AI-Powered Maternal Health Risk Prediction and Prevention

Case Study on Pre-Eclampsia in Women Aged 15–45

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Introduction

Pre-eclampsia is a major global health concern, especially in low-resource settings.

Characterized by hypertension and proteinuria, posing serious risks to mother and child.

The study aims to use AI to detect risk early and improve maternal health outcomes.

Literature Review

Islam et al. (2022)

Comprehensive analysis of machine learning to predict pregnancy outcomes, highlighting the potential for early diagnosis and risk stratification.

Marić et al. (2020)

Demonstrated the capability of machine learning models in pre-eclampsia prediction using maternal health data like blood pressure and BMI.

Lundberg and Lee (2017)

Introduced SHAP, a framework to explain model predictions, enhancing interpretability and fairness of AI models in healthcare.

Chen et al. (2020) applied SHAP to maternal health risk prediction models, showing how explainability can aid healthcare providers.

Elgin & Elgin (2021) surveyed ethical concerns of AI-based clinical decision support systems, highlighting the importance of fairness and transparency.

Justification of Population Chosen

- The selected population includes **women aged 15–45**, representing the typical reproductive age range globally.
- This age group experiences the **highest risk for maternal complications**, including pre-eclampsia.
- Focusing on this population ensures **clinical relevance and impact** in maternal healthcare research.
- The dataset used (Kaggle) specifically includes records from women in this demographic, aligning with study objectives and model applicability.

Working Code Demo with Analysis and Interpretation of Data

Used Python (pandas, scikit-learn, XGBoost, imbalanced-learn, matplotlib, seaborn).

Dataset: *Maternal Health Risk Data* from Kaggle.

Features: Age, Systolic/Diastolic BP, Blood Sugar, Body Temp, Heart Rate.

Target: Risk Level (Low, Medium, High).

[1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
warnings.filterwarnings("ignore")
```

Data Preprocessing

•Checked for missing values (none found).
•Label encoding applied to categorical target (RiskLevel).
•StandardScaler used for feature scaling.
•SMOTE applied to balance the classes before training.

```
# Encode categorical variables (if any)
if df.select_dtypes(include=['object']).shape[1] > 0:
    label_encoders = {}
    for col in df.select_dtypes(include=['object']).columns:
        le = LabelEncoder()
        df[col] = le.fit_transform(df[col])
        label_encoders[col] = le
```

```
# Feature scaling
scaler = StandardScaler()
X = df.drop(columns=['RiskLevel'])  # Assuming 'RiskLevel' is the target variable
y = df['RiskLevel']
X_scaled = scaler.fit_transform(X)
```

```
# Handle class imbalance using SMOTE
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X_scaled, y)
print("\nDataset Balanced Using SMOTE")
```

```
Dataset Balanced Using SMOTE
```

```
# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42, stratify=y_resampled)
print("\nDataset Split into Training and Testing Sets")
```

Model Training

Models trained:

- Logistic Regression, Random Forest, SVM, KNN, Naive Bayes, AdaBoost, MLP, XGBoost.

Data split: 80% training / 20% testing.

Evaluation metrics: Accuracy, Precision, Recall, F1-score, ROC-AUC.

```python
# Define models
models = {
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "Logistic Regression": LogisticRegression(),
    "SVM": SVC(probability=True),
    "KNN": KNeighborsClassifier(),
    "Naive Bayes": GaussianNB(),
    "AdaBoost": AdaBoostClassifier(),
    "MLP": MLPClassifier(max_iter=500),
    "XGBoost": XGBClassifier()
}
```

```python
# Train and evaluate models
for name, model in models.items():
    print(f"\nTraining {name}...")
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    y_pred_prob = model.predict_proba(X_test)[:, 1] if hasattr(model, "predict_proba") else None

    print("Classification Report:")
    print(classification_report(y_test, y_pred))
```

Key Results & Interpretation

Best performing models:

Random Forest (AUC=0.97

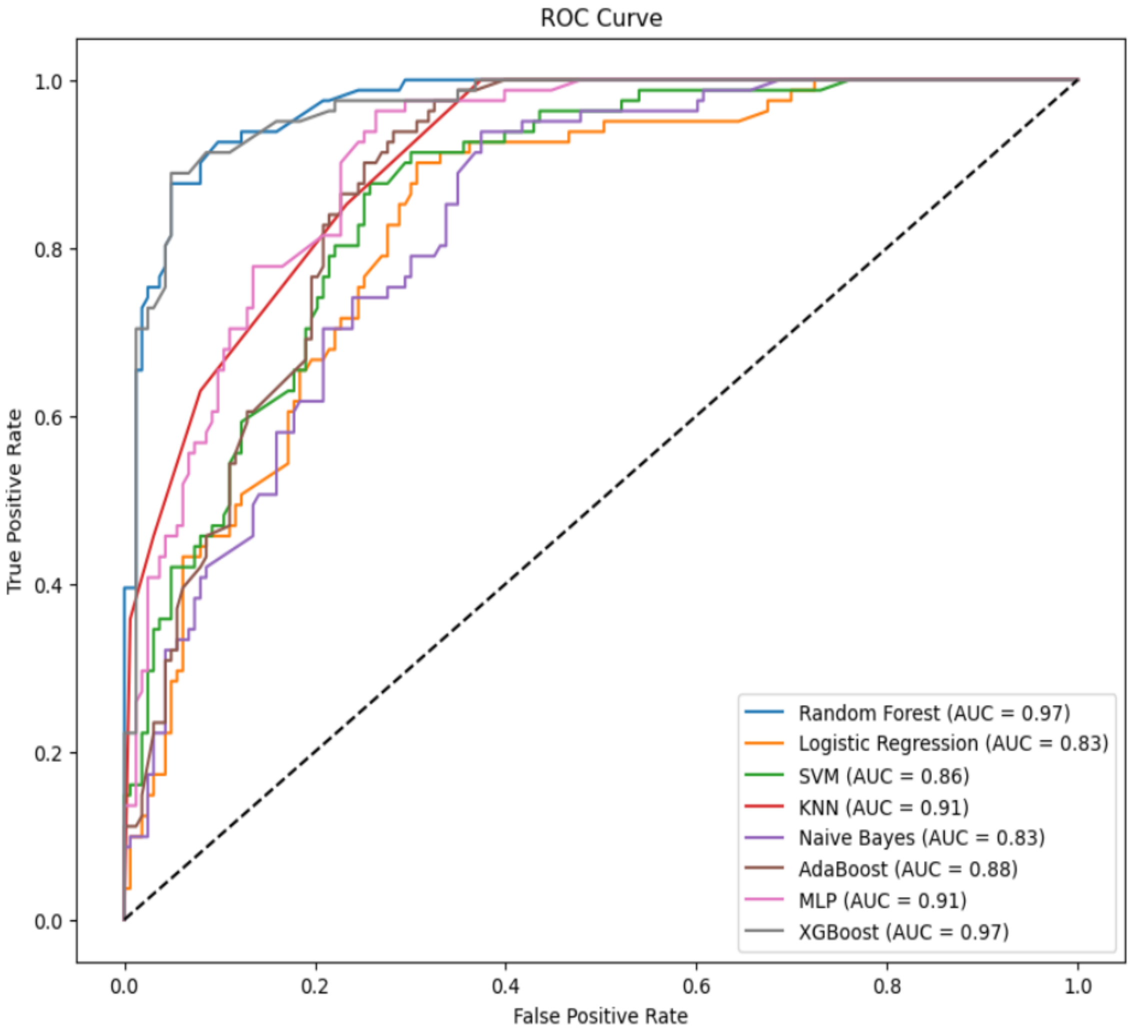
XGBoost (AUC=0.97)

Confusion Matrix showed strong class separation.

ROC curves confirmed high AUC values.

SHAP and feature importance: Key factor were SystolicBP, DiastolicBP, Age, Blood Sugar.

Insight: Ensemble models (Random Forest, XGBoost) handle non-linear patterns effectively.



Logic of Findings

- **High ROC AUC (0.97)**
  This shows that the model can discriminate well between different risk classes (low, medium, high). This means that the model has a strong ability to flag high-risk patients early, enabling timely interventions.

Pre-eclampsia can escalate rapidly and is often undetected until it's severe. Using algorithms like Random Forest and XGBoost, my model offers a way to detect risk *objectively and early*, especially in resource-limited settings.

With these strong metrics, my AI tool can become a decision support system to aid midwives and doctors in reducing maternal and neonatal mortality.

Conclusion

- This project demonstrates the practical application of AI in predicting pre-eclampsia risk, offering a robust, ethical, and interpretable solution. Through comprehensive model testing and real-world applicability, it emphasizes the transformative role of AI in maternal healthcare.

- The development process carefully addressed potential biases by balancing data representation and applying fairness techniques. Interpretability tools like SHAP mitigate risks associated with "black-box" models. Ethical implications regarding healthcare access and automated decision-making were also considered, ensuring responsible AI usage.

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