Maternal health risk classification

Machine learning project

Introduction

- Maternal health is a critical aspect of public health, especially in rural areas where healthcare services may be limited.
- Many pregnant women face life-threatening complications during and post-pregnancy due to insufficient information about maternal health care.
- Addressing this information gap is essential to reduce preventable deaths among pregnant women and neonates.

Problem Statement

- Many pregnant women die from complications due to a lack of adequate information and monitoring during pregnancy and post-pregnancy.
- Traditional risk assessment methods often lack precision and timely intervention capabilities, especially in rural areas.
- There is a need for advanced tools to monitor changes from the beginning of pregnancy to help reduce preventable deaths among pregnant women and neonates.

Project overview

- This project focuses on predicting maternal health risks using machine learning techniques.
- Utilize machine learning to classify risk levels based on health indicators.

Facilitate early intervention and improve maternal and neonatal outcomes.

Dataset

- The dataset titled "Maternal Health Risk" was collected from hospitals, community clinics, and maternal health care centers in rural areas of Bangladesh.
- Data collection was facilitated through an IoT-based system, ensuring real-time and comprehensive data acquisition.
- The dataset includes 1013 instances and 6 features, all significant risk factors for maternal mortality.

Methodology

Data Exploratory Analysis

Univariate and bivariate analysis
PCA for data visualization

Modeling and fine tuning

Training and fine tuning of
decision tree ,Random forest, svm, knn, ann
naive bayes models

Data preprocessing

Normalization , Standardization
Feature engineering ,outliers , Duplicates
Undersampling
oversampling.

Models evaluation

Cross fold validation
Precision
Stratified evaluation
Confusion matrix
Roc curve

Discussion

Comparison of different models performance under different circumstances

2 Problems

50%

50% of data duplicates

50% 25% 25%

Unbalanced distribution of classes

Circumstances

Remove duplicates

Undersample

Oversample

Keep duplicates

Undersample

Oversample

Keep duplicates add noise

Undersample

Oversample

Performance of models with no duplicates in data

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	93%	57%	79%	69%
Random Forest	93%	61%	77%	72%
SVM	74%	69%	81%	68%
KNN	75%	65%	73%	66%
ANN	82%	66%	78%	66%
Naive Bayes	65%	65%	65%	65%

Performance of models with no duplicates tested on different test set

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	93%	53%	79%	58%
Random Forest	93%	57%	74%	60%
SVM	74%	58%	81%	59%
KNN	75%	57%	73%	56%
ANN	83%	57%	81%	58%
Naive Bayes	65%	52%	65%	52%

Classification Report

Naive Bayes:
Training Accuracy (before tuning): 0.6582
Test Accuracy (before tuning): 0.6544
Training Accuracy (after tuning): 0.6582
Test Accuracy (after tuning): 0.6544
Classification Report (after tuning):

	precision	recall	f1-score	support
high risk	0.94	0.50	0.65	34
low risk	0.64	0.99	0.78	70
mid risk	0.30	0.09	0.14	32
accuracy			0.65	136
macro avg	0.63	0.53	0.52	136
weighted avg	0.64	0.65	0.60	136

Random Forest:
Training Accuracy (before tuning): 0.9399
Test Accuracy (before tuning): 0.6176
Training Accuracy (after tuning): 0.7722
Test Accuracy (after tuning): 0.7206
Classification Report (after tuning):

	precision	recall	f1-score	support
high risk	0.90	0.76	0.83	34
low risk	0.67	0.99	0.80	70
mid risk	0.75	0.09	0.17	32
accuracy			0.72	136
macro avg	0.77	0.61	0.60	136
weighted avg	0.75	0.72	0.66	136

Performance of models trained with no duplicates undersampling

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	96%	45%	71%	60%
Random Forest	96%	60%	60%	71%
SVM	68%	61%	68%	61%
KNN	67%	55%	65%	58%
ANN	71%	58%	71%	60%
Naive Bayes	57%	66%	57%	66%

Performance of models trained with no duplicates and undersampling tested with different data set

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	96%	55%	67%	60%
Random Forest	96%	66%	70%	60%
SVM	68%	64%	68%	64%
KNN	67%	54%	65%	60%
ANN	71%	62%	70%	58%
Naive Bayes	57%	56%	57%	56%

Classification Report

SVM:
Training Accuracy (before tuning): 0.6847
Test Accuracy (before tuning): 0.6103
Training Accuracy (after tuning): 0.6847
Test Accuracy (after tuning): 0.6103
Classification Report (after tuning):

	precision	recall	f1-score	support
high risk	0.83	0.74	0.78	34
low risk	0.71	0.60	0.65	70
mid risk	0.34	0.50	0.41	32
accuracy			0.61	136
macro avg	0.63	0.61	0.61	136
weighted avg	0.65	0.61	0.63	136

KNN:
Training Accuracy (before tuning): 0.6757
Test Accuracy (before tuning): 0.5515
Training Accuracy (after tuning): 0.6532
Test Accuracy (after tuning): 0.5882
Classification Report (after tuning):

	precision	recall	f1-score	support
high risk	0.76	0.76	0.76	34
low risk	0.66	0.61	0.64	70
mid risk	0.30	0.34	0.32	32
accuracy			0.59	136
macro avg	0.57	0.57	0.57	136
weighted avg	0.60	0.59	0.59	136

Performance of models with no duplicates and oversampling

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	96%	58%	96%	58%
Random Forest	96%	61%	96%	61%
SVM	73%	71%	80%	64%
KNN	82%	59%	82%	59%
ANN	83%	61%	88%	60%
Naive Bayes	57%	66%	57%	66%

Performance of models with no duplicates and oversampling on different test set

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	96%	54%	96%	57%
Random Forest	96%	60%	96%	59%
SVM	73%	66%	80%	60%
KNN	82%	54%	82%	54%
ANN	85%	62%	91%	60%
Naive Bayes	57%	58%	57%	58%

Classification Report

Training Accuracy (after tuning): 0.9187
Test Accuracy (after tuning): 0.6095
Classification Report (after tuning):

	precision	recall	f1-score	support
high risk	0.81	0.80	0.81	70
low risk	0.55	0.74	0.63	70
mid risk	0.43	0.29	0.34	70
accuracy			0.61	210
macro avg	0.60	0.61	0.59	210
weighted avg	0.60	0.61	0.59	210

Decision Tree:
Training Accuracy (before tuning): 0.9614
Test Accuracy (before tuning): 0.5476
Training Accuracy (after tuning): 0.9614
Test Accuracy (after tuning): 0.5714
Classification Report (after tuning):

	precision	recall	f1-score	support
high risk	0.79	0.74	0.76	70
low risk	0.53	0.69	0.60	70
mid risk	0.37	0.29	0.32	70
accuracy			0.57	210
macro avg	0.56	0.57	0.56	210
weighted avg	0.56	0.57	0.56	210

Performance of models with no duplicates with adaboosting

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	93%	56%	83%	71%
Random Forest	93%	61%	87%	69%
SVM	53%	52%	52%	55%
ANN	76%	71%	76%	73%
Naive Bayes	62%	62%	62%	62%

Performance of models with noise and oversampling

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	87%	76%	99%	83%
Random Forest	82%	74%	99%	86%
SVM	73%	67%	99%	87%
KNN	73%	67%	90%	74%
ANN	76%	69%	%	%
Naive Bayes	61%	60%	61%	62%

Performance of models with noise and oversampling and ensembles

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	87%	76%	99%	82%
Random Forest	82%	74%	99%	86%
SVM	73%	67%	99%	78%
KNN	83%	74%	94%	82%
ANN	76%	69%	%	%
Naive Bayes	61%	60%	71%	68%

Performance of models with noise and undersampling

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	84%	79%	99%	82%
Random Forest	84%	80%	99%	85%
SVM	72%	75%	99%	82%
KNN	79%	76%	88%	74%
ANN	76%	73%	%	%
Naive Bayes	58%	68%	59%	67%

Performance of models with noise undersampling and ensembles

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	84%	79%	99%	82%
Random Forest	84%	80%	99%	86%
SVM	72%	75%	96%	90%
KNN	79%	76%	94%	78%
ANN	76%	73%	%	%
Naive Bayes	58%	68%	61%	64%

Performance of models without noise and oversampling

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	81%	73%	90%	79%
Random Forest	80%	74%	91%	80%
SVM	71%	69%	84%	73%
KNN	85%	75%	91%	80%
ANN	73%	76%	%	%
Naive Bayes	63%	60%	61%	61%

Performance of models without noise and oversampling and ensembles

Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	81%	73%	91%	81%
Random Forest	80%	74%	91%	80%
SVM	71%	69%	77%	87%
KNN	85%	75%	94%	74%
ANN	73%	76%	%	%
Naive Bayes	63%	60%	73%	64%

Performance of models without noise and undersampling

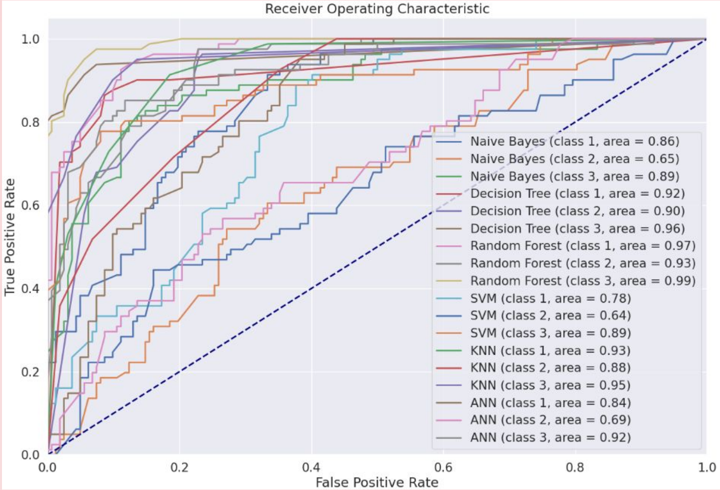
Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	82%	79%	89%	79%
Random Forest	79%	79%	91%	79%
SVM	73%	75%	85%	81%
KNN	82%	79%	86%	74%
ANN	74%	78%	%	%
Naive Bayes	58%	68%	57%	63%

Performance of models with noise undersampling and ensembles

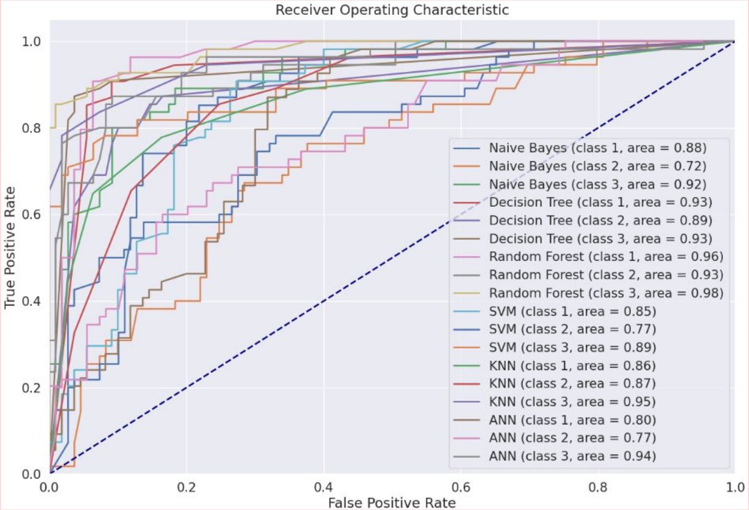
Model	Before Model Tuning		After Model Tuning	
Accuracy	Training accuracy	Testing accuracy	Training accuracy	Testing accuracy
Decision tree	82%	79%	90%	82%
Random Forest	79%	79%	91%	86%
SVM	73%	75%	86%	84%
KNN	82%	79%	82%	78%
ANN	74%	78%	%	%
Naive Bayes	58%	68%	71%	71%

Models evaluation

1. Performance of models without noise and oversampling:



2. Performance of models without noise undersampling:



Interpretation & Recommendations:

- Random Forest stands out for its consistent and exceptional discriminative ability across scenarios.
- Other models like Decision Tree, SVM, KNN, and ANN show potential but require tailored approaches due to varying performance.
- Addressing limitations such as data quality, model complexity, and evaluation metrics is pivotal for enhancing overall model efficacy.
- Future steps include integrating external data, conducting longitudinal studies, validating predictions clinically, and deploying models in real-world settings to advanced maternal health risk assessment and intervention.

Conclusion

- Developed robust ML framework for maternal risk classification.
- Utilized systematic methodology including data exploration, preprocessing, feature engineering, and model evaluation.
- The Random Forest model demonstrated superior performance, aiding healthcare professionals in identifying high-risk cases.
- Future work includes integrating additional data sources and exploring advanced ML techniques for improved accuracy and better maternal health outcomes.

Thank you !!!