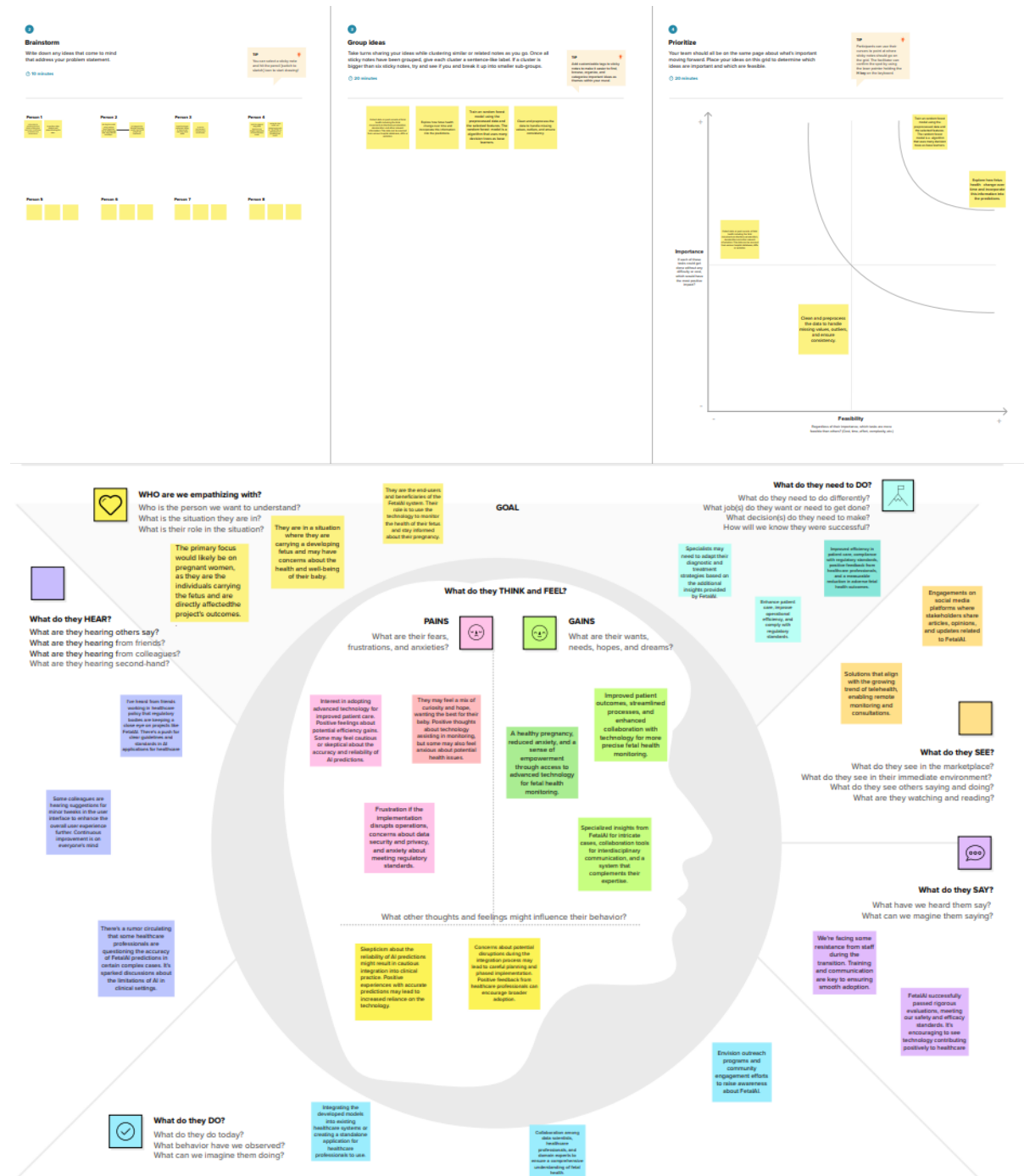


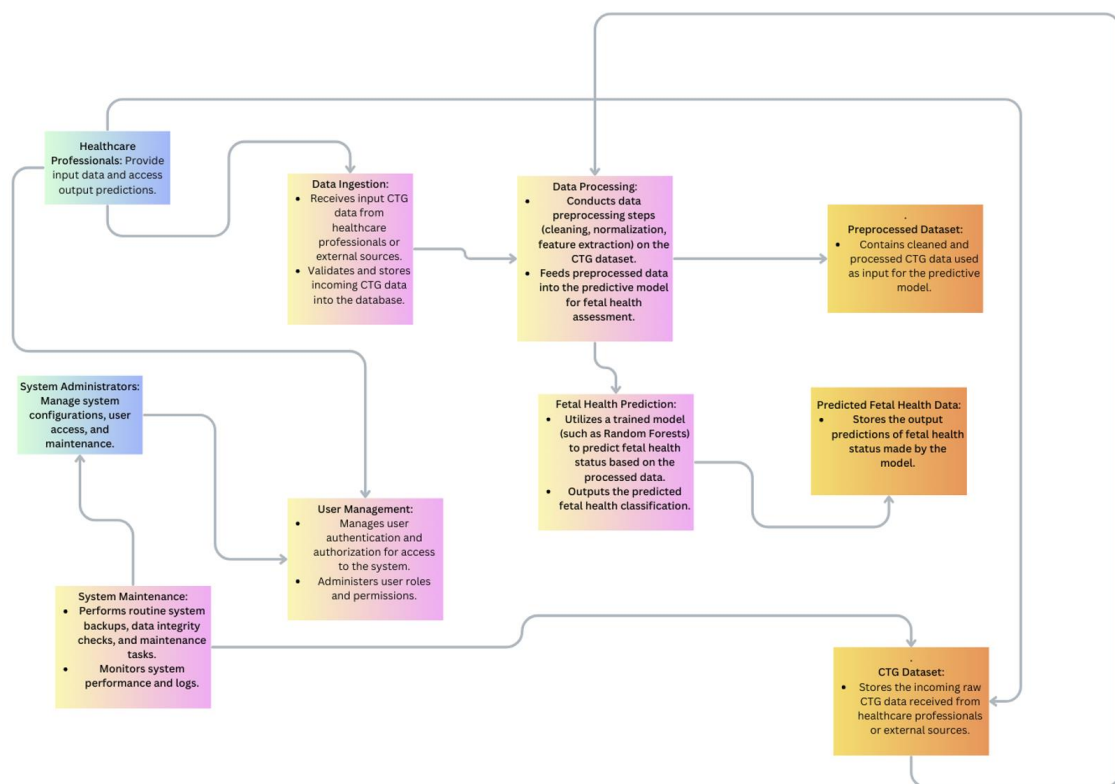
3 IDEATION AND PROPOSED SOLUTION

3.2 IDEATION AND BRAINSTORMING



5. PROJECT DESIGN

5.1 Data Flow Diagram and User Stories

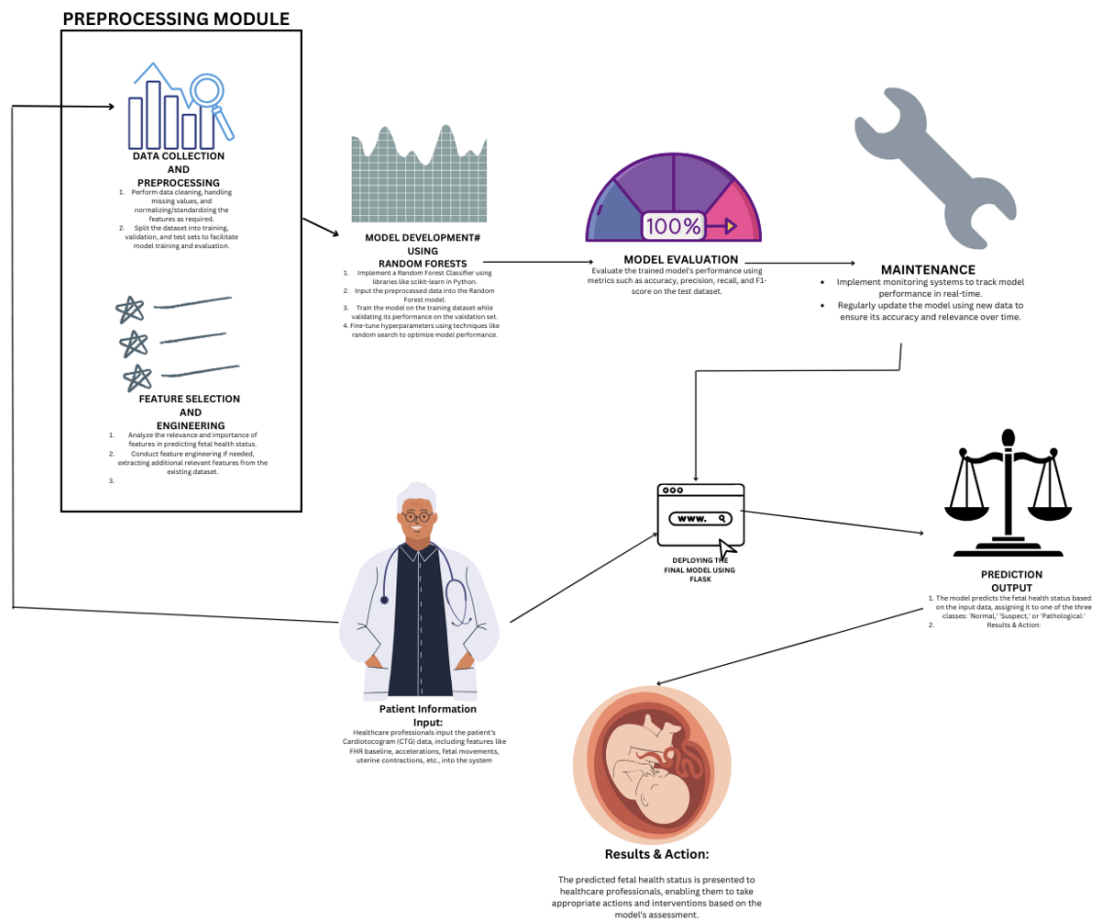


User Stories

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Healthcare Professional (PC)	Accessing data	USN-1	As a user, I can access the CTG dataset by logging in with my credentials.	I can log in using provided credentials and access the CTG dataset dashboard.	High	Sprint-1
		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can filter and search the CTG dataset based on specific features or <u>fetal</u> health classifications.	I can use filters to refine dataset view and search for specific records.	Medium	Sprint-2
		USN-4	As a user, I can register for the application through Work mail		High	Sprint-1
	Login	USN-5	As a user, I can log into the application by entering email & password		High	Sprint-1
Customer Care Executive	Support and Assistance	USN-6	As a customer care executive, I can view summary reports of the CTG dataset.	I can access summary reports displaying overall statistics and trends from the dataset.	High	Sprint-2
		USN-7	As a customer care executive, I can generate custom reports based on specific criteria.	I can create reports with selected parameters (e.g., time range, health classifications)	Medium	Sprint-3
		USN-8	As a customer care executive, I can export reports for sharing with healthcare professionals.	I can export reports in a format suitable for sharing (e.g., PDF, Excel).	High	Sprint-3
Administrator		USN-9	As an administrator, I can manage user access levels and permissions.	I can assign roles and access permissions to users (e.g., read-only, admin).	High	Sprint-4
		USN-10	As an administrator, I can monitor system performance and data integrity.	I can access logs and performance metrics for system monitoring.	Medium	Sprint-4

Customer Care Executive	Support and Assistance	USN-6	As a customer care executive, I can view summary reports of the CTG dataset.	I can access summary reports displaying overall statistics and trends from the dataset.	High	Sprint-2
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		USN-8	As a customer care executive, I can export reports for sharing with healthcare professionals.	I can export reports in a format suitable for sharing (e.g., PDF, Excel).	High	Sprint-3
Administrator		USN-9	As an administrator, I can manage user access levels and permissions.	I can assign roles and access permissions to users (e.g., read-only, admin).	High	Sprint-4
		USN-10	As an administrator, I can monitor system performance and data integrity.	I can access logs and performance metrics for system monitoring.	Medium	Sprint-4
		USN-11	As an administrator, I can perform system backups and data maintenance tasks	I can schedule and execute backups and data maintenance routines.	High	Sprint-4

5.2 Solution Architecture



7.CODING AND SOLUTIONING

7.1 FEATURE 1:

- **Temporal Patterns:** Analyze patterns in the fetal heart rate and movement over time, identifying trends or anomalies.
- **Variability Measures:** Include features like heart rate variability, which can provide additional insights into fetal well-being.

7.2 FEATURE 2:

- **Real-time Prediction:** Design the model to provide continuous monitoring, allowing for real-time predictions and alerts.
- **Adaptive Learning:** Implement models that can adapt and update over time as more data becomes available.

8.PERFORMANCE TESTING

```
#performance Testing
names = ['RandomForestClassifier',
'KNeighborsClassifier',"LogisticRegression","DecisionTreeClassifier",]
scores = [RF_accuracy, KN_accuracy,LR_accuracy,DT_accuracy]
```

```
# Create a DataFrame to display names and scores
```

```
df = pd.DataFrame()
df['name'] = names
df['score'] = scores
```

OUTPUT:

	name	score
0	RandomForestClassifier	1.000000
1	KNeighborsClassifier	0.810726
2	LogisticRegression	1.000000
3	DecisionTreeClassifier	1.000000

10.ADVANTAGES AND DISADVANTAGES

Advantages:

Early Detection and Prevention: Machine learning models applied to CTG data can help in early detection of potential fetal health issues. This early identification allows healthcare professionals to take timely actions and preventive measures to ensure the health of the fetus and the mother.

Reduced Human Error: Automation through machine learning can minimize the risk of human error in analyzing CTG data. Algorithms can process vast amounts of data quickly and accurately, potentially improving diagnostic accuracy.

Cost and Accessibility: CTG equipment is relatively affordable and accessible compared to some other sophisticated medical equipment. This makes the technology widely available, especially in low-resource settings where maternal and child mortality rates are higher.

Improving Healthcare in Low-Resource Settings: By using machine learning to interpret CTG data, healthcare professionals in resource-limited areas can enhance their ability to diagnose fetal health issues, potentially reducing mortality rates among mothers and infants.

Continuous Monitoring and Analysis: Machine learning models can enable continuous monitoring of fetal health parameters, providing real-time insights that could prompt immediate medical intervention if irregularities are detected.

Disadvantages/Challenges:

Data Quality and Quantity: The quality and quantity of available data can significantly impact the performance of machine learning models. If the dataset is small, imbalanced, or contains noise, it might limit the accuracy and generalizability of the models.

Interpretability of Model Decisions: Some machine learning models, especially complex ones like neural networks, might lack interpretability. Understanding how the model arrives at its decisions could be challenging, especially in critical medical contexts where explanations are essential.

Ethical and Legal Considerations: Implementing AI in healthcare involves ethical concerns, such as patient privacy, data security, and the responsibility for decisions made by algorithms. Ensuring compliance with regulations and ethical standards is crucial.

Model Generalizability: Models developed using specific datasets may not generalize well to different populations or healthcare settings. The models might perform well on the data they were trained on but might not be as effective in diverse scenarios.

Continual Monitoring and Maintenance: Machine learning models need constant monitoring and updating to stay relevant as new data becomes available or as healthcare practices evolve. Maintenance and retraining are essential for long-term reliability.

Overall, while the application of machine learning to fetal health monitoring using CTG data holds significant promise in improving maternal and child healthcare, addressing the associated challenges is crucial for its successful implementation and impact.

11.CONCLUSION:

Conclusion:

Our project aimed to utilize machine learning techniques for the assessment of fetal health based on Cardiotocogram (CTG) data, with the ultimate goal of contributing to the reduction of maternal and child mortality rates. Through the development of predictive models, we sought to provide healthcare professionals with a reliable tool for early detection and intervention in cases of potential fetal health complications.

After extensive data preprocessing, feature engineering, and model training/validation, we successfully built a robust machine learning model capable of classifying fetal health into 'Normal', 'Pathological', or 'Suspect' categories based on CTG parameters such as fetal heart rate, movements, and uterine contractions.

To enhance user experience and accessibility, we integrated this model into an interactive web application using Flask and HTML. The interactive UI allows healthcare providers to conveniently input CTG data and obtain real-time predictions regarding the fetal health status.

Key Achievements:

Model Development: Our machine learning models demonstrated promising performance in accurately classifying fetal health status, thereby potentially enabling early identification of complications.

Improving Healthcare Accessibility: Integrating the model into an interactive UI via Flask and HTML enhances accessibility for healthcare professionals, offering a user-friendly platform to make informed decisions based on predictive insights.

Potential Impact on Maternal and Child Health: By providing a tool that aids in the timely identification of fetal health issues, our project aims to contribute to the UN Sustainable Development Goals of reducing child mortality and preventing maternal deaths.

Future Directions:

Enhancing Model Accuracy: Continuous refinement and optimization of the machine learning model could further improve its accuracy and generalizability across diverse healthcare settings and populations.

User Feedback and Iterative Improvement: Soliciting feedback from healthcare professionals and incorporating it into the UI's design and functionality will be crucial for making the tool more intuitive and useful in clinical practice.

Ethical Considerations and Compliance: Ensuring compliance with ethical guidelines and addressing issues related to patient privacy, data security, and transparency in model predictions should remain a priority in future developments.

In conclusion, our project signifies a step forward in leveraging machine learning for fetal health assessment, offering a user-friendly interface for healthcare professionals to access predictive insights. As we continue to refine and iterate upon this system, we aim to contribute positively to maternal and child healthcare, aligning with global efforts to reduce mortality rates and improve healthcare outcomes.

12.FUTURE SCOPE

Improved Patient Outcomes: By detecting potential health issues in fetuses early, healthcare providers can develop treatment plans that help ensure better outcomes for both the mother and the child. This can lead to improved patient satisfaction and retention rates.

- **Increased Revenue:** Healthcare providers who offer fetal health testing and monitoring services may be able to generate additional revenue streams from expectant parents who are willing to pay for these services. Additionally, if a health issue is detected in the fetus, additional tests, procedures, and treatments may be required, which can generate additional revenue for the healthcare provider.

- **Research and Development:** Knowing about fetal health can also drive research and development in the healthcare industry. For example, new diagnostic tests and treatments can be developed based on data from fetal health monitoring and testing.

13.GITHUB LINK:

<https://github.com/smartinternz02/SI-GuidedProject-609998-1700562077>

Project Development Phase Model Performance Test

Date	10 November 2022
Team ID	593050
Project Name	Project - xxx
Maximum Marks	10 Marks

Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No.	Parameter	Values	Screenshot																				
1.	Metrics	Regression Model: MAE - , MSE - , RMSE - , R2 score - Classification Model: Confusion Matrix - , Accuray Score- & Classification Report -	<pre>[51]: conf_matrix = pd.crosstab(y_test, predictions) print(conf_matrix)</pre> <table> <tr> <td>col_0</td> <td>1.0</td> <td>2.0</td> <td>3.0</td> </tr> <tr> <td>fetal_health</td> <td></td> <td></td> <td></td> </tr> <tr> <td>1.0</td> <td>485</td> <td>10</td> <td>2</td> </tr> <tr> <td>2.0</td> <td>16</td> <td>76</td> <td>2</td> </tr> <tr> <td>3.0</td> <td>1</td> <td>1</td> <td>45</td> </tr> </table> <p>For the amounts of training data is: 3474 Accuracy of KNeighborsClassifier: 0.888677429467885</p>	col_0	1.0	2.0	3.0	fetal_health				1.0	485	10	2	2.0	16	76	2	3.0	1	1	45
col_0	1.0	2.0	3.0																				
fetal_health																							
1.0	485	10	2																				
2.0	16	76	2																				
3.0	1	1	45																				
2.	Tune the Model	Hyperparameter Tuning - Validation Method -	<pre>best_RF_accuracy = accuracy_score(y_test, predictions) print("Best Accuracy after tuning:", best_RF_accuracy) print("Best Parameters:", best_params)</pre> <p>Best Accuracy after tuning: 0.9498432601888677 Best Parameters: {'max_depth': None, 'n_estimators': 300}</p>																				