy was determined to be irrelevant and was removed. This step ensured that the model focused solely on meaningful predictors and excluded irrelevant features.

Another example of irrelevant variables is the PRE_CKD, which refers to standard question L26, (Did you do any of the following things at any time during the 12 months before you got pregnant with your new baby?) and (option d: A health care worker checked me for diabetes).

This question asks whether a healthcare provider conducted tests to check for diabetes, regardless of the mother's diabetes status, were removed, recognizing its irrelevancy.

In addition, the inclusion and exclusion of variables were based on data completeness and relevance to the thesis objective. Only eight states with complete and reliable data for key chronic disease variables were retained. Participant records were filtered to include mothers aged 15–55, focusing on the most relevant demographic. Variables critical to the study were prioritized, while redundant or less impactful features were removed using the feature selection algorithm, which is explained in Section 0.

3.2.4 Feature Engineering and Derived Variables

Feature engineering involves transforming and creating features to make data suitable for modeling. Correcting irregularities, enhancing feature relevance, and meaningful transformations of raw data are the main processes involved in feature engineering [71].

Feature engineering was conducted to create new variables such as ABUSE and CHRONIC (Flag type). Derived variables from existing features were introduced to the dataset by transforming or combining existing variables. Thus, additional features, such as MOM_AGE from MDOB_YR4 and ID and YEAR from ID, were created. Creating these new features helps reveal hidden patterns in the data, enhancing the accuracy and performance of the model's prediction. All these processes resulted in a final dataset comprising 23,855 records and 42 features. A nurse practitioner reviewed and confirmed the selection of these final variables, ensuring the clinical relevance and validity of the data used for analysis.

3.2.5 Data Encoding and Scaling

Data transformations and scaling are vital to address issues arising from disparate data ranges and categorical representations, which can otherwise result in biased predictions or inefficiencies in model performance [71]. Encoding categorical data and scaling numerical values makes the data more suitable for analysis, fostering accurate and reliable predictive outcomes.

Encoding such as one-hot or label encoding involves converting categorical variables into numerical formats which can be interpreted by the model. Tree-based models, such as Random Forests (RF), natively handle such data through their tree-splitting mechanism allowing them to evaluate categories directly without assuming specific relationships between data types, thus eliminating the need for encoding. Pre-processed data was scaled for features such as maternal and paternal race and month of birth to be utilized in the LR, NN, and SVM. These ML models are further explained in Section 3.4.

Scaling ensures that numerical variables are standardized to a consistent range or distribution, improving model convergence and performance. Variables such as infant age were scaled for NN and SVM because of their sensitivity to feature magnitude or distribution. Similar to encoding, tree-based models such as RF do not require scaling.

3.2.6 Challenges

Unbalanced data

Conducting thorough exploratory data analysis (EDA) is essential to identify imbalances in datasets, which can severely affect the performance of ML models. Unbalanced data can skew the model predictions toward the majority class. SMOTE was applied to handle imbalances in data. SMOTE generates synthetic samples for the minority class to balance the dataset and improve the model's generalization ability across classes.

Item non-response

When individuals choose not to respond to survey questions, it can result in a biased survey. PRAMS relies on surveys that are sent to new mothers. Not all mothers who receive the questionnaires opt to participate and provide their responses due to a variety of reasons, such as time constraints, privacy concerns, or a lack of interest. This non-response can introduce bias, as non-respondents may have different characteristics or experiences than respondents, posing a significant challenge. It affects the quality and representativeness of the data. With this bias, the data accurately reflects only part of the population, impacting the validity of research findings and decisions based on the data. To address this, biased records were removed, and subgroup analyses were conducted to assess whether non-response bias varied across different demographic groups.

3.3 SPSS Modeler

Although previous research on PRAMS data has relied heavily on SAS (Statistical Analysis System), SPSS (Statistical Package for Social Science), and STATA as the primary analysis software, data mining and ML techniques have gained attention. As a result, some researchers have started to explore open-source software such as IBM's SPSS Modeler, which offers robust analytical capabilities. The reason behind choosing this tool is its following capabilities:

1. The software itself finds the appropriate model for given data.
2. Automated feature selection and classification model selection.
3. Easy to use with a simple drag-and-drop interface.
4. Easy to add source data from multiple sources.

A node in SPSS Modeler represents a specific operation or analysis and is interconnected to other nodes to form a stream that sequences data analysis process steps from input to output. This tool was selected for this thesis for specific tasks such as feature selection and selecting the best predictive models for classification using nodes explained below [73]:

Feature Selection Node:

The most significant predictors for a given analysis are identified using this node. It evaluates input fields relative to a specified target, ranking them based on importance. This process involves:

- Screening: Eliminate inputs such as those with excessive missing values or minimal variation that are unimportant or outliers.
- Ranking: Sort and assign ranks.
- Selecting: identifies the subset of features to utilize in the selected models.

Auto Classifier Node:

It compares multiple predictive models for nominal or binary targets and selects suitable models for the given dataset and target. It allows users to:

- Select Algorithms: Choose from various modeling methods, such as decision trees, neural networks, or support vector machines.
- Experiment with Options: Test multiple combinations of algorithm parameters to identify the optimal configuration.
- Rank Models: Evaluate and rank each candidate model based on criteria such as accuracy or F1 score.

3.4 Predictive Model

Once the data is prepared and cleansed, the next step is to use it for predictive modeling. The four models used for this study are NN, LR, RF, and SVM. The rationale for selecting these models is based on their demonstrated superior performance in predicting PPD, as identified in the literature. Model-specific reasons are provided in Section 4.3.

Input data

The preprocessed dataset was imported from the SQL server to Jupyter Notebook in the Visual Studio environment and read using pandas' data frame. Considering the target variable 'PP_DEPRESS,' the dataset was partitioned into training and testing sets. Better results are achieved when 20–30% of the data is allocated for testing, with 70–80% used for training [74]. Therefore, a 70:30 split ratio was selected for training and testing to ensure sufficient data for model training while reserving enough data to evaluate the trained model's performance on unseen data.

Model Training (Learning)

The ML models were trained on the prepared dataset. In this phase, the models learned the underlying patterns and associations between the input features and the target variable 'PP_DEPRESS.' The models were retrained by tuning hyperparameters, which are configurable settings influencing the learning process and model performance. A stratified fold cross-validation was applied to ensure that each fold maintains the same proportion of each class as the original dataset, which is important given the imbalanced nature of the data.

Model Testing (Decision-Making)

After training, the model's effectiveness was assessed using a separate, smaller test dataset without the target variable. Accuracy and F1 scores were calculated from test results to evaluate how well the models learned to predict PPD. This is described in detail in Section 4.2.

3.4.1 Artificial Neural Network

Artificial Neural Networks (ANNs) are advanced ML models inspired by the human brain's neural structure. Models learn and recognize the patterns by designing the network to process the data in layers [75]. The structure of these layers can solve complex, non-linear problems. Mainly, an ANN consists of three components:

Input Layer: Accepts raw input data and forwards it to the neurons of another layer in the network for processing.

Hidden Layers: This layer applies weights, biases, and activation functions to uncover relationships within the data. An activation function introduces non-linearity to an NN and learns complex patterns and relationships in data. Deeper networks use multiple hidden layers.

Output Layer: Final predictions or classifications are produced in the output layer.

The data flows from the input layer to the output layer through the hidden layer, and each layer's neurons are interconnected. ANNs learn by adjusting weights during training using backpropagation to compute error gradients. Optimization methods such as gradient descent utilize the gradients to reduce prediction errors and enhance model performance. Figure 7 shows the schematic diagrams of ANN.

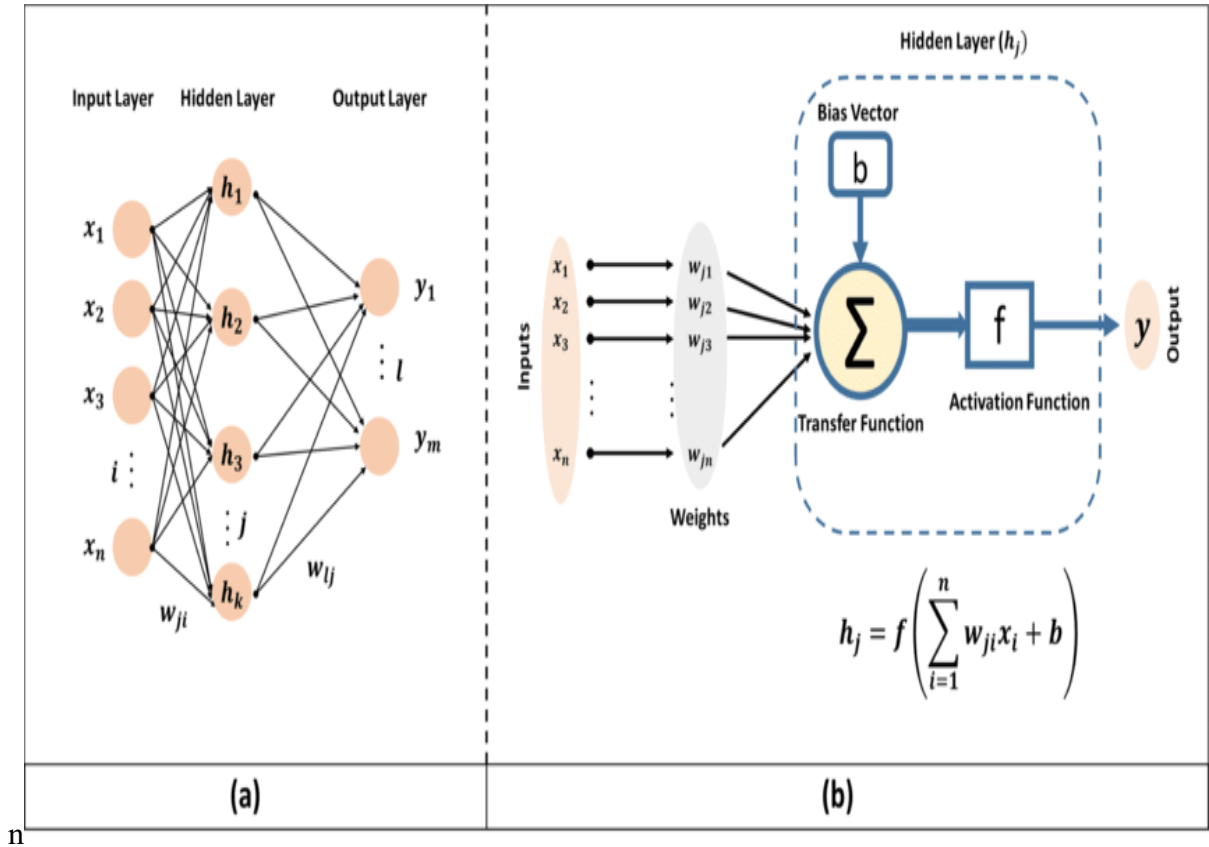


Figure 7. a) ANN (b) Structure of ANN for a Neuron in a Hidden Layer with One Output [76].

The output of a neuron in an artificial NN is evaluated as

$$h_j = f \left(\sum_{i=1}^n w_{ij} x_i + b_j \right)$$

Equation 1. Output of the Neuron

where

x_i : Input values

w_{ij} : Weight connecting input x_i to neuron h_j

b_j : Bias term for neuron h_j

f : Activation function

h_j : Output of the j -th neuron

The versatile characteristics of ANN make it suitable in fields such as image recognition, language processing, predictive modeling, handwriting recognition, fraud detection, and speech-to-text systems. A Multi-Layer Perceptron (MLP) NN classifier was chosen due to its ability to balance complexity and flexibility, making it well-suited for binary classification tasks.

3.4.2 Logistic Regression

Logistic regression (LR) is the most commonly used regression model that creates a linear relationship between the independent variables and the logarithm of the odds for the target variable. This method is designed for binary classification problems where the target variable has two possible outcomes (e.g., success/failure, yes/no, or 0/1). Its straightforward implementation and efficiency make it a reliable choice for classification tasks, predicting the probability of a target class using the sigmoid function, which outputs values between 0 and 1 [77]

The logarithmic odds are transformed into probabilities using the sigmoid function. A threshold (commonly 0.5) is applied to these probabilities to classify the outcomes. Each

coefficient in the model reflects the predictor's impact on the log-odds of the target, aiding in understanding its effect on the outcome. Figure 8 is a visualization of the sigmoid function used in LR, illustrating how LR transforms input features into a probability distribution suitable for binary classification.

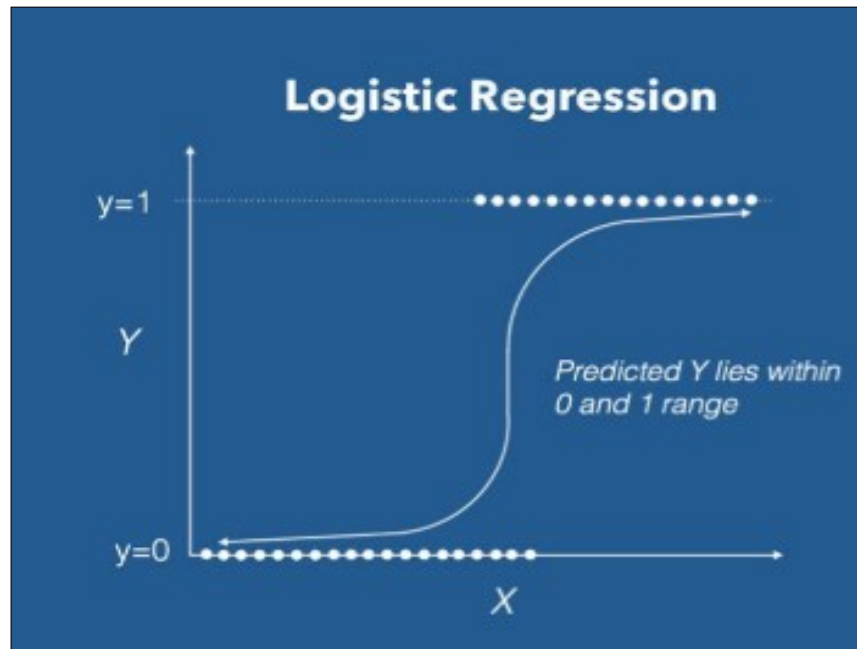


Figure 8. The Sigmoid Curve in LR [78]

The sigmoid function, also known as the logistic function, is a mathematical function that maps any real-valued number into a value between 0 and 1, producing an S-shaped curve. This characteristic makes it particularly useful in LR for modeling probabilities. The function is defined as:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Equation 2. Sigmoid Function

In this equation, e represents the base of the natural logarithm, and x is the input value. The sigmoid function effectively compresses input values into a range between 0 and 1, which can be interpreted as probabilities in the context of binary classification. LR is widely recognized for its practical healthcare, social sciences, and finance applications [77].

3.4.3 Random Forest Tree

RF is a powerful ensemble learning model used for classification and regression tasks. It constructs multiple decision trees during training and combines them to make predictions to improve accuracy and reduce overfitting. Unique trees are built by selecting random data and features. Robust and accurate models are created with a reduced likelihood of overfitting, with the diverse nature of the randomly constructed trees in the forest [79]. This makes it a popular choice for ML tasks for its robustness and reliability of results. Figure 9 shows the RF algorithm, which combines the results of multiple decision trees by majority voting or averaging to produce robust and accurate predictions. Structure and Functioning of RF:

- 1) Ensemble of Decision Trees: Each decision tree is trained on multiple random subsets of the data (with replacement, known as bootstrapping).
- 2) Feature Selection: A random selection of attributes is made at each division in a tree, promoting variety among the trees.

- 3) Prediction Aggregation: For classification tasks, the final prediction is determined by a majority vote, where the class predicted by most trees is chosen. For regression tasks, the final prediction is the average of all individual tree predictions.

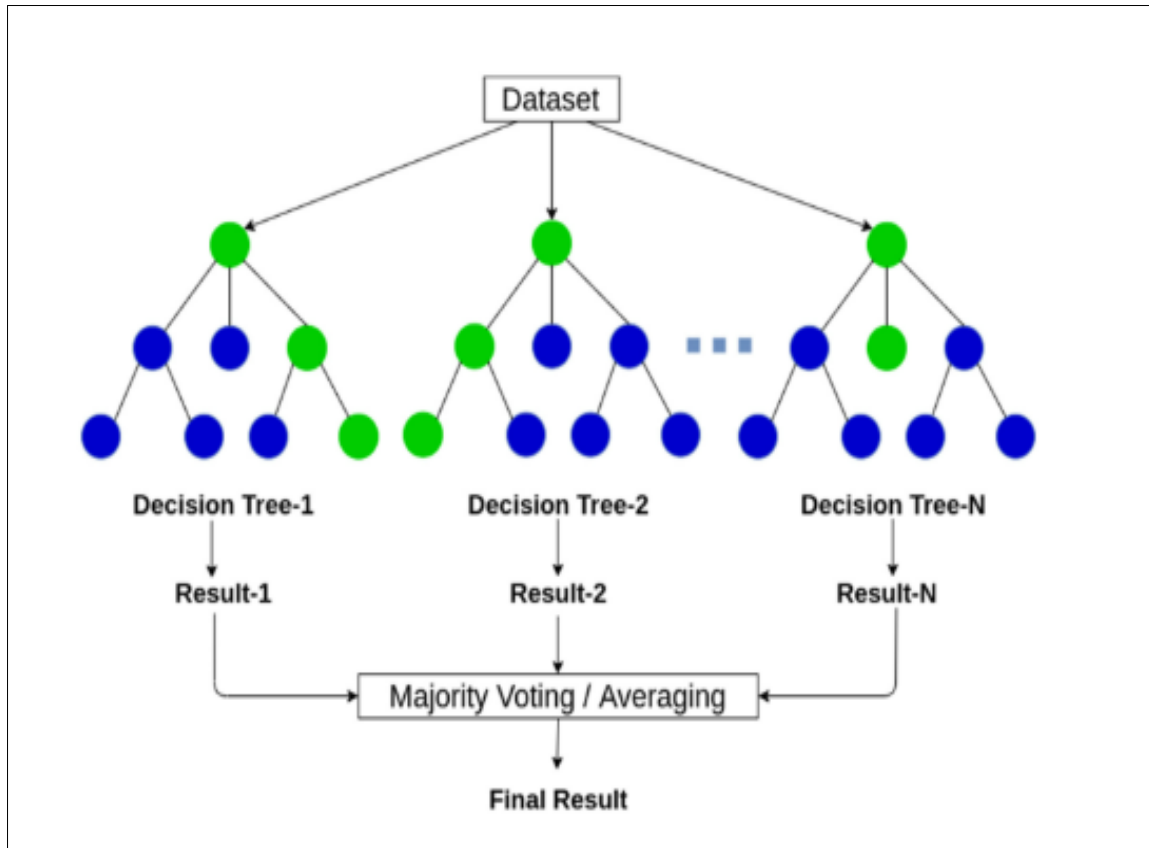


Figure 9. RF: An Ensemble Learning Algorithm [80].

These ensemble characteristics reduce the overfitting that generalizes better than individual decision trees, making it suitable for applications such as medical diagnosis, fraud detection, and customer segmentation.

3.4.4 Support Vector Machine

SVM is one of the most robust prediction methods and a powerful supervised ML models primarily used for classification and regression tasks. It identifies support vectors, which are the closest data points to the hyperplane, and uses them to maximize the margin between classes and ensure the best possible separation of classes. This makes SVM improve generalization, reduce misclassification, and handle high-dimensional spaces and complex datasets [81].

SVM can effectively handle non-linear relationships by transforming data into a higher-dimensional space using kernel functions (e.g., linear, polynomial, radial basis function). For example, a radial basis function kernel allows SVM to create flexible decision boundaries for complex datasets. Figure 10 presents a simple SVM with a linear kernel.

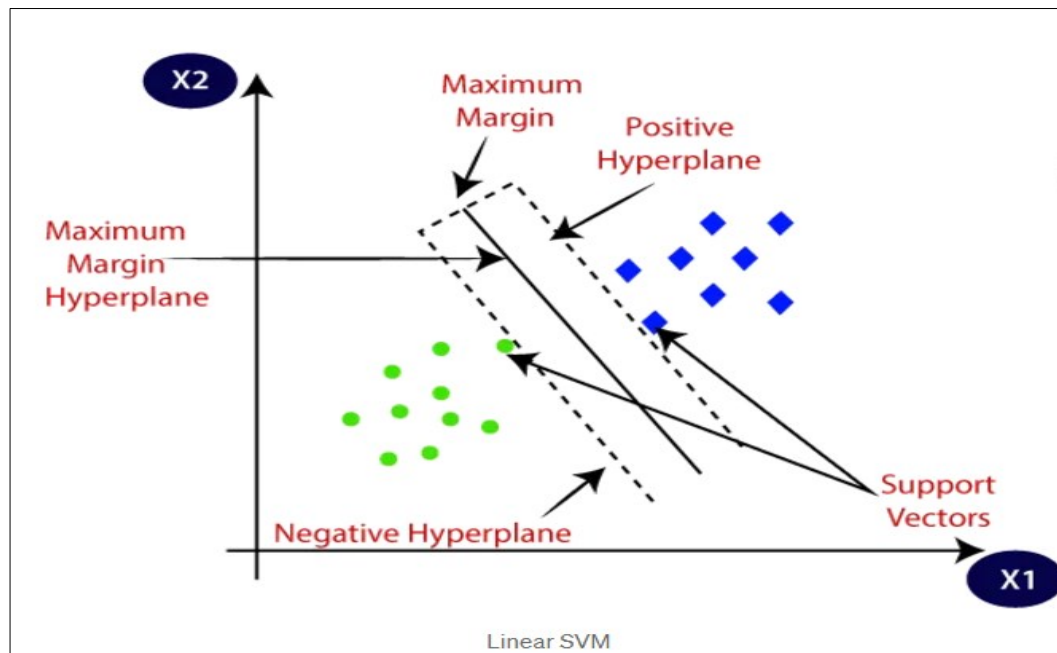


Figure 10. Linear SVM [82].

SVM is widely used in applications such as image recognition, spam detection, and bioinformatics [82]. It is robust to overfitting, especially in cases where the number of dimensions exceeds the number of data points.

3.5 Dashboard

A business intelligence (BI) dashboard allows users to analyze and report on key performance indicators and other metrics. Many health organizations have online visualization tools available for the public to explore trends of incidence, mortality, demographics, and other statistics etc., to intuitively visualize vast amounts of data. BI dashboards are effective as they reduce the time needed to visualize data in charts, graphs, and maps.

A dashboard was built using Power BI for several reasons such as its capability to connect to various data sources, built-in insights with drag-and-drop features, and the creation of a shareable and customizable wide range of visuals. Power BI also offers a free standalone desktop application. It offers a user-friendly platform that integrates data cleaning, statistical analysis, and interactive visualizations, enabling seamless collaboration, cost-effective solutions, and powerful insights backed by Microsoft's robust support and extensive ecosystem [83].

3.6 Summary

This chapter outlined the methodology used in this research, describing various components ranging from data sources to visualization techniques. The experiments and outcomes are explained in the following chapter.

Chapter 4

Experiment and Results

This chapter outlines the data visualization, evaluation of selected ML models that predict the risk of PPD, and a PPD web-based tool. The post-training analysis section identifies key predictors, focusing on the relationship between chronic diseases and the risk of PPD. The predictive modeling sub-section presents results from various ML models and provides a comparative performance evaluation. The post-training analysis examines the selected chronic diseases to demonstrate the validity of the hypothesis. Finally, the functionality of a tool that predicts PPD based on user inputs is presented.

4.1 PPD Dashboard

A dashboard created using Power BI is presented in this section, which supports EDA in exploring the data to gain insights and identify trends along multiple key performance indicators (KPIs) (Figure 11). The dashboard showcases data segmented across various dimensions, including maternal age groups, PPD prevalence, disease variables, maternal education groups, prenatal variables, and infant factors over the years and states. Of the 23,855 individuals in the cleaned dataset, 3,259 (13%) were identified as having PPD, and 11,000 were reported to have chronic diseases.

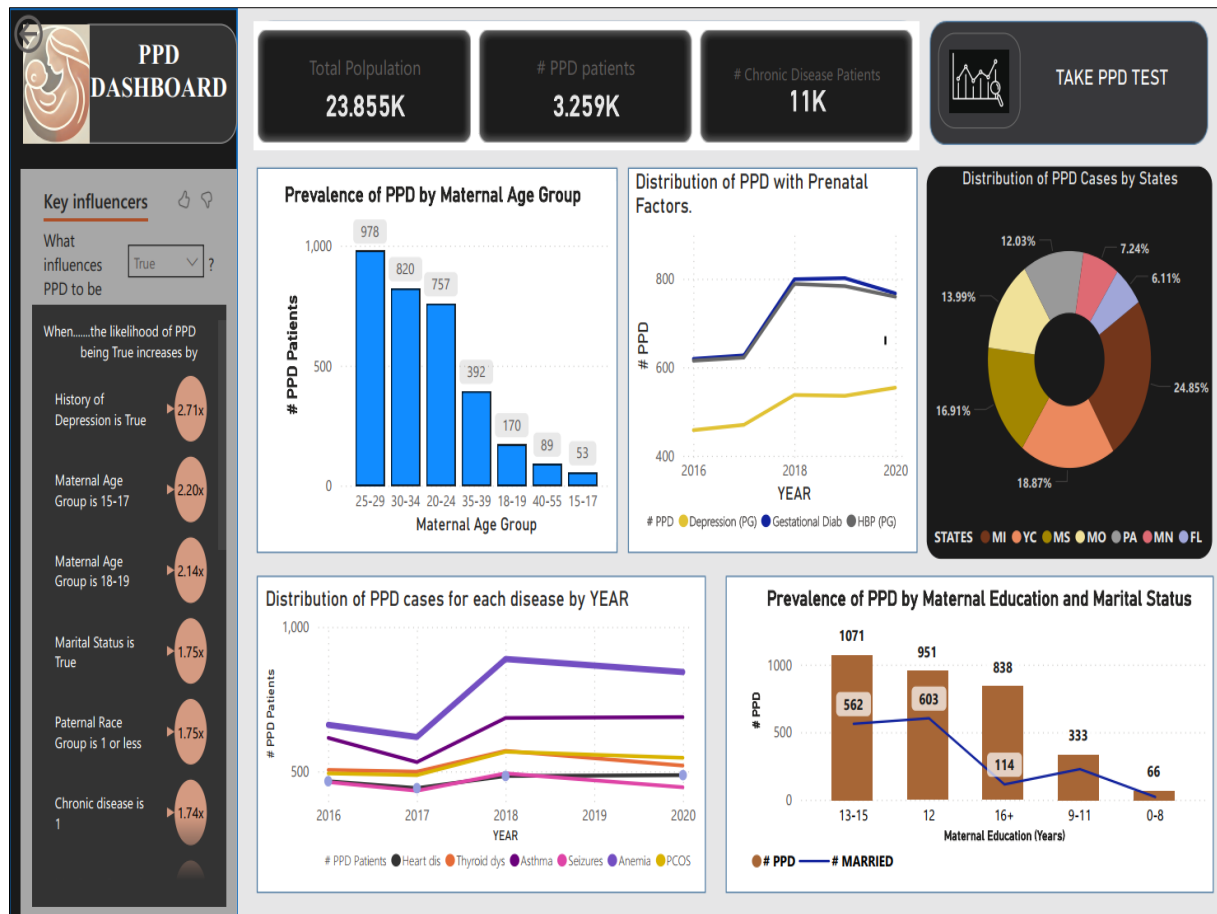


Figure 11. PPD Dashboard

The Key Influencers

The Key Influencers functionality in Power BI uses statistical methods along with odds ratios to identify and rank factors that most influence the target outcome. Figure 12 reveals the factors that significantly influence the likelihood of depression during postpartum. Individuals having a history of depression in specific maternal age groups are 2.2 times more likely to experience PPD. Being married and belonging to paternal race group 1 (Asian, excluding Indian, Japanese, Filipino, or Chinese) increases the likelihood of PPD by 1.75 times, whereas having a chronic disease raises the probability by 1.74 times. Additional factors such as having a history of

hypertension increase the probability by 1.51 times, and Type 1 or Type 2 diabetes diagnosis raises the likelihood by 1.23 times. These insights provide valuable information for understanding the drivers of PPD in the population.

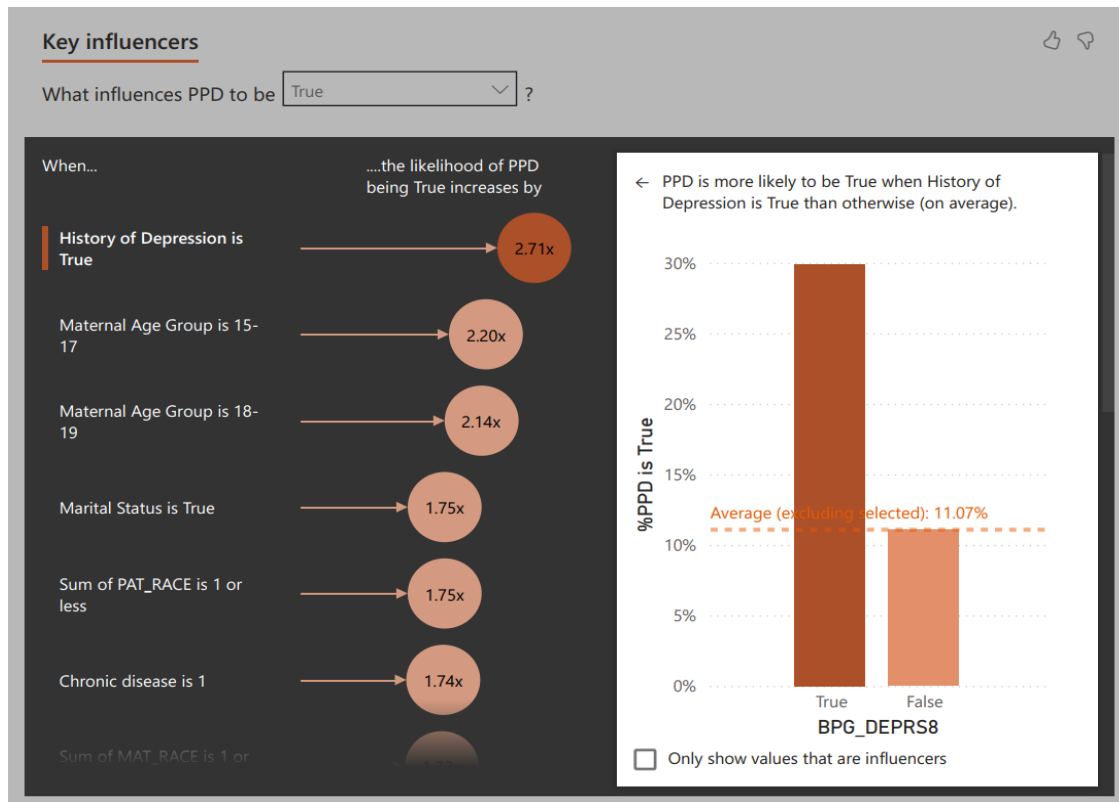


Figure 12. PPD Key Influencers

Demographic Features

Figure 13 and Figure 14 highlight the prevalence of PPD across maternal age groups and education levels. The 25-29 age group (978 cases) has the highest number of cases, followed by the 30-34 (820 cases), and the lowest in the 15-18 (53 cases) group. PPD prevalence also increased with education levels, with the highest cases in women with 13-15 years of education (1,071 cases) and the lowest in those with 0-8 years (66 cases). Marital status shows more

married individuals with PPD in higher education categories, particularly among those with 12-15 years of education (1,165 married).

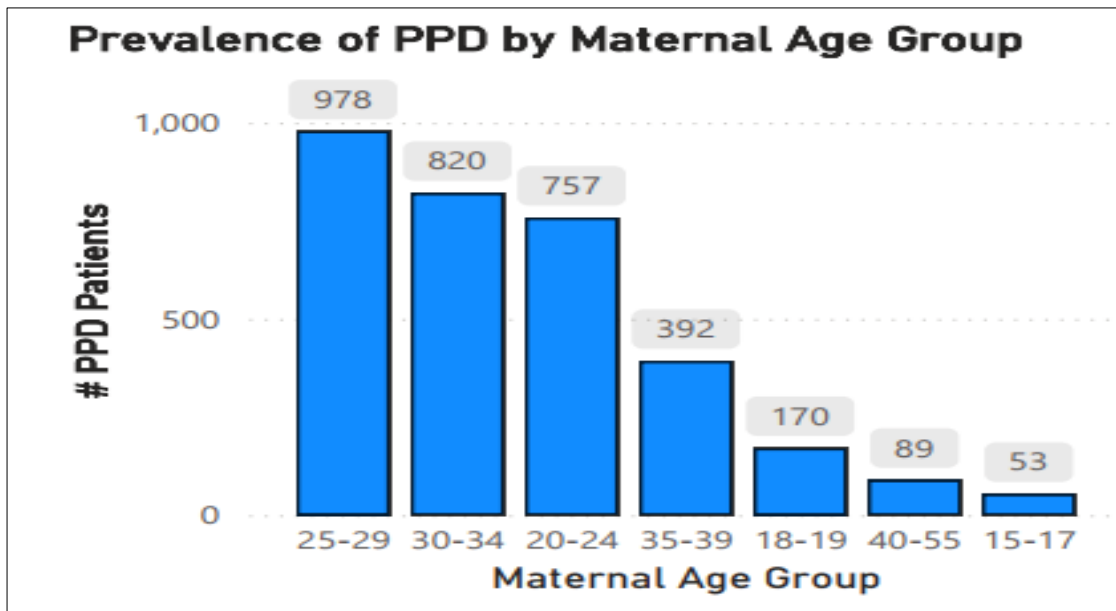


Figure 13. PPD and Maternal Age Group

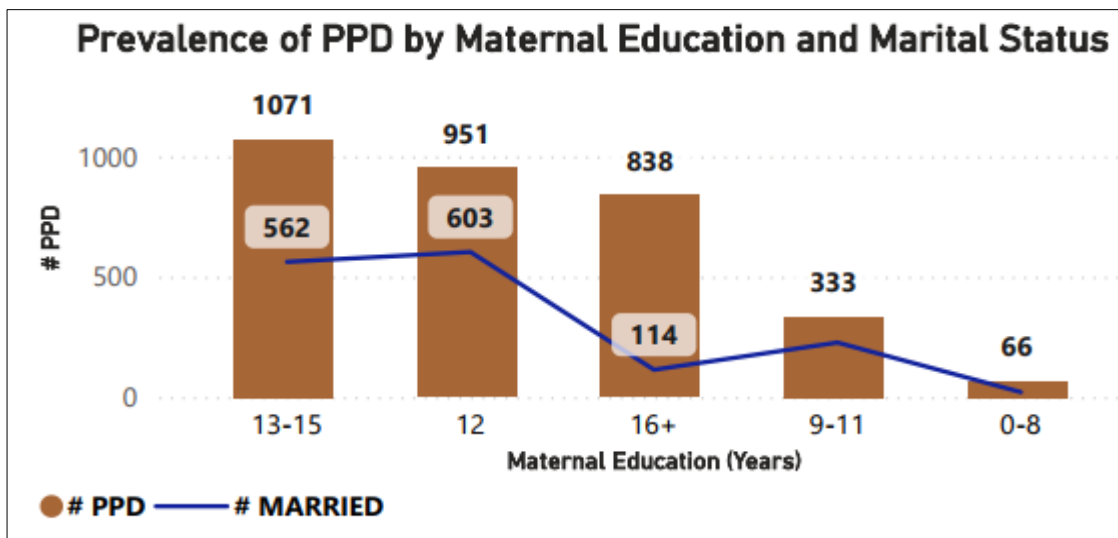


Figure 14. PPD by Maternal Education Level and Marital Status (Married)

Disease Factors

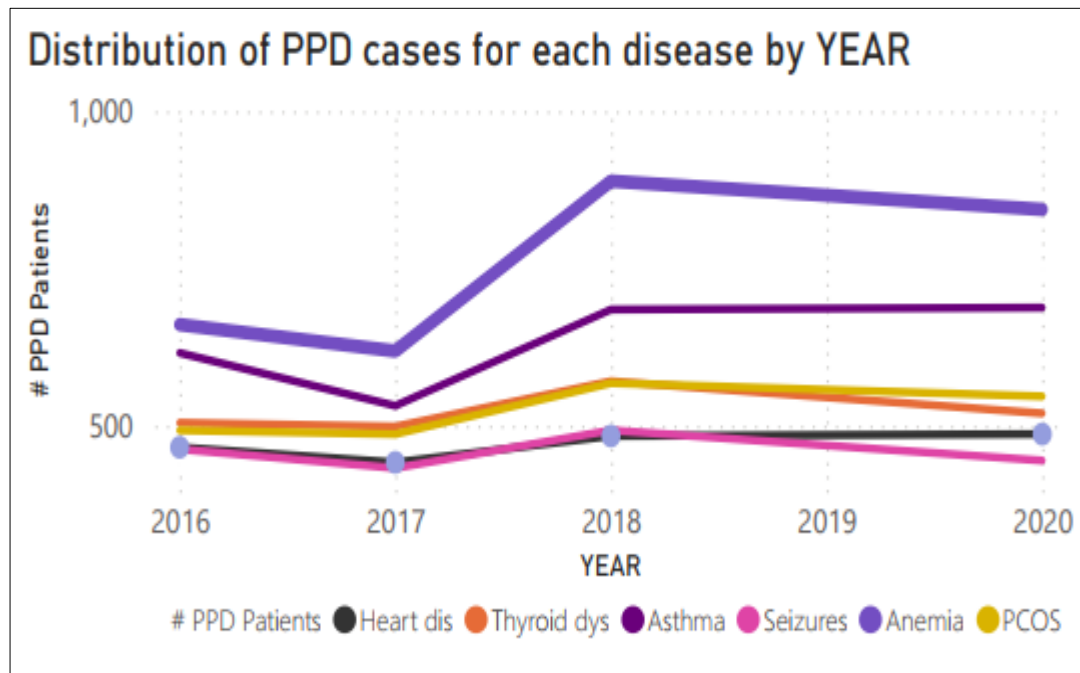


Figure 15. PPD by Disease Factors

Figure 15 depicts the trends in various health conditions among patients from 2016 to 2020, including heart disease, thyroid dysfunction, asthma, seizures, chronic disease, anemia, and PCOS. Anemia and Asthma exhibit moderate increases over the years, while the remaining diseases remain relatively stable with minimal fluctuations. All features with PPD show similar trends in their increase, which could have an impact on PPD.

Prenatal Factors

Figure 16 illustrates the trends in the prevalence of PPD, with gestational diabetes, depression, and high blood pressure (HBP) from 2016 to 2020. Though gestation diabetes shows the

highest and depression the lowest, all factors show a steady increase throughout the period. These patterns indicate a potential relationship between prenatal health conditions and PPD.

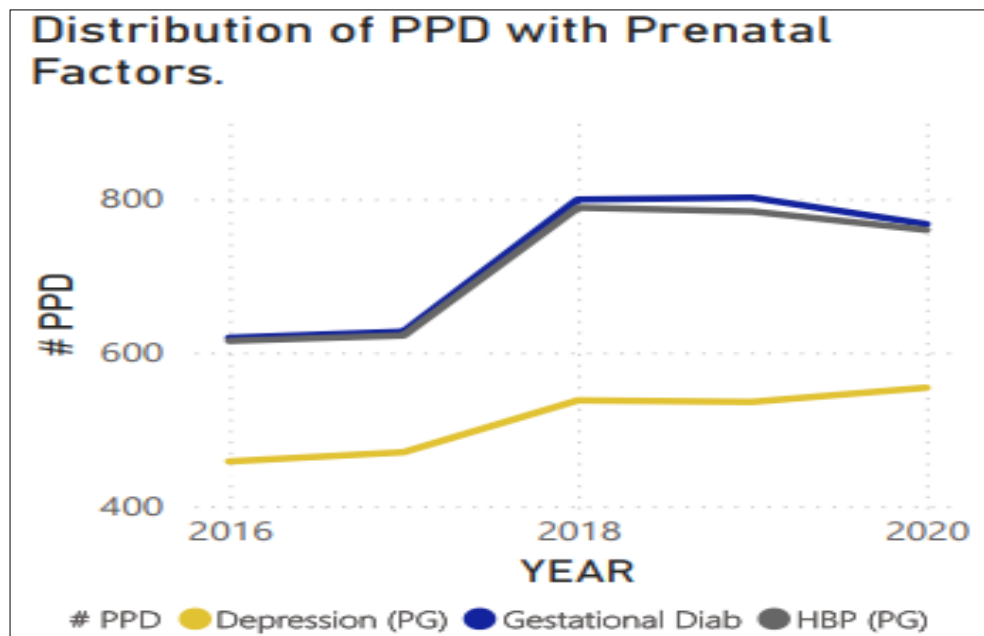


Figure 16. PPD by Prenatal Factors.

4.1.1 Summary

The dashboard provides a concise overview of PPD prevalence. The Key Influencers tool identifies critical factors impacting PPD, such as history of depression, maternal age, chronic disease, and marital status, enabling data-driven insights that are consistent with the important predictors identified by ML models. Visualization helps ensure accurate insights into patterns and relationships between features and the target variable and helps identify imbalances in the data.

4.2 Evaluation Metrics: Accuracy and F1 Score

The accuracy of the model is determined by dividing the number of instances where the predicted values match the actual values by the total number of predictions [84],

$$\text{Accuracy (\%)} = \left(\frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \right) \times 100$$

Equation 3. Accuracy by Percentage

In addition, the F1 score, the harmonic mean of precision and recall, provides a more detailed evaluation, which is especially useful in imbalanced datasets. It helps to balance the trade-off between false positives and false negatives, ensuring a thorough assessment of the model's predictive capabilities. Accuracy and F1 [87] scores provide a complete view of the model's effectiveness in accurately classifying observations.

$$\text{F1 Score} = 2 \times \left(\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right)$$

Equation 4. F1 Score Formula.

where

Precision is the ratio of correctly predicted positive observations to the total predicted positives, given by [85]:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

Equation 5. Precision Formula

Recall (or Sensitivity) is the ratio of correctly predicted positive observations to all the actual positives, given by [85]:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Equation 6. Recall Formula

4.3 Predictive Modeling: An Analysis of Four Models to Predict PPD

During the training phase, the performance of the models was improved by tuning the hyperparameters. This section presents the selected parameters for each model and compares the corresponding performance metrics.

Hyperparameter optimization was conducted on NN and SVM using RandomizedSearchCV to efficiently explore a wide range of hyperparameter combinations, while LR and RF employed GridSearchCV to search for the best configurations. The search was performed in parallel to enhance computational efficiency. Each model's decision threshold was optimized to improve the balance between precision and recall. The models were trained using sample weights to account for class imbalances.

4.4 Model Comparison

Figure 17 illustrates the performance of models on selected features, showing their influence on the probability of PPD. The models were evaluated based on their accuracy and F1 scores defined earlier.

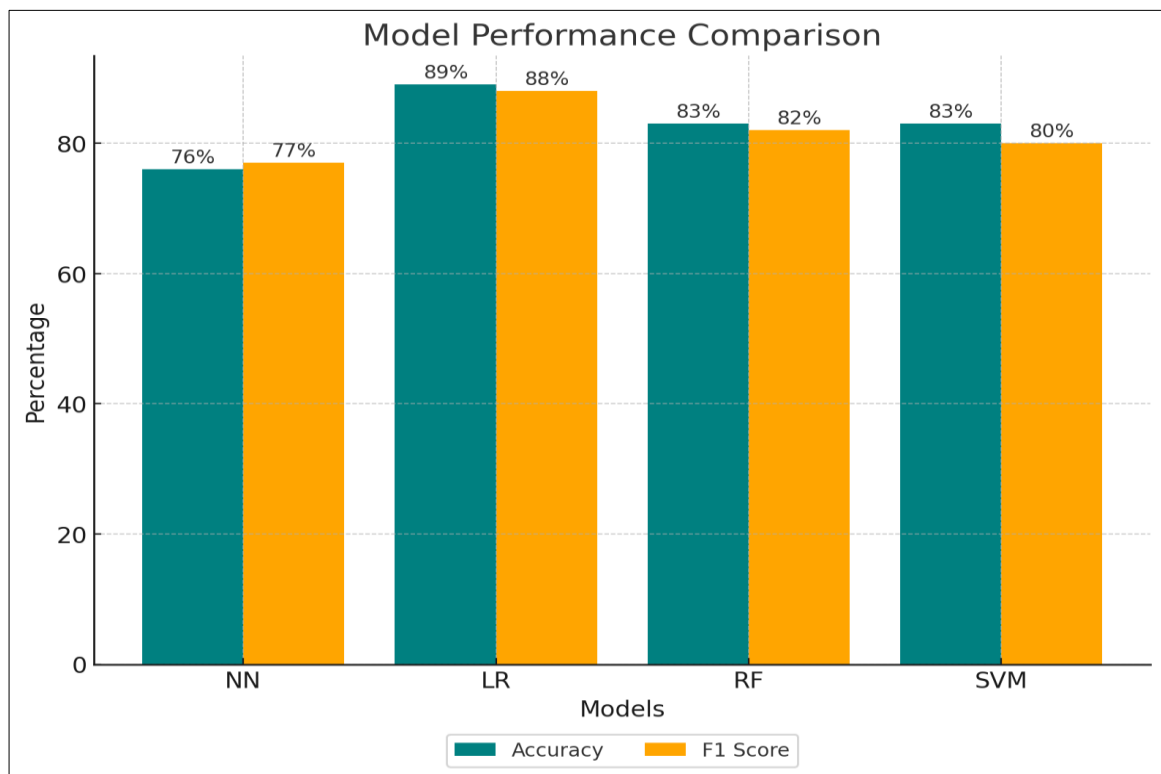


Figure 17. Model Comparison: Accuracy and F1 Score.

Table 2. Precision, Recall, and F1 Score

Model	Precision	Recall	F1 Score
NN	0.75	0.79	0.77
LR	0.90	0.86	0.88
RF	0.79	0.85	0.82
SVM	0.79	0.81	0.80

The model comparison reveals that LR attained 89% accuracy and an 88% F1 score. The RF model achieved 83% accuracy and 82% F1 score, followed by the SVM model with 83% accuracy and 80% F1 score. The NN model demonstrated 76% accuracy and 77% F1 score. The close similarity between accuracy and F1 scores across models suggests balanced performance across the majority and minority classes. This balance indicates that the models are not biased toward one class, effectively managing the trade-off between precision and recall, as presented in Table 2.

4.4.1 Performance Metrics: Discussion

This section discusses the performance metrics observed during the model evaluation, with a particular focus on the influence of parameter tuning. The results were analyzed to understand how different tuning approaches influenced the selected models' overall accuracy and F1 score. A stratified cross-validation was applied to test if the model was biased or overfitted.

Neural Network

- An initial 75% F1 score was achieved using Python's MLPclassifier with default parameters.
- Tuning the parameters to two layers with a ReLU (Rectified Linear Unit) activation function, an Adam optimizer, and L2 regularization set at 0.001, along with a sigmoid (output layer), improved the F1 score to 77%.

Logistic Regression

- Tuning the solver parameter for liblinear, saga, and lbfgs resulted in varying accuracy scores. The saga solver achieved around 65% accuracy, while the other two solvers—liblinear and lbfgs (Limited-memory Broyden-Fletcher-Goldfarb-Shanno)—each achieved approximately 89% accuracy, finding the optimal threshold value of 46 instead of 50.
- LR achieved 89% and 88% accuracy and F1 score, respectively, using GridSearchCV with a maximum of 5000 iterations, an L2 penalty, liblinear solver, and a regularization strength (C) of 0.01.

Random Forest

- The basic RandomForestClassifier configuration with default parameters—100 trees, a minimum of 2 samples required to split an internal node, no maximum tree depth, and at least 1 sample per leaf—achieved an F1 score of 80%.
- Tuning hyperparameters with GridSearchCV, the RF model was configured with 300 trees, a minimum of 2 samples required to split a node, no maximum tree depth, and max_features set to 'sqrt' yielded an F1 score of 82%.

Support Vector Machine

- The SVM model, initially configured with parameters such as enabling probability estimation and setting the random state to 42, achieved an F1 score of 77%.
- Tuning the 0.01 RBF (Kernel Coefficient) and adjusting the C (regularization parameter) improved the F1 score to 80%.

The performance achieved by LR is likely due to its ability to effectively model linear relationships between features and the binary target, as well as the use of optimized hyperparameters that balance precision and recall. The ensemble learning approach in RF effectively captures complex nonlinear relationships in the data by creating multiple decision trees, likely resulting in robust classification performance. Likewise, capturing complex nonlinear relationships through the RBF kernel in SVM might have resulted in enhanced predictions. Stratification ensures that each fold reflects the class imbalance in the dataset, forcing the model to learn from both classes, which may slightly reduce accuracy but improve generalization.

4.5 Post-Training Analysis: Identify Key Predictors

This section identifies key predictors, focusing on the relationship between chronic diseases and the risk of PPD. SHAP (Shapley Additive exPlanations) [86], a game theoretic approach, was utilized in this post-training model analysis. Other model-explaining techniques, including the Permutation Importance and Partial Dependence plots, allow us to understand the importance of features but lack local interpretability. Since the SHAP can be model-specific or agnostic, it has the flexibility to adapt to various ranges of models.

The SHAP value was calculated to interpret the impact of input features on the target PP_DEPRESS. The 'SHAP' Python package enabled the creation of various plots to understand the key predictors and how the values of each predictor impact the target. Plots were based on the mean absolute SHAP values of each critical feature. The Beeswarm plots in Figure 19, Figure 21, Figure 23, and Figure 25 show a deeper insight into each value of every significant

predictor, whether it has a positive or negative impact. Each dot corresponds to an individual prediction, shifting the color gradient from blue for lower feature values to red for higher ones. The positive SHAP value for a feature value indicates that it has a strong positive contribution to predicting PPD, and the negative value indicates the reverse. Table 3 shows the key features and their predictive strength by selected models with label information. The SHAP values for significant features using each model are presented below.

Neural Network

Figure 18 demonstrates the key features identified by the NN model using SHAP. The bars show the absolute SHAP value, meaning a more critical feature with a higher SHAP value on the top. The feature CHRONIC was on the top, having a SHAP value of 1.33, followed by other selected chronic diseases, anxiety, anemia, and asthma, which are consistent (except anxiety) with other models described later.

Key chronic predictors of PPD identified are anxiety, anemia, heart disease, PCOS, epilepsy, thyroid dysfunction, and pre-pregnancy diabetes. Other features such as length of stay at the hospital, infant sex, high blood pressure, both father's and mother's race, paternal education, and Kessner Index² are also underscored as key predictors.

² The Kessner Index measures the adequacy of prenatal care by evaluating when prenatal care began, the total number of visits, and the length of the pregnancy [87].

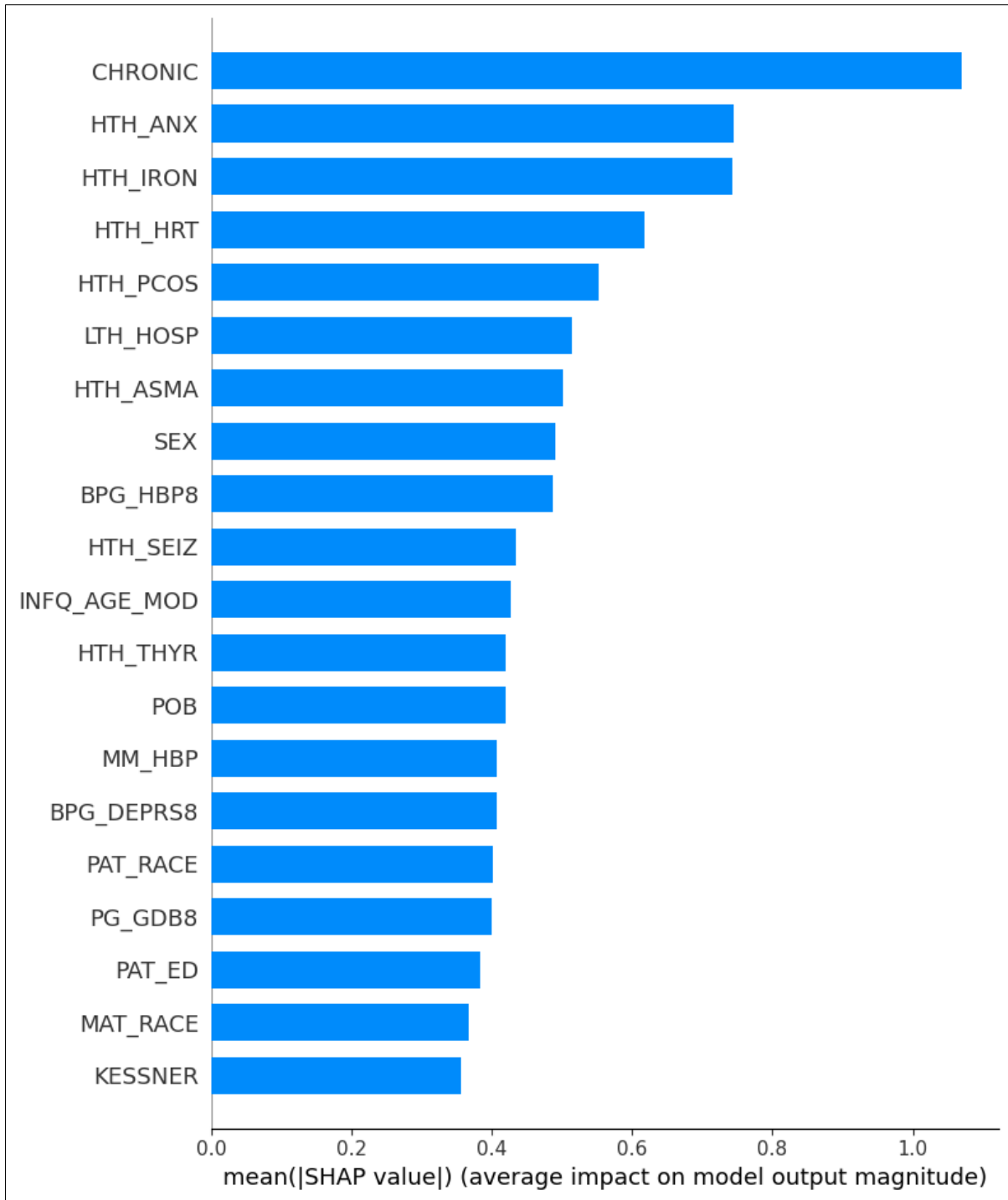


Figure 18. Feature Significance Using SHAP on NN Model

Figure 19 displays the contribution of the feature CHRONIC towards PPD with a higher value (1- presence). Chronic diseases such as heart disease, anxiety, anemia, asthma, PCOS,

epilepsy, thyroid dysfunction, and pre-pregnancy diabetes had lower SHAP value for their presence. The other vital features identified are infant sex and place of birth. Having high blood pressure during pregnancy had a significant influence on predicting PPD.

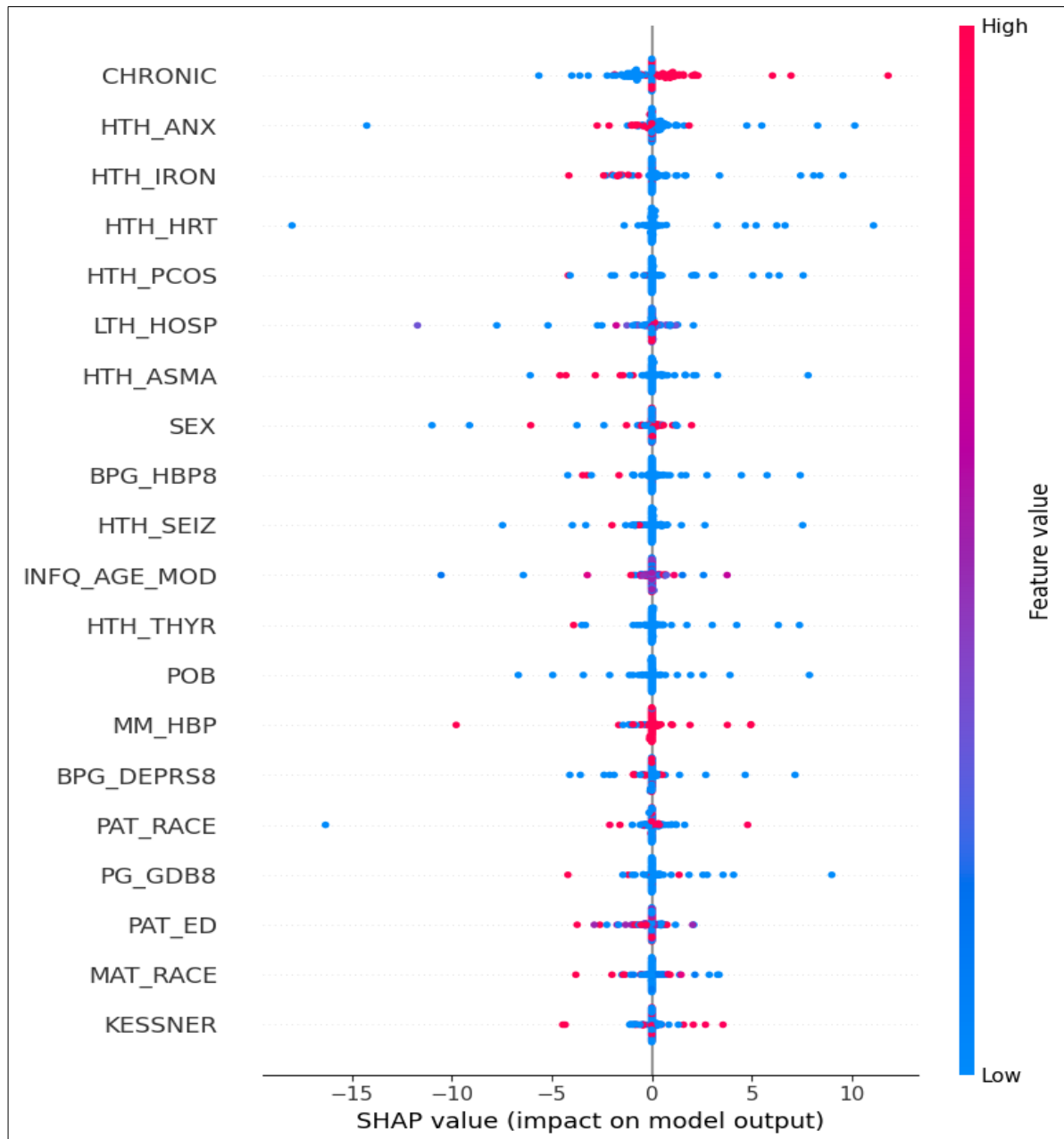


Figure 19. SHAP Summary: Visualizing Feature Impact and Distribution Using NN Model

Logistic Regression

Figure 20 shows the key predictors of PPD. The feature CHRONIC comes after paternal and maternal race and the infant's birth month. CHRONIC and MH_PGDX8 (Health problems during pregnancy – Depression) got the same SHAP value of .29.

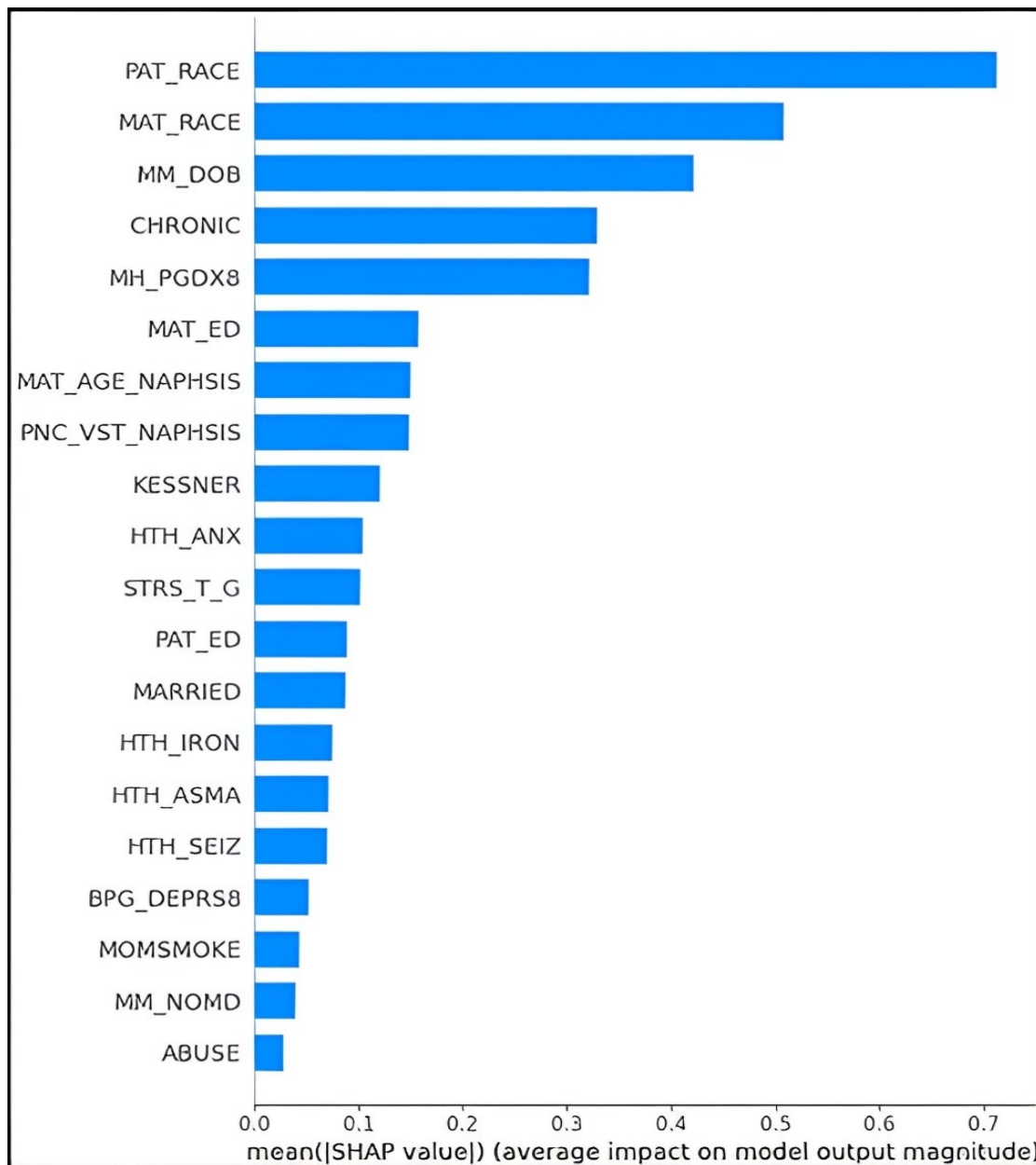


Figure 20. Feature Significance Using SHAP on LR Model

The SHAP analysis across each feature is shown in Figure 21. Considering the feature CHRONIC, a red marker (1-presence of chronic disease) falls in the positive SHAP value region, indicating that the mother with chronic disease had a higher chance of getting PPD.

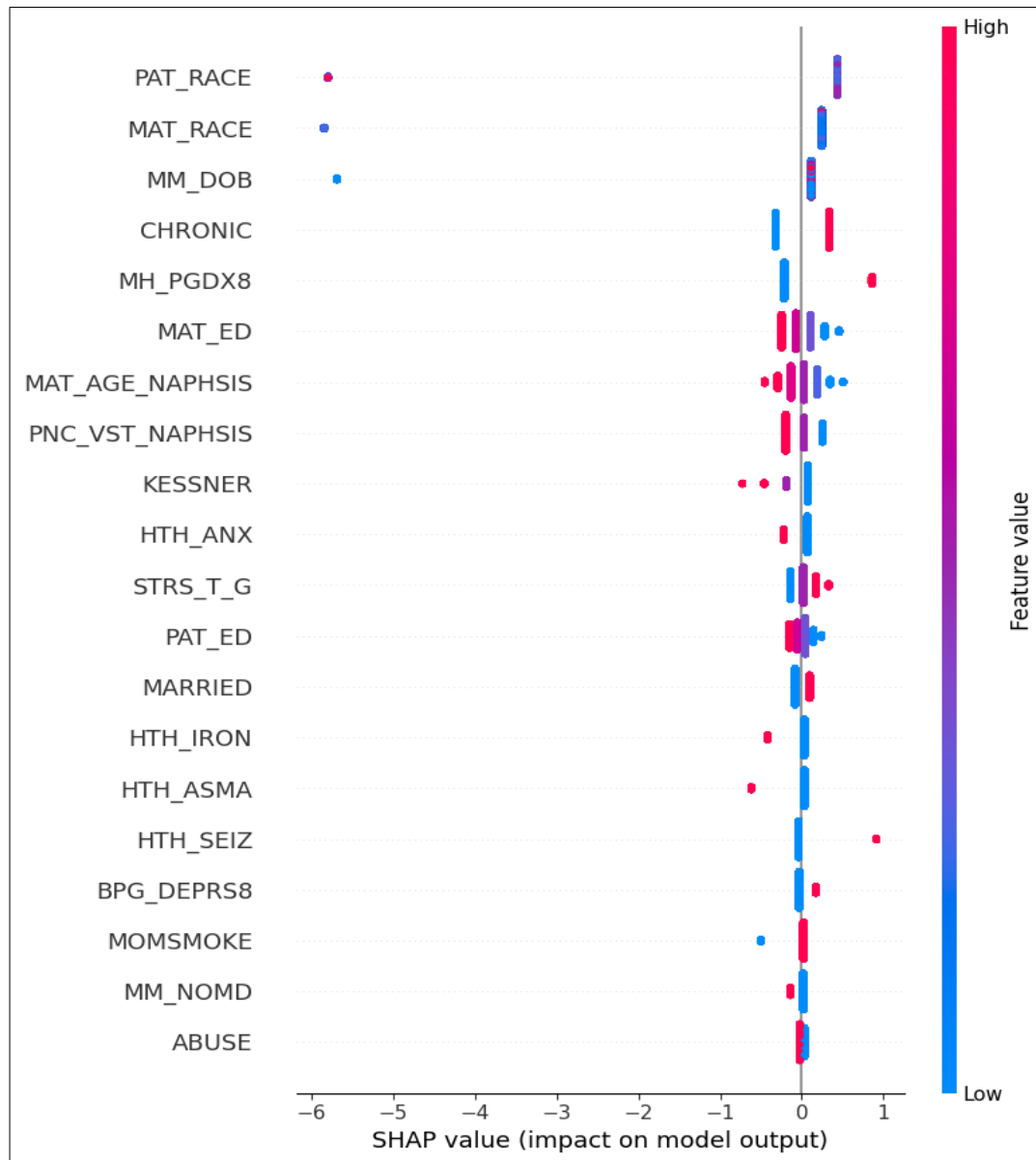


Figure 21. SHAP Summary: Visualizing Feature Impact and Distribution Using LR Model

In addition to the presence of chronic disease, depression during pregnancy, younger age of mother, lower Kessner Index, having high stress, "Other" marital status, history of depression, smoking behavior, and lower paternal education level have been identified as the key factors in predicting risk of depression. When considering specific chronic diseases, epilepsy emerges as a strong contributor, while the presence of asthma, anxiety, and anemia show a lesser impact.

Random Forest

The key features identified by the RF model using SHAP are shown in Figure 22. Similar to LR and NN, the feature CHRONIC is indicated as one of the key predictors of PPD. In addition, other similar features such as Kessner Index, depression during pregnancy, paternal and maternal race, paternal education, asthma, and anemia are found in the top predictors.

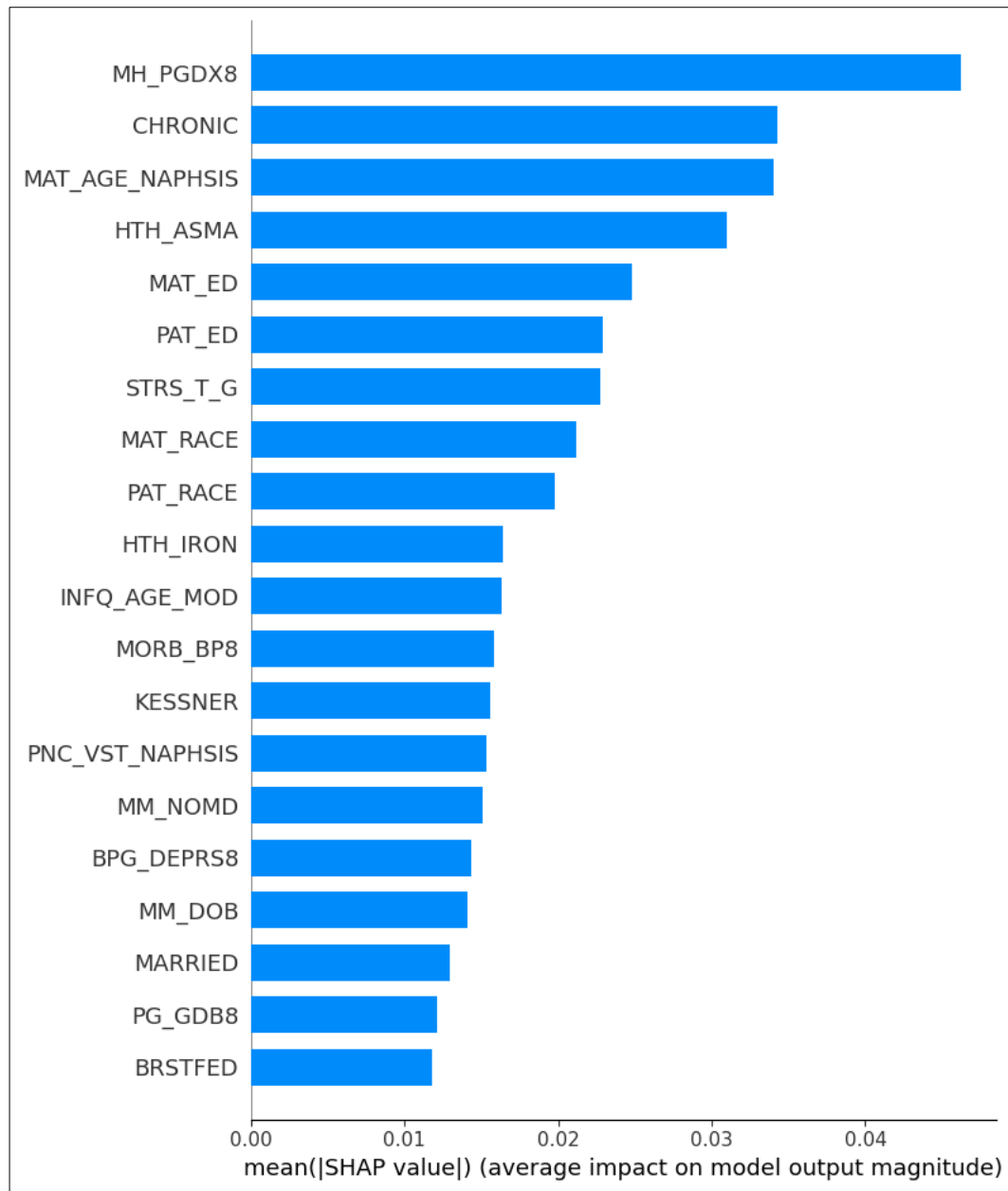


Figure 22. Feature Significance Using SHAP on RF Model

The SHAP plot in Figure 23 shows the detailed effect of each feature value in predicting PPD, highlighting that the feature CHRONIC has a positive contribution, consistent with both the LR and SVM models.

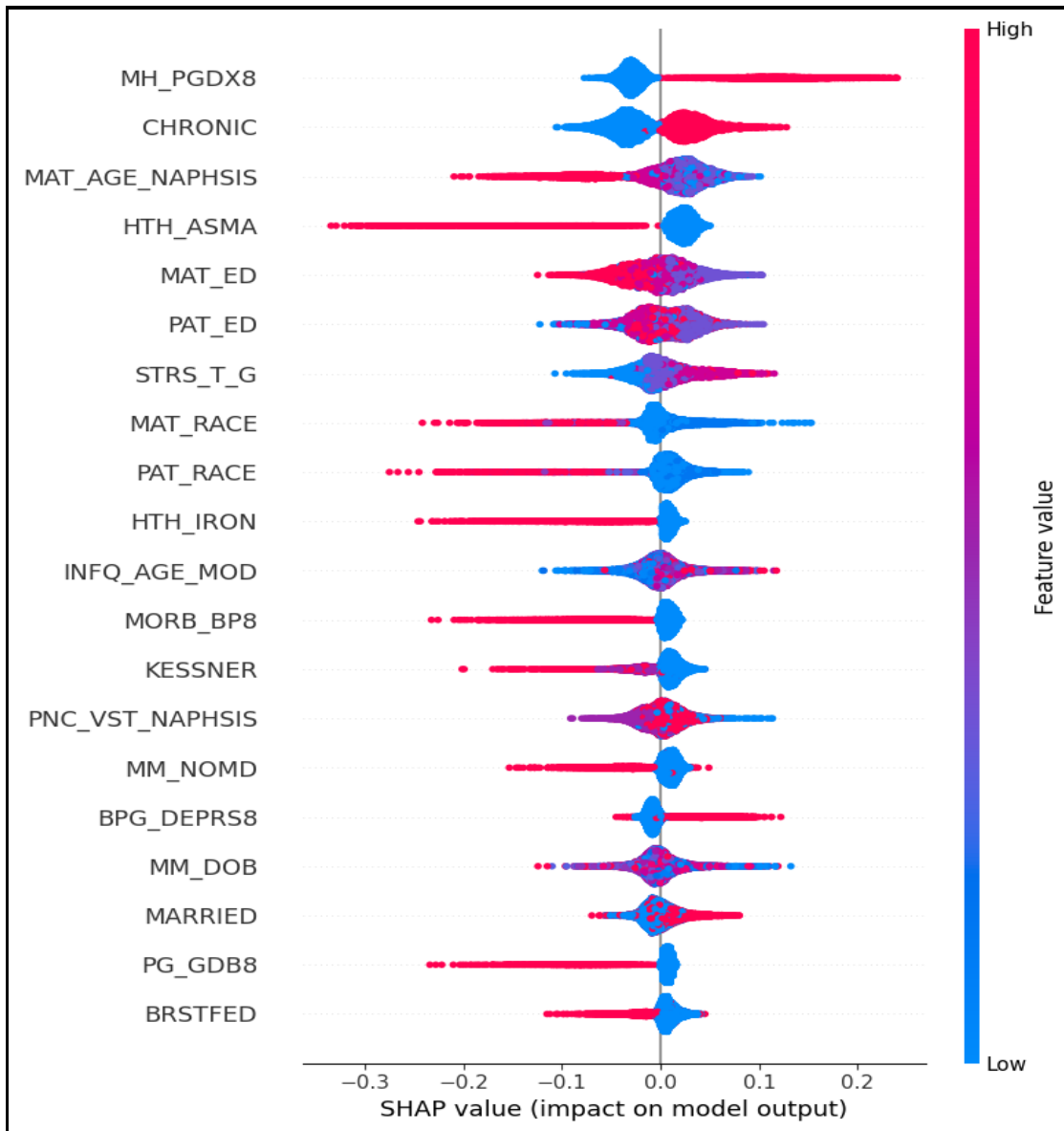


Figure 23. SHAP Summary: Visualizing Feature Impact and Distribution Using RF Model

It is noted from the above chart that depression during pregnancy, younger maternal age, high-stress levels, older infant age, being of a race such as Chinese, Japanese, Filipino, or Hawaiian, and lower paternal and maternal education levels are strong contributors to predicting PPD risk. Additionally, diseases such as asthma and anemia show lower SHAP values, which are consistent with LR and SVM. Having depression (prenatal and before pregnancy), younger

maternal age group, "Other" marital status, lesser prenatal care visit, and a lesser Kessner Index aligns with LR results. Not being breastfed emerges as an additional vital contributor to the feature importance analysis.

Support Vector Machine

Figure 24 illustrates the key features identified by the SVM model using SHAP. The feature CHRONIC was at the top, with a SHAP value of more than 0.90, followed by other selected chronic diseases, such as anxiety, anemia, and asthma. Further down, thyroid dysfunction is also identified as an essential feature in predicting PPD.

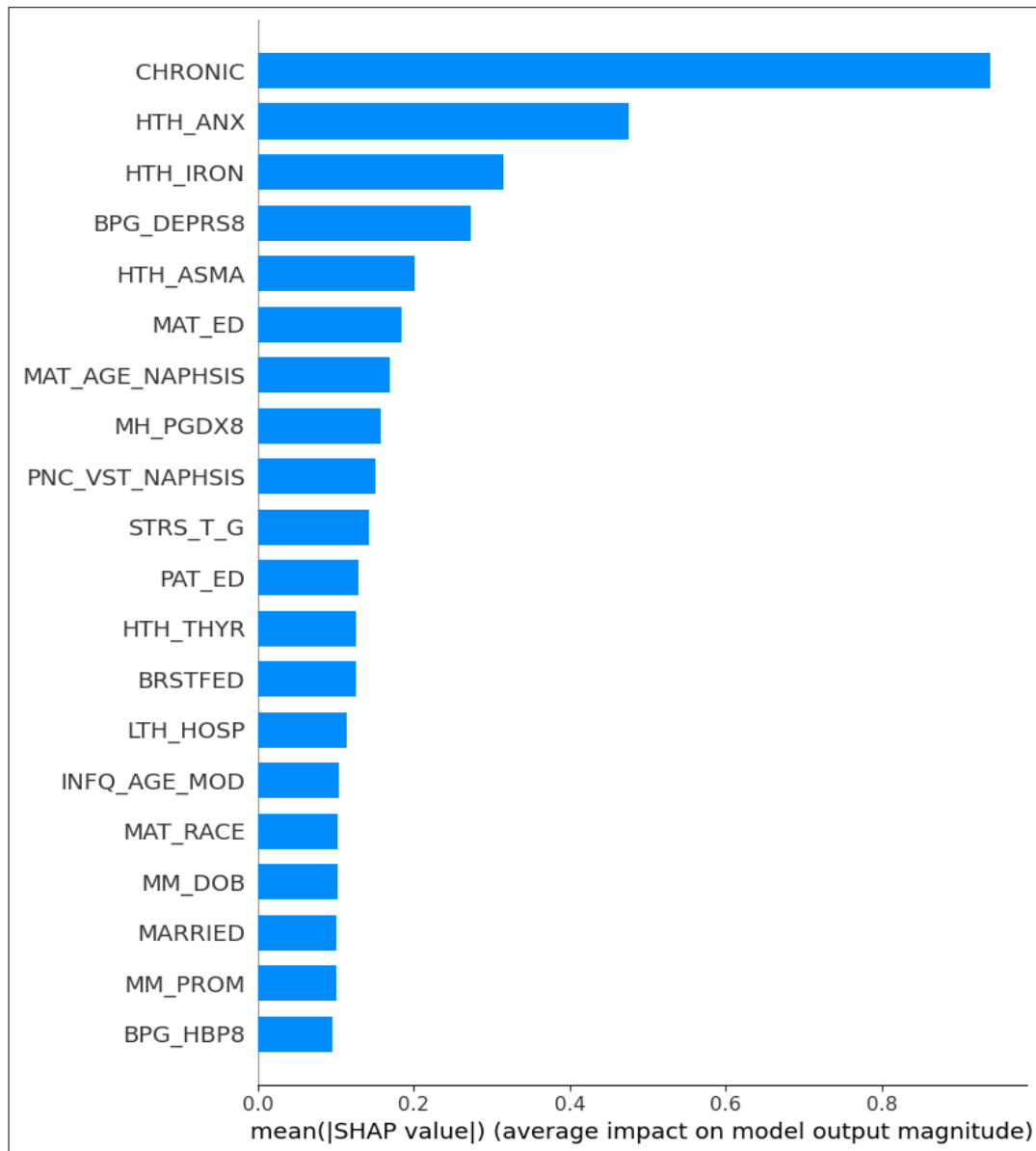


Figure 24. Feature Significance Using SHAP on the SVM Model

The beeswarm plot in Figure 25 visualizes a detailed overview of how individual feature values affect the target PP_DEPRESS. The distribution reveals that when the binary feature CHRONIC is 1 (presence), it gives a positive SHAP value, thus contributing positively to the PPD prediction. Consistent with the LR model, the mother's depression during pregnancy (MH_PGDX8) holds similar significance in predicting PPD. In contrast to LR, marital status

(MARRIED) shows mixed values in both directions, making it difficult to determine which category of this feature is a vital contributor.

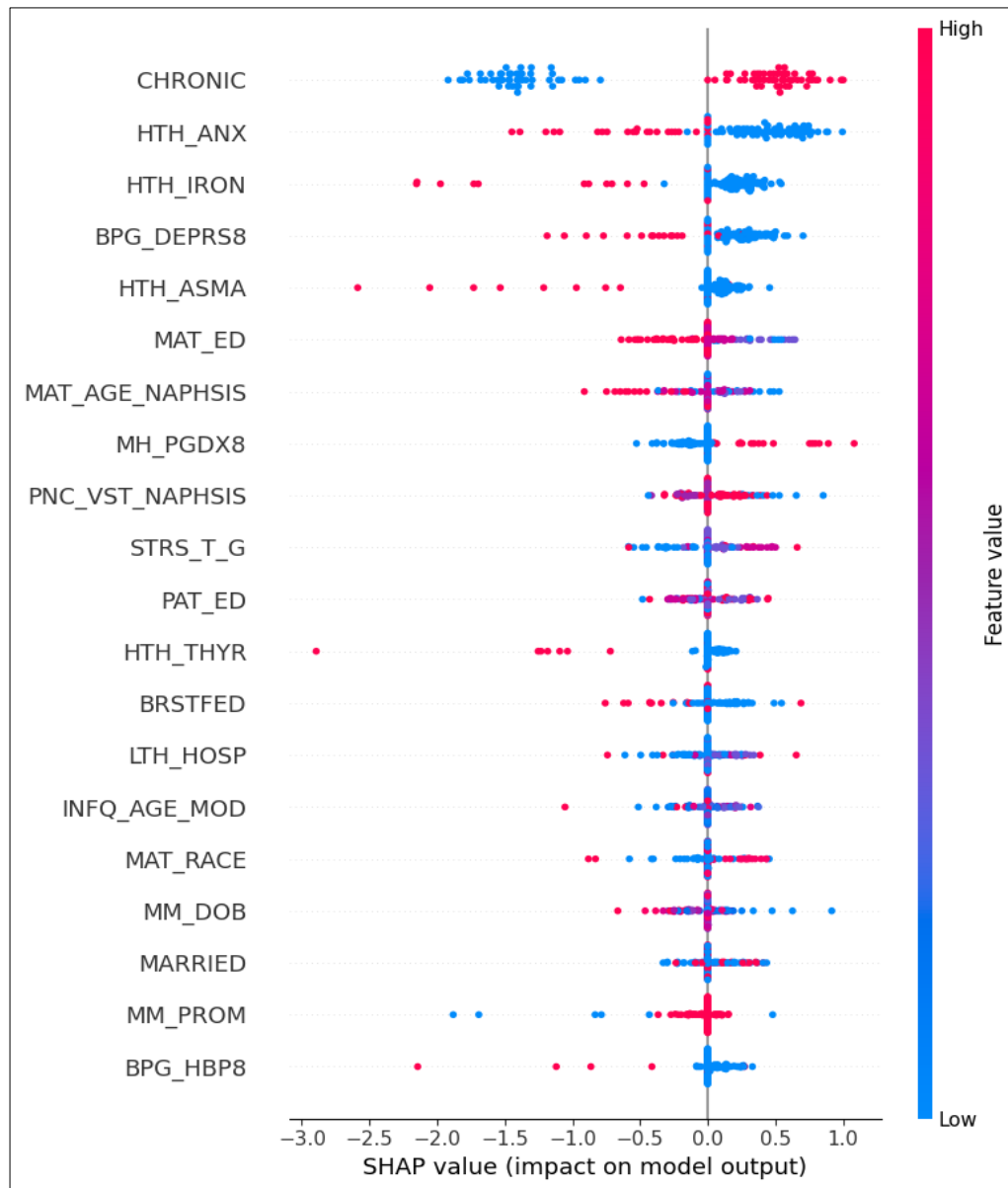


Figure 25. SHAP Summary: Visualizing Feature Impact and Distribution Using SVM Model

Features like maternal age group, stress level, and maternal education level exhibit effects similar to LR. The SHAP value indicates that mothers in the younger age group or with lower

education are more strongly linked to PPD. Other key chronic disease predictors, such as anxiety, anemia, asthma, and thyroid dysfunction, exhibit lower SHAP values, indicating a diminished influence on predicting PPD. In comparison with RF, the SHAP plot for breastfeeding shows a similar pattern, with non-breastfeeding being denser in the positive direction.

4.5.1 Summary: Post-Training Analysis

Table 3 presents key features that strongly contribute to predicting PPD across selected ML models. Features such as CHRONIC, asthma, anemia, maternal race, paternal education, and history of depression are consistently presented as key features with comparable SHAP values. Additionally, stress level, maternal age, maternal education, paternal race, marital status, Kessner Index, depression during pregnancy, infant age, and anxiety were identified as key features among at least three out of the four models. Diabetes before pregnancy is common in both RF and NN, breastfeeding is common in both RF and SVM, and length of stay in the hospital is common in both NN and SVM. Only a few additional vital features emerged uniquely in each model. Notably, LR and RF show a presence of a history of depression, while SVM shows an absence of a history of depression, indicating variability in its influence across models.

Table 3. Key Features and Their Predictive Strength by Model

Feature	Label	NN	LR	RF	SVM
CHRONIC	Chronic disease	Presence	Presence	Presence	Presence
MH_PGDX8	Depression during pregnancy (binary)	NA	Presence	Presence	Presence
KESSNER	Kessner Index – number of prenatal care (ordinal)	Uneven effect	Lower	Lower	NA
STRS_T_G	Stress level group (ordinal)	NA	Higher	Higher	Higher
INFQ_AGE_MOD	Infant age (days)	Uneven effect	NA	older	older
MAT_AGE_NAPHSIS	Maternal age group (ordinal)	NA	Younger	Younger	Younger
MAT_ED	Maternal education group (ordinal)	NA	Medium-Lower	Medium	Medium-Lower
PAT_ED	Paternal education group (ordinal)	Uneven effect	Medium-Lower	Medium	Uneven effect
HTH_ASMA	Asthma (binary)	Absence	Absence	Absence	Absence
HTH_IRON	Anemia (binary)	Absence	Absence	Absence	Absence
HTH_ANX	Anxiety (binary)	Absence	Absence	NA	Absence
MARRIED	Marital status (binary)	NA	Married	Married	Uneven effect
MAT_RACE	Maternal race (nominal)	Uneven effect	Uneven effect	Other Asian, White, Black, Indian, and Chinese	Uneven effect
PAT_RACE	Paternal race (nominal)	Uneven effect	Other Asian, White, Black, Indian, Chinese, Japanese, and Filipino	Other Asian, White, Black, Indian, and Chinese	NA
BPG_DEPRS8	History of depression (binary)	Uneven effect	Presence	Presence	Absence

The identified key predictors contributing to PPD are greatly consistent across all models. Moreover, deeper individual feature value analysis revealed that the strength of these features in predicting PPD is also closely aligned across the models. Any minor differences between the models are likely due to the handling of nonlinearities and interactions.

Additionally, the feature CHRONIC was consistently identified in all models and showed similar strength in predicting PPD. However, the SHAP values for the presence of individual chronic diseases were low, indicating a need for further interaction analysis. Such patterns often occur when models see these features as part of broader interactions rather than as strong individual predictors.

4.6 Identifying and Analyzing Interactions Among Key Predictors

The low SHAP values for individual chronic diseases indicated the likelihood for these features to contribute more significantly through interactions rather than as standalone predictors. New features were generated to assess the combined effect of features identified as important through SHAP analysis. The following steps involve extracting the combination and analyzing the interaction for all selected models.

Step 1: Generating Interaction Features

Interaction features were developed by combining selected input features. Since the nominal features were encoded, the selected features had Boolean and ordinal datatypes. A bitwise "AND" operation was performed between feature pairs. Each new feature was given a meaningful name and added to the original dataset as a new column.

Step 2: Data Preparation and Modeling with Interaction Features

After creating interaction features, they were filtered to retain only those identified as significant in the feature selection node in SPSS Modeler [73]. Figure 26 shows the feature selection node for interaction features.

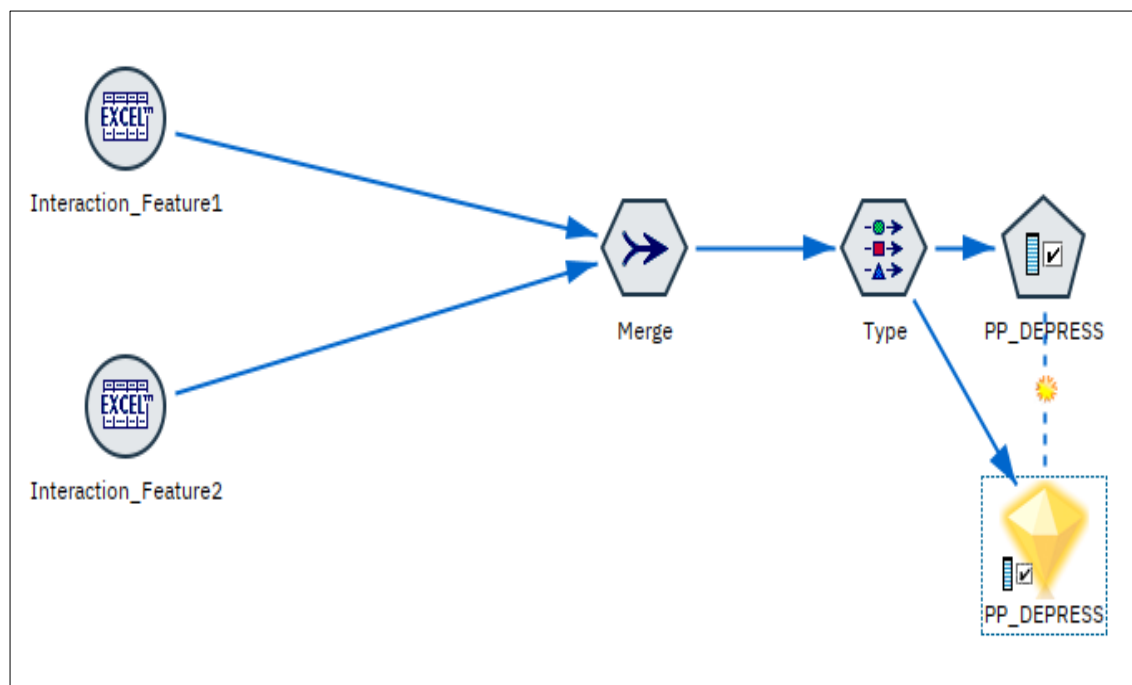


Figure 26. SPSS Feature Selection Node

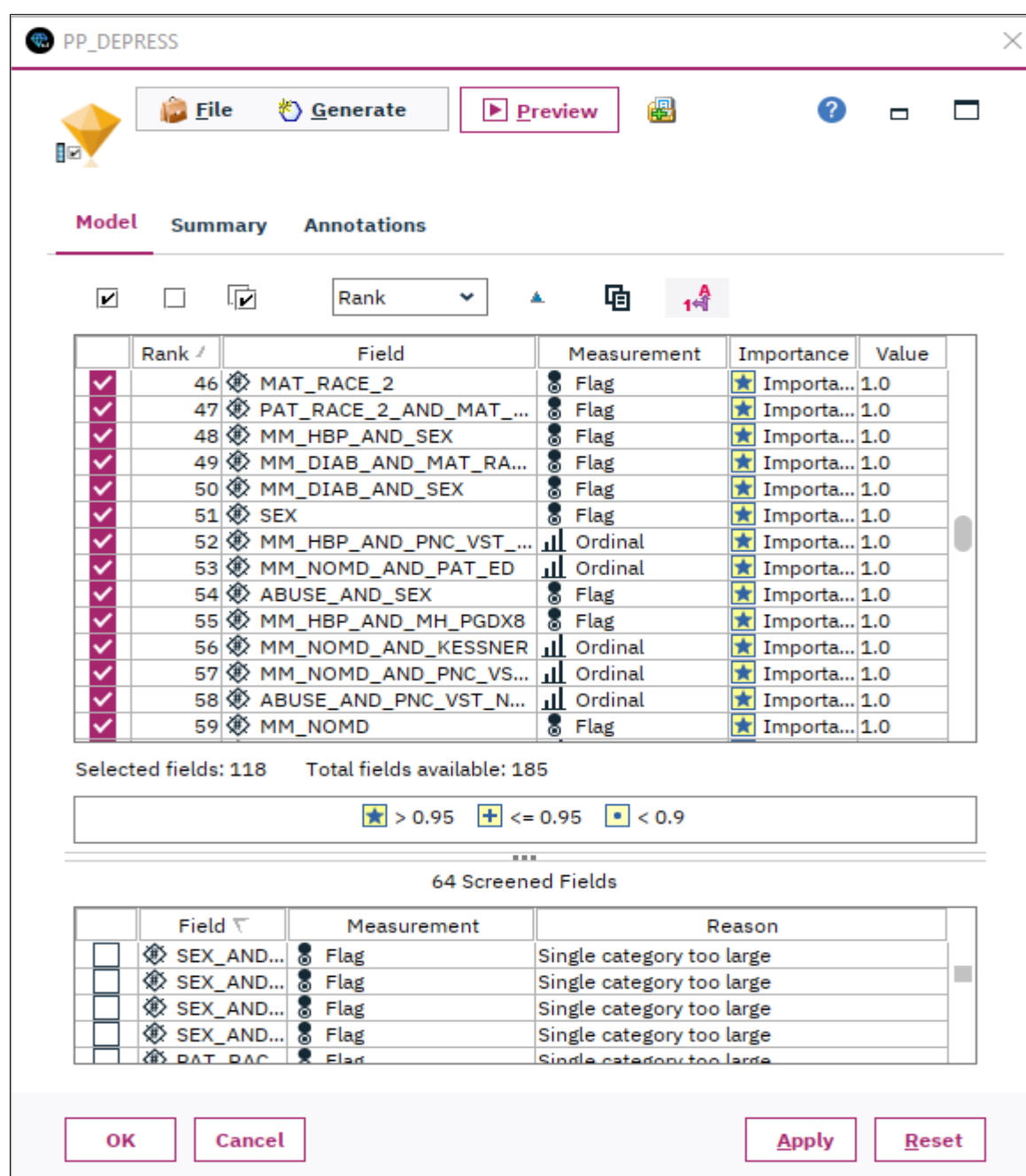


Figure 27. Feature Selection Results

The generated features were loaded using the Excel data source node of the SPSS Modeler. A Merge node was used to merge the data, which was connected to a Type node. The Type node helped define each feature, including its type and target. The measurement column describes

the datatypes, and the least key features were ignored due to their large single category. These results were then used to filter and create a final dataset with relevant input features. Finally, the dataset used in the model to identify the significant interaction.

Step 3: Post-Training SHAP Analysis of Interactions

SHAP analysis was conducted to identify the most impactful interactions and provided insights into how feature combinations influence the predictions. The following results of SHAP values highlight significant feature interactions for each model.

Neural Network

Figure 28 illustrates the key interaction features of the NN model identified using SHAP. Maternal education is found at the top as a significant feature, along with other features, such as ‘No medical risk factors,’ high blood pressure and gestational diabetes, number of perinatal care visits, chronic diseases, anemia, and asthma. Similarly, the number of prenatal care visits, along with factors such as the absence of medical risk factors, high blood pressure, and diabetes during pregnancy ranks top on the chart.

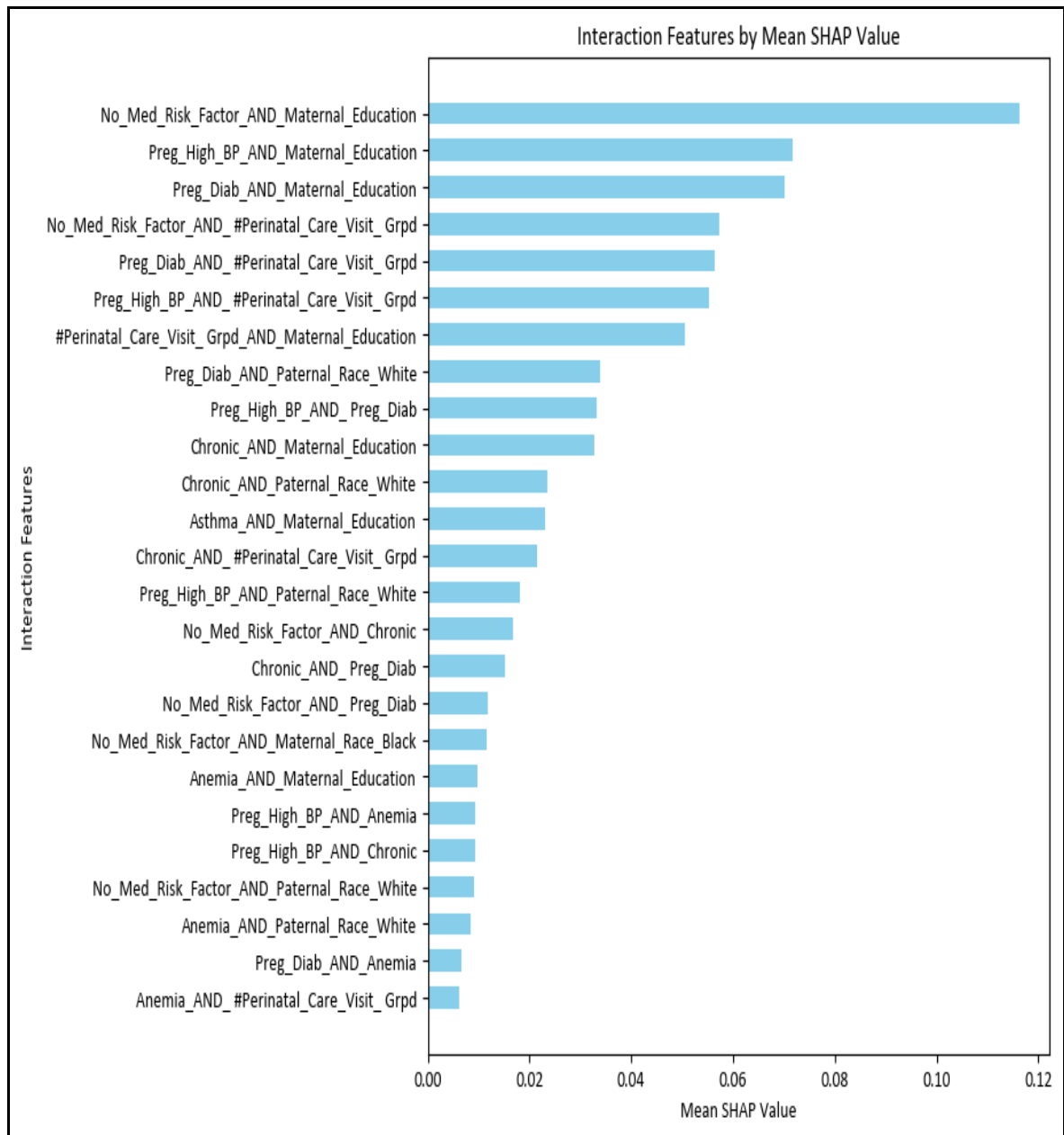


Figure 28. Interaction Feature Significance Using SHAP on NN Model

The feature Chronic emerges as a key predictor for PPD when interacting with factors such as maternal education level, gestational diabetes, hypertension during pregnancy, Number of perinatal care visits, and paternal racial background. Also, two chronic diseases, asthma, and anemia, interacted similarly with the maternal education level.

Logistic Regression

Figure 29 highlights the key interaction predictors for PPD using LR. Similar to NN, maternal education is shown at the top of the chart. Maternal age groups are the most common significant interaction features with maternal and paternal education and marital status. Additionally, the number of perinatal care visits interacts with the history of depression, abuse, maternal education, and the Kessner Index.

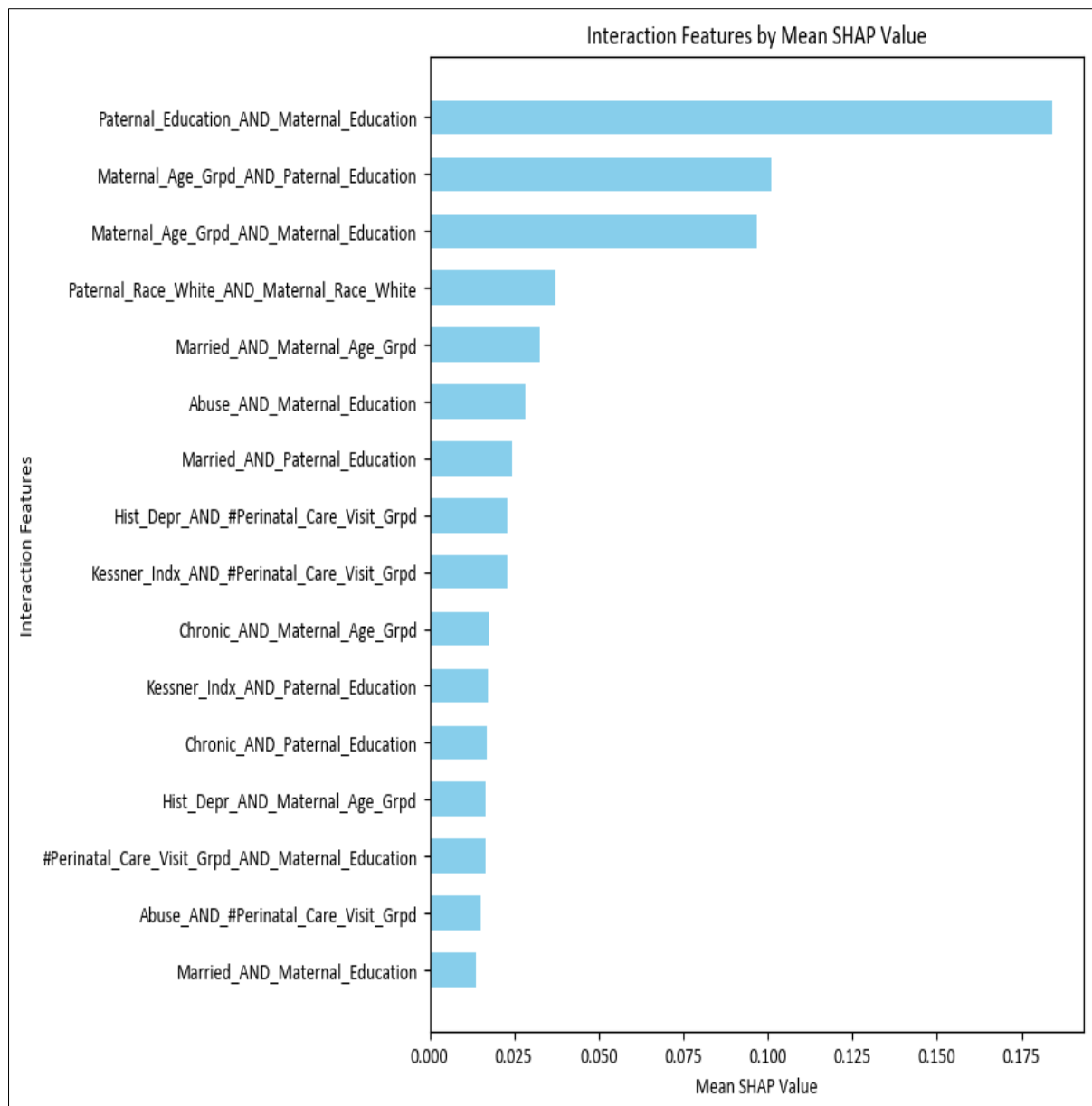


Figure 29. Interaction Feature Significance Using SHAP on LR Model

Maternal and paternal education features were identified with a SHAP value of 0.18. Considering the chronic feature, the analysis found a moderate interaction with the maternal age group (SHAP value 0.017) and paternal education (SHAP value .012). No other relevant interactions were found between specific chronic diseases and any other feature. Other key interaction predictors include paternal and maternal race, abuse and maternal education, and

the Kessner Index with the number of perinatal care visits, paternal education, and number of perinatal care visits with a history of depression, maternal education, and abuse.

Random Forest

Figure 30 shows the key interaction features identified by SHAP in the RF model. The significance of paternal education and maternal education are found to resemble the LR model. In addition, other similar inactive features include paternal education with ‘No medical risk factors,’ maternal age, maternal education, asthma and stress level. The interaction of Chronic disease with paternal education and maternal age were identified as key predictors of PPD, which is similar to the LR model. In contrast to NN and LR, maternal education with ‘No medical risk factors’ was found to be the top predictor of PPD. Additionally, the feature Chronic shows interactions with the infant age, history of depression, paternal and maternal education, and stress level. Finally, one of the chronic diseases, asthma, interacts with the maternal age group, paternal education, and infant age.

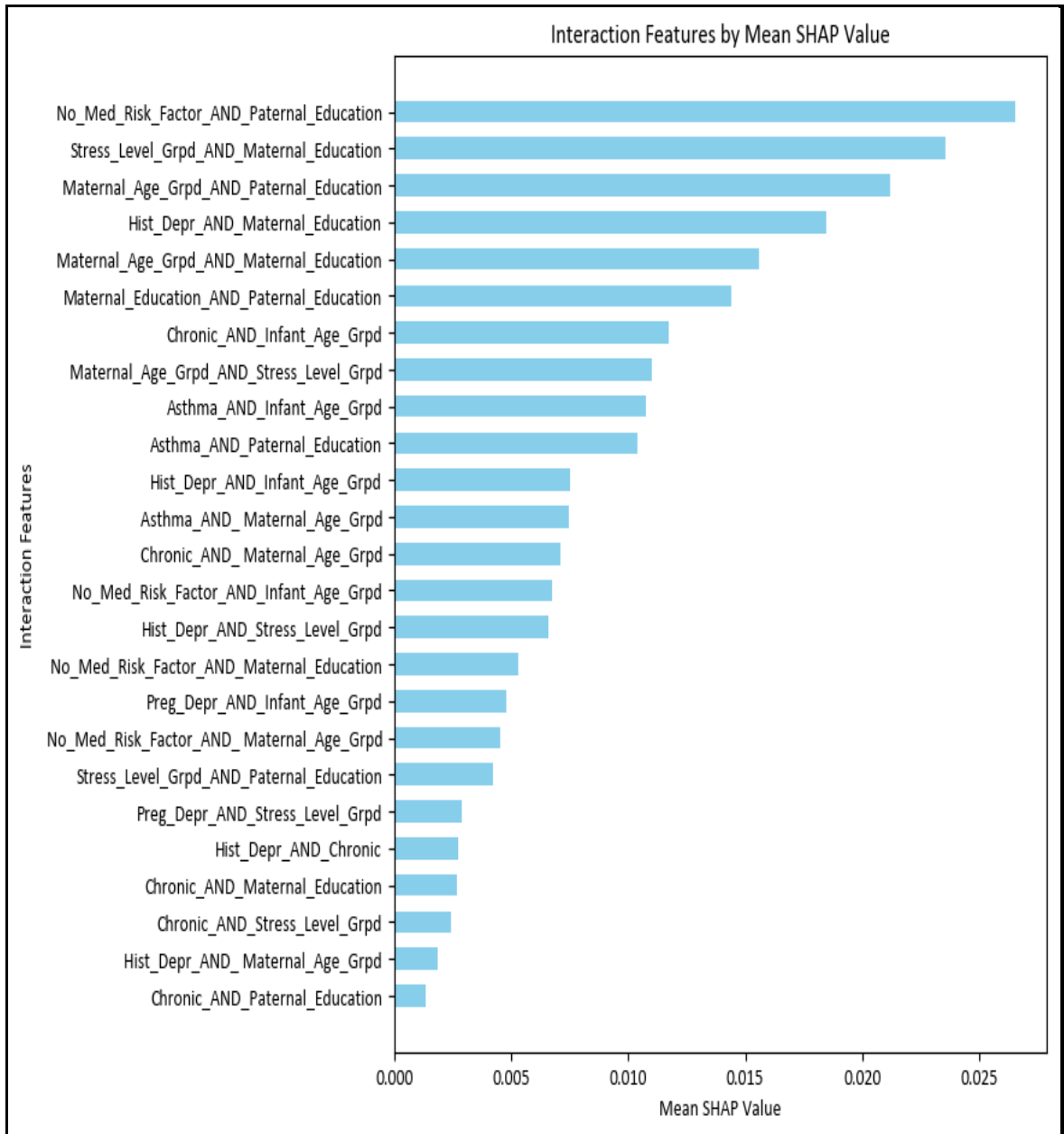


Figure 30. Interaction Feature Significance Using SHAP on RF Model

Support Vector Machine

The key interaction features for predicting PPD using the SVM are presented in Figure 31. In alignment with NN, paternal education is found at the top of the chart, with diabetes, high

blood pressure during pregnancy, and the absence of medical risk factors. Similarly, the maternal age group with maternal education, ‘No medical risk factors,’ and paternal education are aligned with RF. Paternal education and maternal education are similar to those of the LR model.

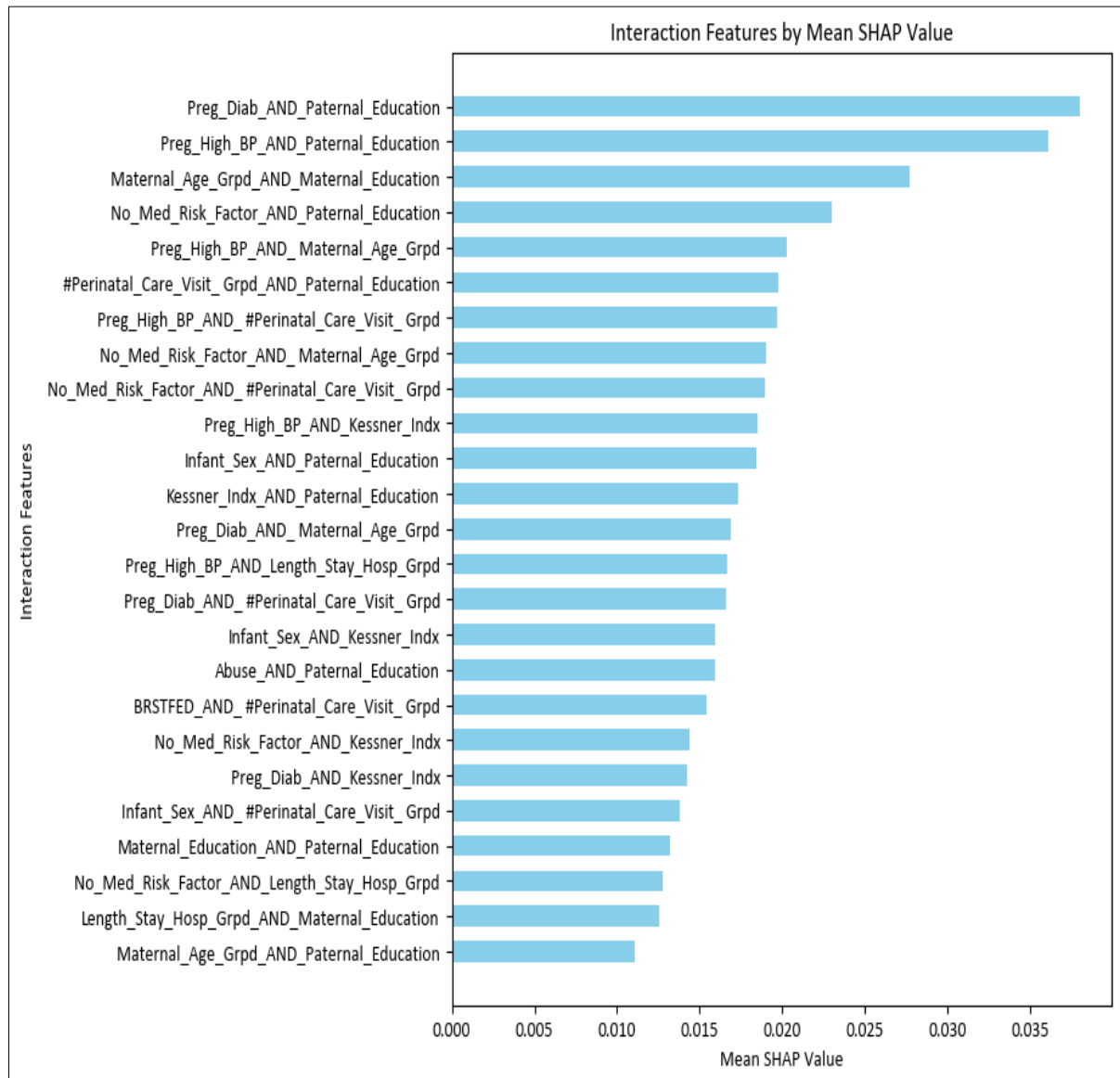


Figure 31. Interaction Feature Significance Using SHAP on the SVM Model

Key interaction predictor features identified in the SHAP plot include paternal education interacting with the number of perinatal care visits, infant sex, Kessner Index, and abuse. Kessner Index, together with high blood pressure and diabetes during pregnancy, paternal education, infant sex, and the absence of medical risk factors, also show significant interactions. Hospital length of stay also interacts notably with high blood pressure, the absence of medical risk factors, and maternal education in predicting PPD. No relevant interactions were found with the feature Chronic.

4.7 Summary: Interaction Analysis

Rather than examining features individually, interaction analysis captures the combined influence of multiple features. This approach enhanced the model's interpretability in the prediction process. Table 4 presents common key interaction features identified in the selected models.

Each model captures distinct interaction features for predicting PPD. In the SVM model, features such as infant sex and length of hospital stay showed interactions with other variables and were uniquely significant to this model. Similarly, in the NN model, interactions involving anemia were uniquely significant.

Features such as high BP, gestational diabetes, maternal age group, 'No medical risk factors,' number of perinatal care visits, chronic disease, and maternal and paternal education frequently interact with other predictors, emphasizing their roles in PPD prediction modeling. Notably, paternal education and maternal education appear across all models, while chronic disease

appears in three models: NN, LR, and RF.

Table 4. Top Common Key Interactive Features Identified by the Selected Models

Feature	Models
Chronic_AND_Maternal_Education	NN and RF
Chronic_AND_Paternal_Education	LR and RF
Chronic_AND_Maternal_Age_Group	LR and RF
No_Med_Risk_Factor_AND_Maternal_Education	NN and RF
No_Med_Risk_Factor_AND_#Perinatal_Care_Visit	NN and SVM
No_Med_Risk_Factor_AND_Maternal_Age_Grpd	RF and SVM
No_Med_Risk_Factor_AND_Paternal_Education	RF and SVM
Preg_Diab_AND_#Perinatal_Care_Visit_Grpd	NN and SVM
Preg_High_BP_AND_#Perinatal_Care_Visit_Grpd	NN and SVM
Maternal_Age_Grpd_AND_Paternal_Education	LR, RF, and SVM
Maternal_Age_Grpd_AND_Maternal_Education	LR, RF, and SVM
Maternal_Education_AND_Paternal_Education	LR, RF, and SVM

4.8 PD Screening Tool

An interactive machine-learning-based tool was developed to predict the likelihood of PPD for mental health assessment. The backend of this tool incorporates pre-trained models and associated scaling and encoding mechanisms necessary for preprocessing the user input. The front end, shown in Figure 32 and Figure 33, allows users to input values for a reduced set of critical features identified during feature selection, while non-critical features are automatically assigned default values based on insights from post-training analysis.

Once the user submits their input, the backend processes the data, applying the necessary transformations based on the trained models, and predicts the probability of PPD using multiple machine learning models. An ensemble model aggregates predictions from the individual models, with weights assigned based on the F1 scores of each model to ensure accurate and reliable results. The final output, expressed as a percentage likelihood of PPD, is sent back to the front end for user interpretation. For instance, a 74.90 % likelihood of PPD was identified for the sample inputs (Figure 34). This result is consistent with the patient's disease history and related factors observed in the training dataset. This personalized assessment of PPD risk will aid healthcare professionals in assessing and predicting PPD risks more effectively, showcasing the practical use of ML techniques in improving PPD care.

Patient Data Entry

Please provide the following information about your recent pregnancy:

Number of Prenatal Care Visits

Less than or equal to eight times

Maternal Age (Grouped)

20-24

Abuse

Yes

During your most recent pregnancy, did you have depression?

Yes

Next

Figure 32. PPD Screening Tool - Front End

Patient Data Entry

During the 3 months before you got pregnant with your new baby, did you have:

- ☒ Asthma
- ☒ Depression
- ☒ High blood pressure or hypertension
- ☒ Type 1 or Type 2 diabetes
- ☐ Anemia
- ☒ Anxiety Disorder
- ☐ Thyroid Dysfunction
- ☐ Polycystic Ovarian Syndrome

Select the level of stress you experienced:

- ☐ No Stress
- ☐ Low Stress
- ☐ Moderate Stress
- ☒ High Stress

Previous

Predict

Figure 33. PPD Screening Tool - Front End

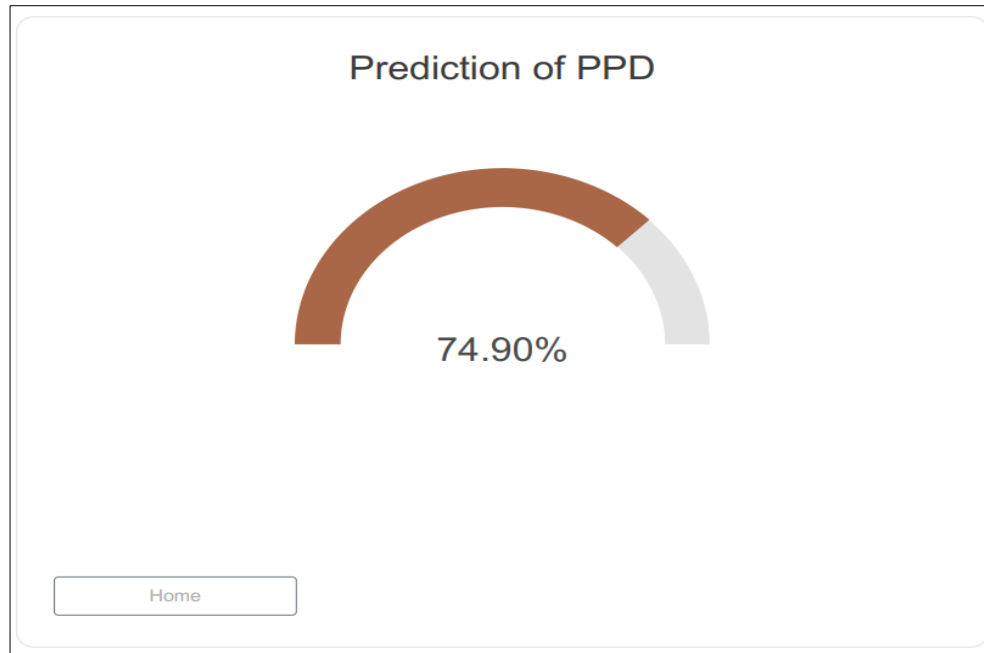


Figure 34. PPD Screening Tool - Prediction

4.9 Conclusion

The ML models exhibited a range of performance scores, from NN achieving 77% accuracy and 76% F1 score to LR reaching 89% accuracy and 88% F1 score. Overall, the results underscore differences in how each model captures and interprets the underlying patterns in the data. LR's optimized parameters would have enabled effective classification of the target, balancing precision, and recall. Additionally, RF's robust ensemble learning and SVM's effective margin optimization with the RBF kernel likely contributed to their performance scores. The NN might have faced challenges in capturing complex data patterns.

In conclusion, all models demonstrate a close alignment in their SHAP analysis in identifying key predictors. The SHAP summary plots reveal similar positive and negative SHAP values for multiple key features across the models. Disease features such as CHRONIC, asthma,

anemia, and a history of depression were consistently identified as key predictors across all models, with comparable SHAP values. Demographic features such as younger maternal age, lower education, race, infant age, and being married were found to be strong predictors. In addition, variables such as depression during pregnancy and higher stress levels contributed to the prediction of PPD.

When identifying the key features, CHRONIC is consistently presented among the top four predictors across all models, supporting the research hypothesis that CHRONIC is a significant predictor. Furthermore, the positive SHAP values across all models confirm that the presence of CHRONIC is a vital contributor to PPD.

Integrating interaction features offered valuable insights into influential factors of PPD. When considered together, the SHAP analysis highlights that certain demographic, health, and situational factors significantly predict PPD risk factors. A few interaction features appeared as the key predictors across all models, while a few other features were distinct. These results indicate that chronic disease, paternal and maternal education, maternal age group, high BP, gestational diabetes, 'No medical risk factors,' and number of perinatal care visits are key predictors. This consistency highlights their significance in predicting PPD.

Chronic disease was once again identified as an important predictor in three models (NN, LR, and RF), frequently interacting with other features and highlighting its vital role in predicting PPD. Identifying independent chronic diseases, asthma, and anemia are repeatedly found as key predictors, along with other features in the analysis using interaction features, reinforcing the hypothesis. Thus, results show that chronic diseases play a significant role in PPD risk.

Chapter 5

Conclusion and Future Work

PPD is a significant global concern that affects both new mothers and their infants. Despite its prevalence, awareness and understanding of PPD remain limited, leading to many cases being undiagnosed and untreated. When left unaddressed, this condition can escalate into severe psychosis over time. Early detection is crucial, as untreated PPD can lead to self-harm. Recognizing key risk factors allows healthcare professionals to identify women who are at a higher risk of developing PPD. This research presents a comprehensive process designed to prepare, analyze, visualize, and calculate PPD probabilities to identify PPD risk factors, specifically when chronic diseases are present.

Five years of data (over 200,000 records) obtained from CDC_PRAMS was used to demonstrate the predictive power of ML models. The research methodology started with implementing various preprocessing techniques such as encoding, scaling, and balancing data using SMOTE on the raw data. Subsequently, the most relevant variables, such as asthma, heart disease, diabetes, and thyroid dysfunction, were selected to address the hypothesis. Power BI was utilized to visualize the prepared data along various dimensions. The dashboard highlights a higher prevalence of postpartum depression among young mothers aged 25-29 and those with higher education levels (13-15 years of education). Key Influencer functionality on the dashboard highlights factors such as history of depression, being married, paternal race, and having a chronic disease that increases the likelihood of PPD. These insights offer a valuable understanding of the population, feature relationships, and underlying patterns.

Four predictive models, NN, LR, RF, and SVM, were implemented to predict the risk factors of PPD. The evaluation was based on accuracy and F1 scores, ensuring the model predicts accurately and handles class distributions appropriately. All models achieved over 75% accuracy and F1 scores, demonstrating satisfactory predictive performance across the test dataset. The metrics revealed that accuracy and F1 scores were closely aligned, indicating that the model performs well across both majority and minority classes. The predicted risk factors are mostly consistent across all models, and the feature CHRONIC was highlighted as a significant predictor, thereby supporting the research hypothesis. Also, key predictors such as depression (during and before pregnancy), higher stress, and maternal age are consistent with other findings [20], [24], [42], [60], [64]. Additionally, the SHAP analysis provided an in-depth understanding of each contributing factor of PPD. It further indicated the potential for feature interactions, particularly with those that showed a low SHAP value. The interaction analysis revealed factors such as high blood pressure, gestational diabetes, maternal age group, number of prenatal care visits, chronic disease, and maternal and paternal education interacting with other predictors frequently.

A web-based tool utilized the developed model as the backend for generating individualized predictions, allowing users to input relevant data and calculate the probability of PPD. This tool provides proof of concept for PPD screening in real-world scenarios.

In summary, the objective of this thesis was to identify the risk factors, particularly focusing on chronic diseases. These findings aim to support timely identification and intervention, reduce the risk of prolonged mental health challenges for mothers, and enhance their overall well-being.

5.1 Future Work

Although the PRAMS dataset provides valuable insights, its state-specific focus may limit the applicability of the model to more diverse populations. Also, a deeper investigation of interaction features, and incorporation of additional disease variables and clinical features is recommended to enhance the understanding of predictor impacts. Developing interaction features and including them in ML models has shown the importance of how input features interact. A detailed analysis of these interactions could help optimize the models to improve their performance and make them more valuable as a backend for the PPD prediction tool, providing more reliable screening results.

Also, the use of a broader dataset could improve the evaluation of predictive models and PPD calculation tool. Furthermore, the study can apply a longitudinal approach to identify how risk factors and symptoms change over time. Time-series data from longitudinal studies could capture these trends and make more accurate predictions.

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