Outline of Presentation

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- Phase 2 Literature Review
- Summary of Literature (Phase 1 and 2)
- Problem Statement
- Objectives
- Methodology
- Work Progress
- Intermittent Results and Analysis
- Project Deliverables
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Introduction

- Postpartum depression (PPD) is a complex mix of physical, emotional, and behavioral changes that happen in some women after giving birth.

- There is no single cause of postpartum depression, but genetics, physical changes and emotional issues may play a role.

- PPD is a form of depression that typically begins in the first month after giving birth and is characterized by symptoms including sadness, fatigue, changes in eating and sleeping patterns, crying episodes, anxiety, and irritability.

Introduction

- Pre-eclampsia is a pregnancy complication characterized by hypertension typically after 20 weeks of gestation.
- Risk factors include first pregnancies, multiple pregnancies, maternal age extremes, and certain medical conditions.
- Symptoms include high blood pressure, proteinuria, swelling of legs, headaches, and vision changes.

Introduction

- Both pre-eclampsia and postpartum depression share common stress factors, impacting mothers during high-risk pregnancies.

- Pre-eclampsia's physical toll such as high blood pressure, can contribute to postpartum depression, affecting emotional well-being.

- Hormonal fluctuations in pre-eclampsia and postpartum depression contribute to mood disorders. Long-term health concerns may contribute to ongoing stress impacting mental health.

Motivation

- Global maternal depression: 10%-15% during and after pregnancy, reaching 18%-25% in low/middle-income countries (National Institute of Mental Health, US).

- Impact on mother-infant relationship: Hinders positive development, affecting children from toddlerhood.

- Infant issues: Poor nutrition, compromised health, increased diarrheal episodes linked to depressed mothers.

- Extreme cases: Maternal suicide and infanticide are potential outcomes.

Literature Survey

[1] A. Paul, S. D. Pragada, D. N. Murthy, M. L. J. Shruthi and S. Gurugopinath, "**Performance Comparison of Machine Learning Techniques for Early Detection of Postpartum Depression Using PRAMS Dataset**," *2023 IEEE 15th International Conference on Computational Intelligence and Communication Networks (CICN)*, Bangkok, Thailand, 2023, **(Base paper)**

PROBLEM ADDRESSED	METHODOLOGY	ACHIEVEMENT	LIMITATIONS
• Prediction of Post-Partum Depression(PPD) using the **PRAMS dataset** and comparing different ML models based on performance parameters.	Models implemented: • **Random Forest(RF)** • **K-Nearest Neighbours(KNN)** • **Logistic Regression** • **Support vector machine(SVM)** • **TabNet**	• The **SVM** model was found to achieve the best performance metrics of all models with **accuracy(0.7441)** and **AUC(0.7166)** but **TabNet** outperforms if **AUC(0.7779)** is considered	• Detecting PPD after 6 weeks of childbirth is early but limited, as it could be identified even earlier in the gestational period. • The classification of distinct stages within postpartum depression (PPD) is not currently undertaken.

Literature Survey

[13]B. C. Loftness, I. Bernstein, C. A. McBride, N. Cheney, E. W. McGinnis and R. S. McGinnis, "**Preterm Preeclampsia Risk Modelling: Examining Hemodynamic, Biochemical, and Biophysical Markers Prior to Pregnancy,"** *2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Sydney, Australia, 2023,*

PROBLEM ADDRESSED	METHODOLOGY	ACHIEVEMENTS	LIMITATIONS
• Machine learning based approach for detecting individuals who are at risk for developing preterm PE before they become pregnant. • Development and optimization of pre-pregnancy biomarkers for improving the identification of preterm (early-onset)	Hemodynamic (HD) data were collected continuously via a Finipres Pro (FMS, Netherlands) **Models implemented** • Random forest • Support vector machine	• Models achieved both high classification performance **(0.88 and 0.85)** and detection rates **(0.6 and 0.7)**. • ROC AUC varied only slightly between the top 6 modality combinations **(~0.8-0.92)**	• Data set was consist of only 80 samples • The analysis included **4 normotensive** samples, but without biochemical testing, confirmation of their normal blood pressure status was limited."

Literature Survey

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[14]Toledo, C., Cianelli, R., Villegas Rodriguez, N., De Oliveira, G., Gattamorta, K., Wojnar, D., & Ojukwu, E. (2022). **"The significance of breastfeeding practices on postpartum depression risk".** *Public Health Nursing, 39, 15−23.*

PROBLEM ADDRESSED	METHODOLOGY	ACHIEVEMENT	LIMITATIONS
• Examining the relationship between breastfeeding practices and PPD using the 2016 PRAMS questionnaire.	• A cross-sectional, correlational study design was used. A secondary analysis was conducted using descriptive and bivariate analyses.	• Women currently breastfeeding and women who breastfed for longer periods of time had statistically lower PPD risk.	• The dataset used was questionnaire based . • The authors have used only three variables related to breastfeeding.

Literature Survey

[15] Li X, Ono C, Warita N, Shoji T, Nakagawa T, Usukura H, Yu Z, Takahashi Y, Ichiji K, Sugita N, Kobayashi N, Kikuchi S, Kunii Y, Murakami K, Ishikuro M, Obara T, Nakamura T, Nagami F, Takai T, Ogishima S, Sugawara J, Hoshiai T, Saito M, Tamiya G, Fuse N, Kuriyama S, Yamamoto M, Yaegashi N, Homma N and Tomita H (2022) **Heart Rate Information-Based Machine Learning Prediction of Emotions Among Pregnant Women.** *Front. Psychiatry* 12:799029. doi: 10.3389/fpsyt.2021.799029

PROBLEM ADDRESSED	METHODOLOGY	ACHIEVEMENT	LIMITATIONS
• Different emotions**(happy, sad, anxiety , frustration)** of pregnant women can be predicted using **heart rate-relevant information** as indicators	• Data collected of over **85 pregnant** women during 23rd-32nd week of pregnancy • **<u>Models implemented:</u>** **Random Forest(RF)** **K-Nearest Neighbor** **Decision tree (DT)** **Logistic Regression** **Support vector machine (SVM)**	• The **Random Forest (RF)** algorithm was identified as producing the highest prediction **accuracy** among the algorithms tested. **Accuracy(0.74)** **AUC(0.70)**	• **Sample Size**: The study had a relatively small sample size of **85 pregnant women**. • There might be variability in **self-reporting** of emotions among the participants as they may **under-report or over-report** their emotions.

Summary of Literature

- One notable finding in the study was the significance of certain variables in predicting preeclampsia. Such as underlying **health conditions, level of education, timing of pregnancy and the number of previous pregnancies** emerged as key factors.

- Studies shows that factors affecting Pre Eclampsia are similar to the factors affecting PPD.

- PE study based on socio-demographic and health information obtained in a local population can be valid and extensive to other communities

Problem Statement

"To Design a model that can expedite the early detection of Postpartum Depression "

Objectives

- To preprocess the **PRAMS**(Pregnancy Risk Assessment Monitoring System) dataset for early prediction of PPD with the inclusion of Preeclampsia as the major indicator.

- Designing a model for **early detection of PPD** with improved performance.

- Performance analysis of the design and it's comparison with **S-O-T-A** techniques.

Dataset

- The **Pregnancy Risk Assessment Monitoring System (PRAMS)** constitutes a dataset upheld by the **Centers for Disease Control and Prevention (CDC)**, a U.S. government health agency.

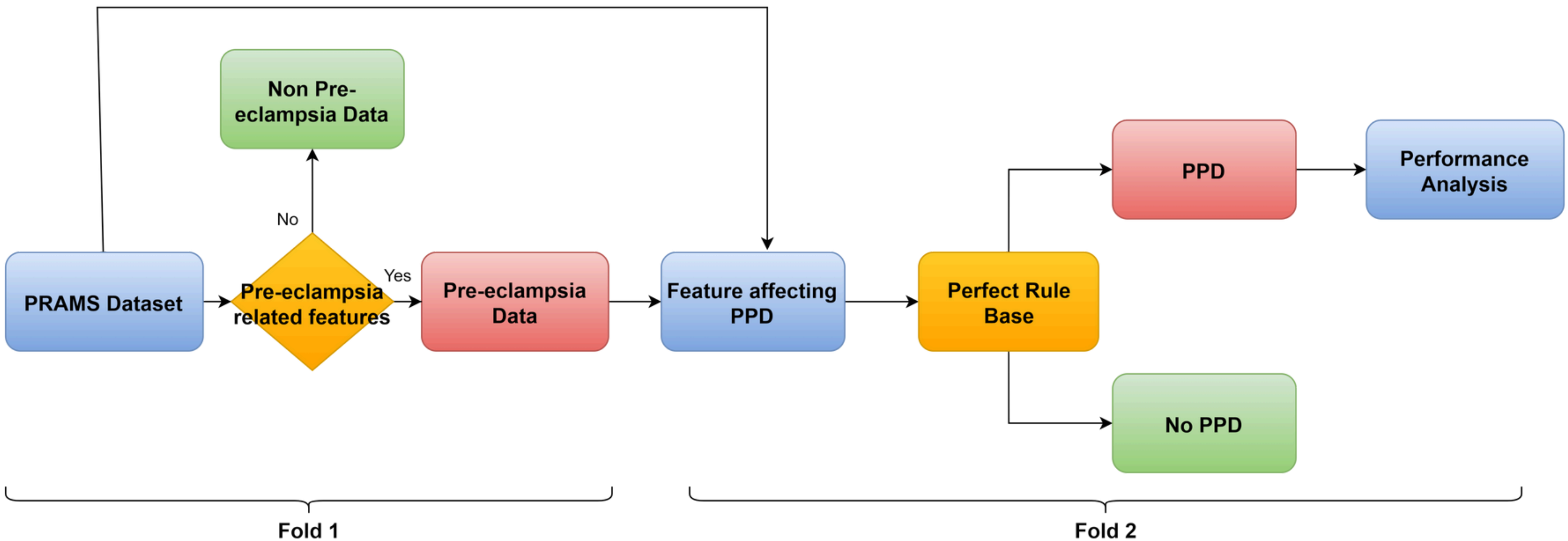
- PRAMS is geared towards identifying populations of mothers and babies who are most at risk for health issues, monitoring their health status, and tracking efforts to improve maternal and infant health.

- Initiated in 1987, PRAMS collects jurisdiction-specific, population-based data on maternal attitudes and experiences **before, during, and shortly after pregnancy**

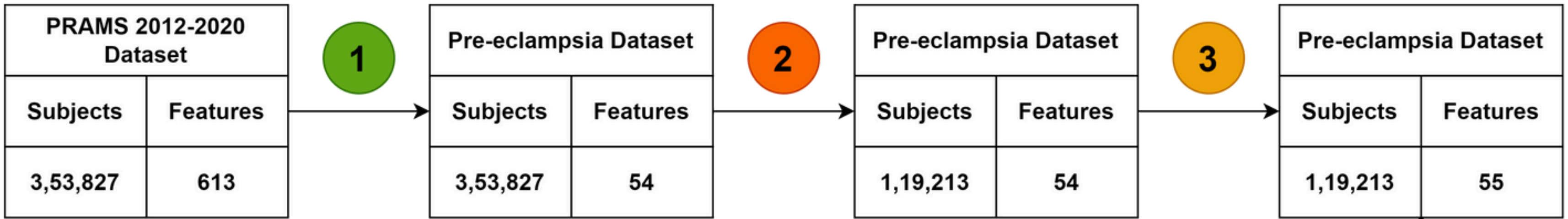
- The survey encompasses various subjects, including **prenatal care, breastfeeding, infant feeding, childbirth,** and more.

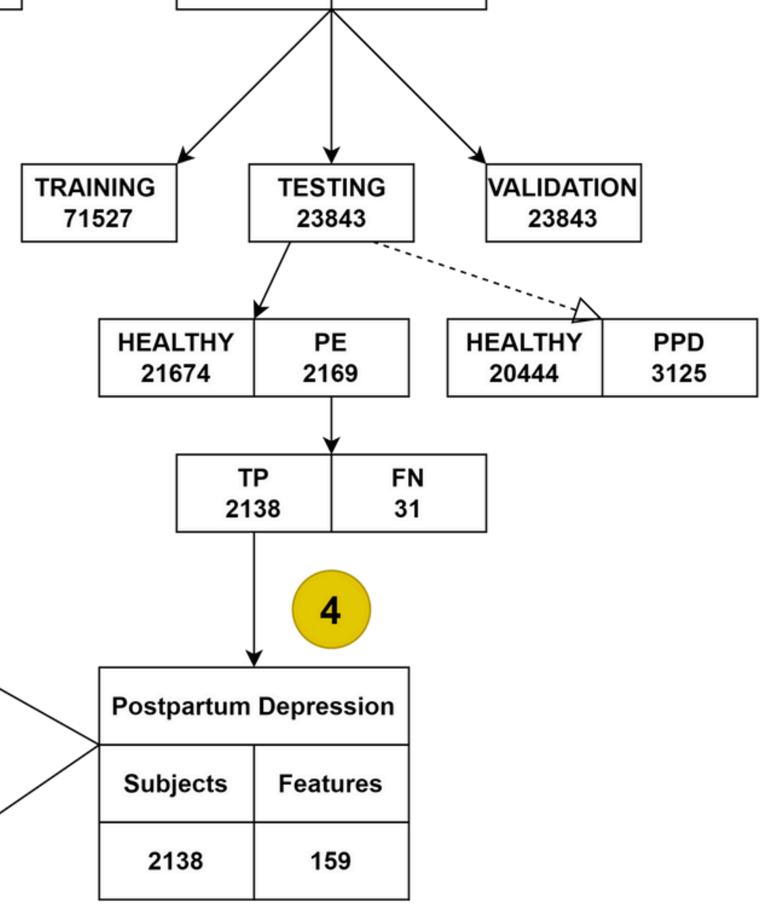
- The **PRAMS dataset (2012-2020)** contains around **353,827 rows and 613 columns** representing different features.

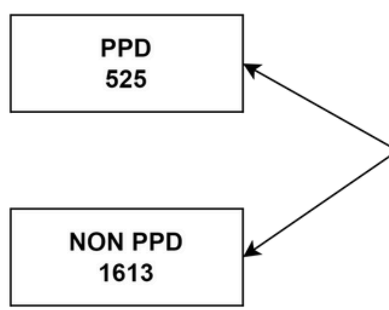
Methodology



Work Progress







1. Selecting features to create dataset for Pre-eclampsia.
2. Handling NULL values as data preprocessing.
3. Labelling the dataset for Pre-eclampsia.
4. Creating a new dataset for Postpartum Depression using the samples which were positive for Pre-eclampsia.

Work Progress (Yet to be Implemented)

- Out of 3,125 PPD subjects, 525 were successfully predicted during the early gestational stage, specifically during the pre-eclamptic phase. Our goal is to enhance this early prediction rate by incorporating more parameters.

- We aim to apply state-of-the-art techniques across multiple models to refine and develop an optimal solution for this two-fold process.

- We also need to employ more advanced performance evaluation metrics to ensure a more comprehensive assessment of the model's effectiveness.

FEATURES

Pre-eclampsia Number of features considered=53	Postpartum Depression Number of features considered =159
MM_HBP = 5	BABYDEAD
MM_DIAB = 5	VITAMIN
PLURAL = 5	MOMSMOKE
MOMSMOKE = 5	DRK_2YRS
MOM_BMIG_QX_REV = 4	DDS_CARE
DRK_2YRS = 1	SLEEPPOS_RAW
MH_PGDX8 = 1	BRSTFED

Total(Threshold) = 26

There are 39 common features between PE and PPD Datasets.

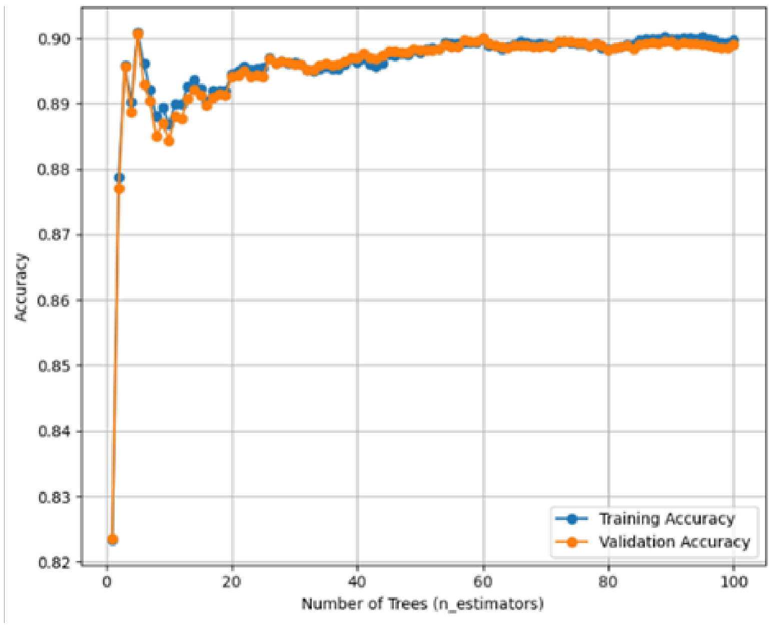
IMPUTATION METHODS

MICE (Multiple Imputation by Chained Equations)
It is a statistical method used to handle missing values by performing multiple imputations using a series of regression models. It treats each variable with missing data as a dependent variable in turn, predicts its missing values based on the other variables, and cycles through the dataset iteratively.

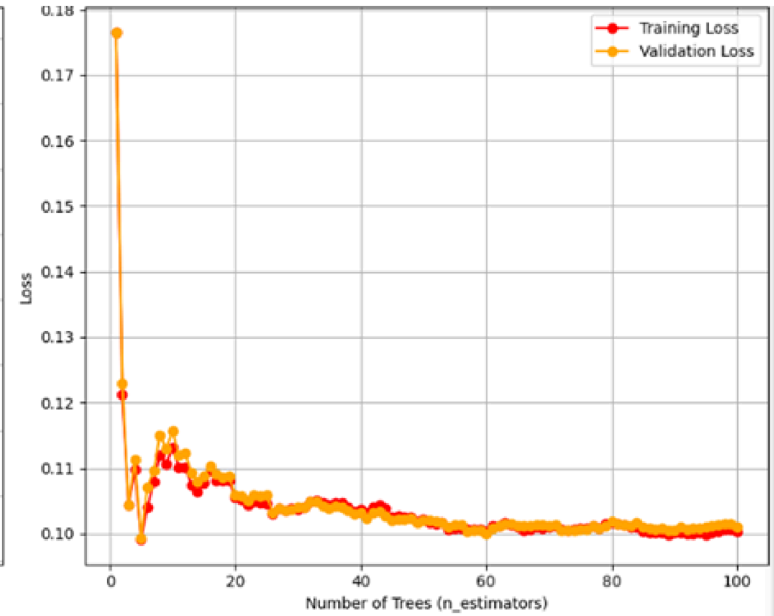
Decision Tree Imputation
This method imputes missing values iteratively. It first guesses missing values, builds a decision tree to model each column, and uses the tree to fill missing values. The process is repeated several times to improve accuracy.

Results and Analysis

MICE Imputed Random Forest model(fold1)



Accuracy Plot



Loss Plot

Test Set Size= 23843

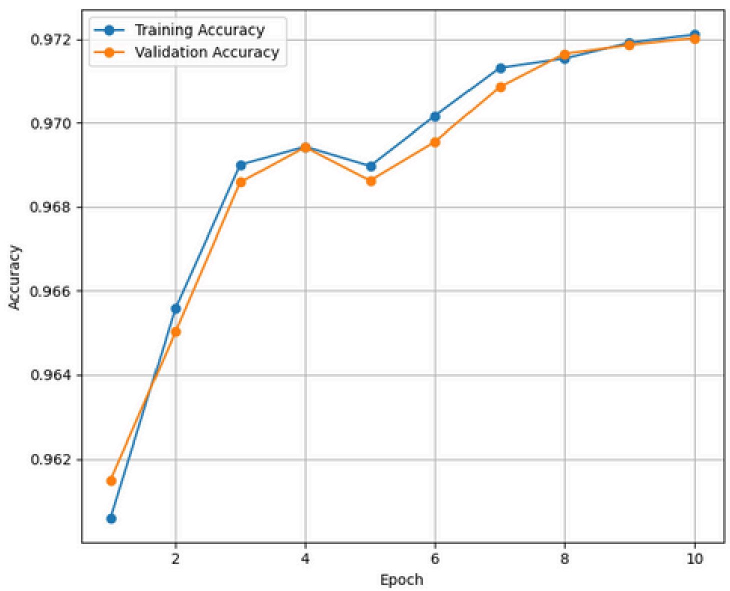
TP **2018**	**FN** **151**
FP **2241**	**TN** **19433**

Optimal number of Trees = 5

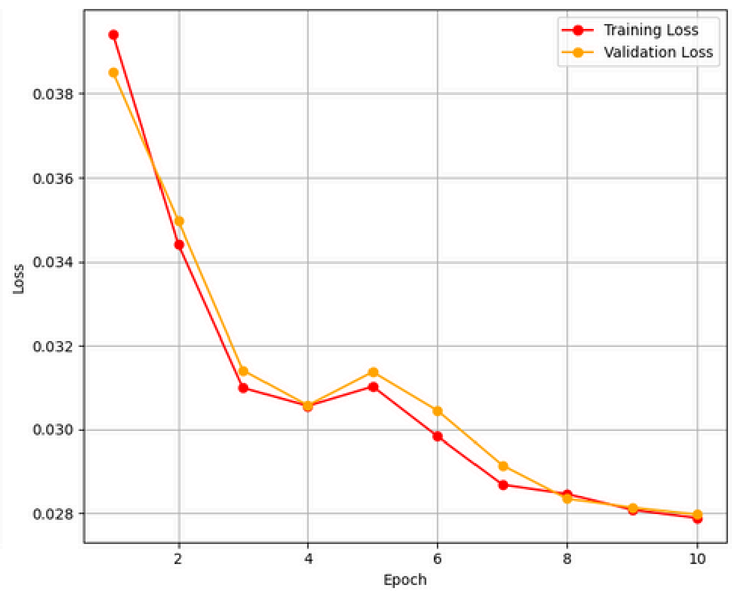
Fold	Precision	Recall	f1-score	Accuracy
1	0.47	0.93	0.63	0.90

Results and Analysis

MICE imputed SVM model(fold1)



Accuracy Plot



Loss Plot

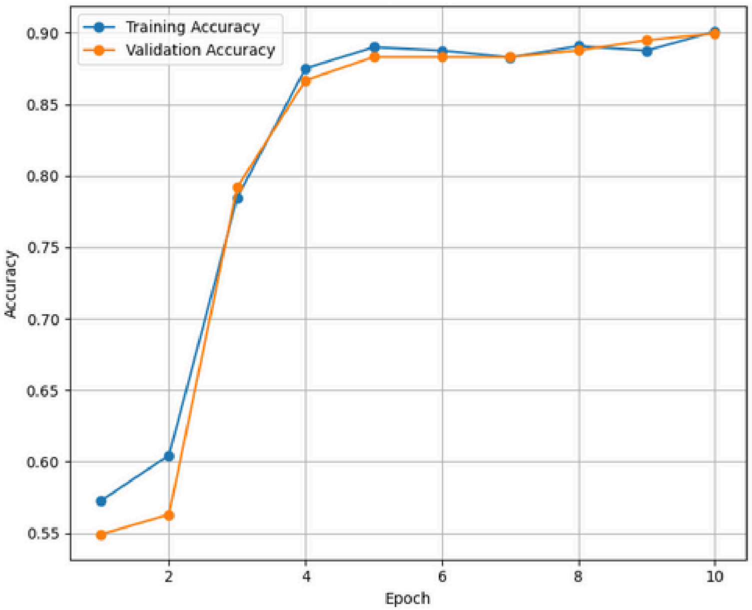
Fold	Precision	Recall	f1-score	Accuracy
1	0.77	0.99	0.87	0.97

Test Set Size= 23843

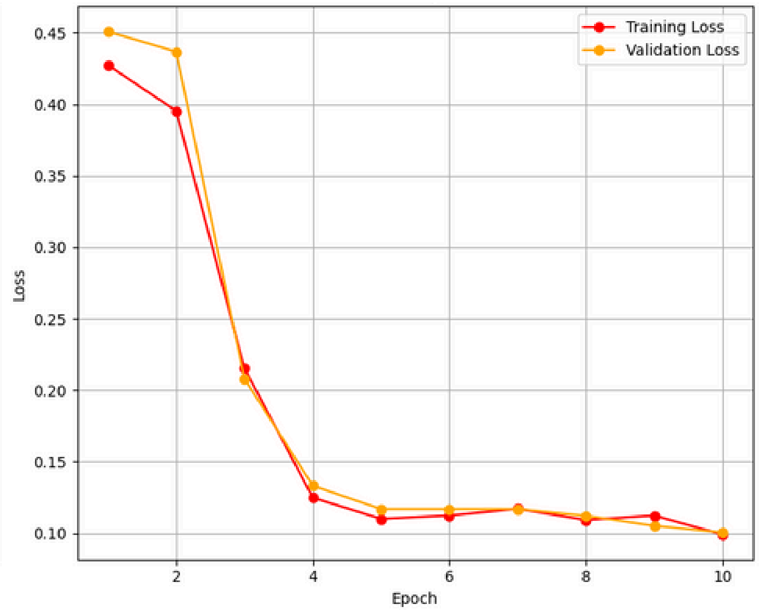
TP 2138	FN 31
FP 634	TN 21040

Results and Analysis

MICE imputed SVM model(fold2)



Accuracy Plot



Loss Plot

Fold	Precision	Recall	f1-score	Accuracy
2	0.79	0.98	0.88	0.93

Test Set Size= 428

TP 108	FN 2
FP 28	TN 290

Results and Analysis

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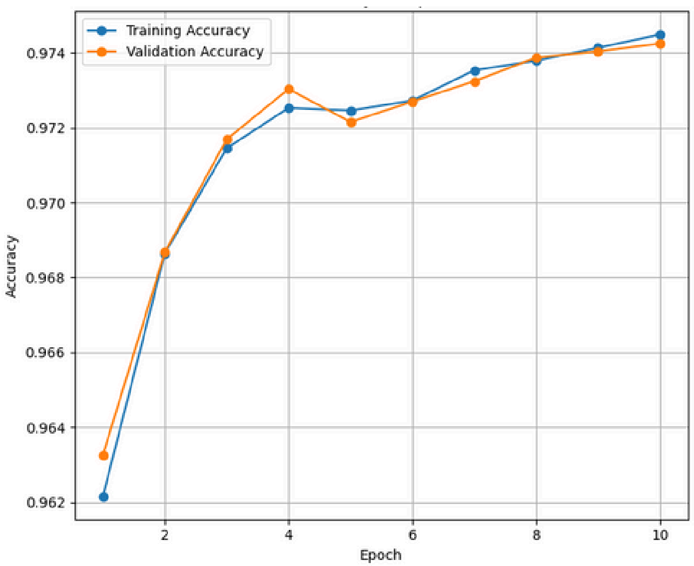
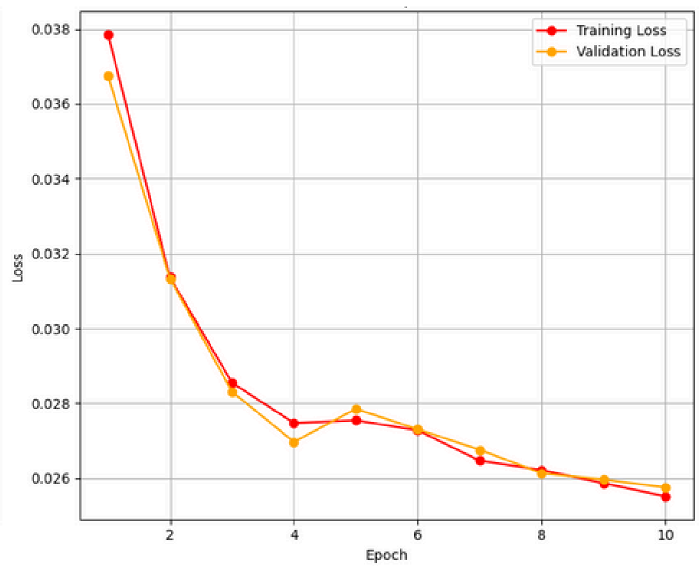
Decision tree imputed SVM model(fold1)



Accuracy Plot



Loss Plot

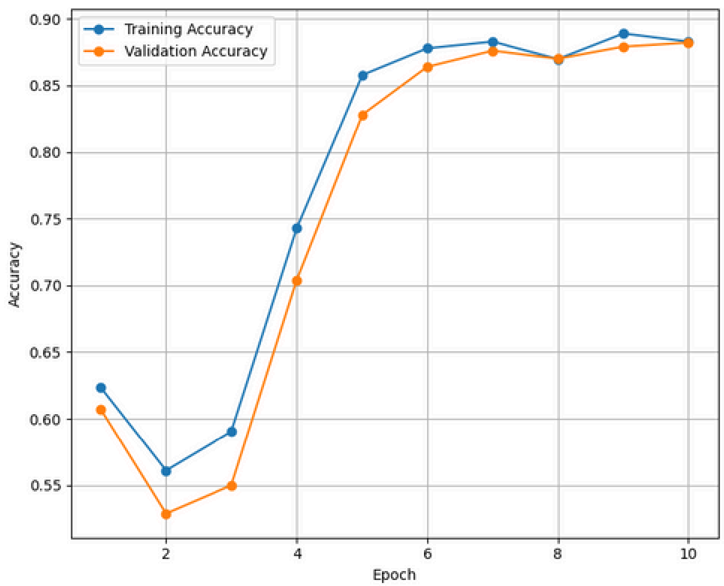
Test Set Size= 23843

Fold	Precision	Recall	f1-score	Accuracy
1	0.74	0.99	0.85	0.97

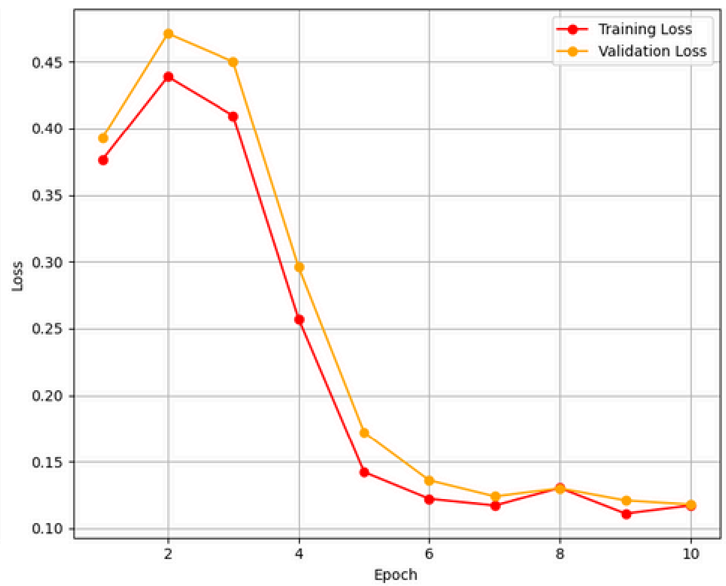
TP 1653	FN 17
FP 589	TN 21584

Results and Analysis

Decision tree imputed SVM model(fold2)



Accuracy Plot



Loss Plot

Fold	Precision	Recall	f1-score	Accuracy
2	0.71	0.95	0.81	0.89

Test Size= 331

TP 79	FN 4
FP 33	TN 215

Deliverables

Phase 2 : 1)Dataset for Pre-eclampsia linked to PPD.

2)The two fold Classification Model.

3)Project Report.

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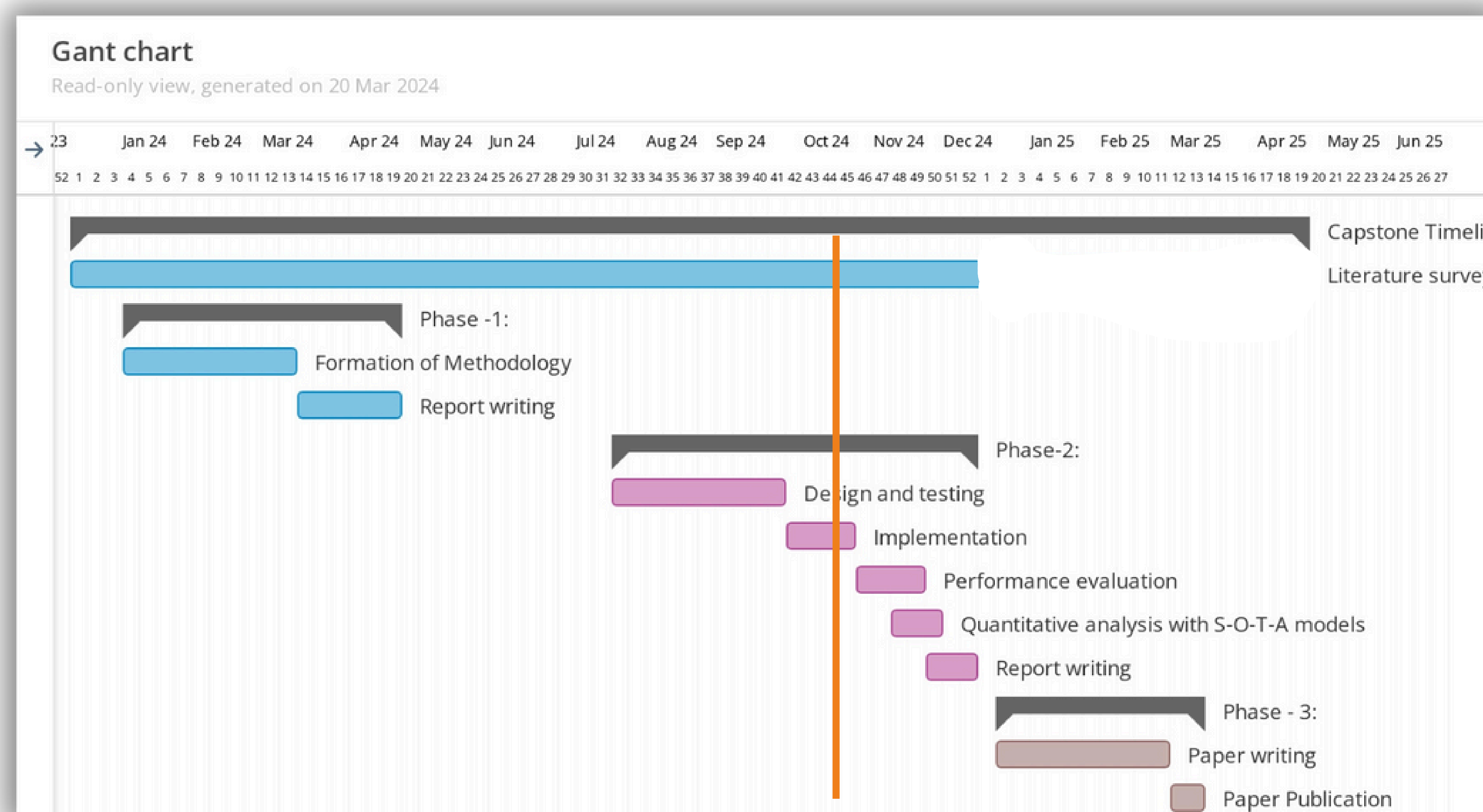
Project timeline



Q & A

Thank You