Fetal Health Classification

Project Summary:

This project aimed to build and deploy a machine learning model to classify fetal health outcomes based on cardiotocography (CTG) parameters. The process involved comprehensive data analysis, model training and tuning, and the development of an interactive Streamlit application.

Key Findings from Data Analysis

Initial data inspection revealed a clean dataset with no missing values, comprising 21 numerical features and a 'fetal_health' target variable (categorized as 1: Normal, 2: Suspect, 3: Pathological). Exploratory Data Analysis (EDA) provided several key insights:

- **Linear Relationships (lmplot)**:
    - A slight positive linear trend was observed between 'baseline value' and 'fetal_health', suggesting higher baseline heart rates might correlate with poorer outcomes, though with significant data spread.
    - 'Accelerations' showed a negative linear trend, indicating higher acceleration values are generally associated with healthier fetuses.
    - 'Uterine_contractions' displayed a very weak, almost negligible, positive correlation with fetal health, suggesting it's not a strong linear predictor on its own.
- **Distribution of Data Points (swarmplot)**:
    - 'Mean_value_of_short_term_variability' was found to be higher for normal fetal health and progressively lower for suspect and pathological cases, suggesting decreased variability is a marker of distress.
    - 'Histogram_min' showed a wider spread for normal fetuses at lower heart rates, while suspect and pathological cases exhibited narrower distributions shifted towards higher minimum heart rates.
- **Distributions and Outliers (boxplot)**:
    - 'Histogram_variance' was generally lower with a tighter range for normal fetal health, increasing in median and spread for suspect and pathological categories,

often accompanied by more outliers, indicating significant heart rate fluctuations in less healthy cases.

  - 'Histogram_mode' showed a trend of decreasing median mode as fetal health deteriorated, implying a shift towards lower typical heart rates in compromised fetuses.

These analyses revealed that several CTG parameters are indicative of fetal health status, guiding subsequent model development.

Performance of the Chosen Model

After preprocessing steps including outlier treatment (replacing values outside 1.5 IQR with the median) and feature scaling using StandardScaler, multiple classification models were trained and evaluated: Logistic Regression, SVM, Decision Tree, Random Forest, and Gradient Boosting.

Hyperparameter tuning using GridSearchCV was performed to optimize model performance. The **Gradient Boosting Classifier** emerged as the best-performing model, achieving a **best cross-validation accuracy of 0.9424**.

An initial evaluation of the untuned Gradient Boosting model on the test set showed:

- **Accuracy**: 0.9155
- **Classification Report**:
  - Class 1 (Normal): Precision 0.95, Recall 0.97, F1-score 0.96
  - Class 2 (Suspect): Precision 0.75, Recall 0.69, F1-score 0.72
  - Class 3 (Pathological): Precision 0.84, Recall 0.74, F1-score 0.79
- **Confusion Matrix**:
- [[323   8   1]
   [14 41   4]
   [3   6 26]]

The strong performance, particularly the high recall for the 'Normal' class and reasonable metrics for the 'Suspect' and 'Pathological' classes, indicates the model's effectiveness in distinguishing between fetal health outcomes. The tuned Gradient Boosting model is expected to provide even better generalization.

Streamlit Application Overview

A Streamlit web application (app.py) was developed to allow interactive prediction of fetal health. The application features:

- **Model and Scaler Loading**: It loads the best-performing Gradient Boosting model (best_fetal_health_model.joblib) and the fitted StandardScaler (scaler.joblib), ensuring consistency with the preprocessing applied during training.
- **User Input Interface**: A user-friendly sidebar provides sliders for all 21 CTG parameters, allowing users to adjust input values. These sliders are initialized with estimated ranges to guide user input effectively.
- **Prediction and Display**: Upon clicking a "Predict Fetal Health" button, the application takes the user's inputs, scales them using the loaded scaler, makes a prediction using the model, and displays the predicted fetal health outcome (Normal, Suspect, or Pathological) along with the prediction probabilities for each class.
- **Informative Context**: The main content area includes introductory text about the model, the dataset, and the preprocessing steps, providing transparency and context to the user.
- **Local Deployment with ngrok**: The Streamlit application was successfully deployed locally and made publicly accessible via an ngrok tunnel, generating a public URL for external access and demonstration.

The Streamlit dashboard provides an accessible and interactive way for users to understand and utilize the fetal health classification model.
