Data Dreamers

FETAL HEALTH CLASSIFICATION

Leveraging AI for proactive prenatal care.

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March, 2024

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Introduction

Reducing child mortality rates stands as a paramount objective within the global health agenda, intricately linked with the United Nations' Sustainable Development Goals. By 2030, nations aspire to eradicate preventable deaths among newborns and children under the age of five, striving to diminish under-5 mortality to as low as 25 per 1,000 live births. Concurrently, maternal mortality remains a concerning issue, claiming 295,000 lives during and post-pregnancy in 2017, with the majority transpiring in low-resource settings and often preventable.

In response to these challenges, technologies such as Cardiotocography (CTGs) have emerged as accessible tools for assessing fetal health, empowering healthcare practitioners to preemptively address risks to both child and maternal well-being. Operating through the transmission and analysis of ultrasound pulses, CTGs provide critical insights into fetal heart rate (FHR), movements, uterine contractions, and more.

The convergence of health complications during gestation as a global concern underscores the urgency for innovative solutions. Machine learning (ML) algorithms offer promising avenues for predicting fetal health based on cardiotocographic (CTG) data, categorizing health states into normal, needing assurance, or indicative of pathology. This research endeavors to harness various ML algorithms such as support vector machine, random forest (RF), multi-layer perceptron, and K-nearest neighbors, alongside regression and correlation analyses, to discern influential factors within CTG data and enhance predictive accuracy.

Perinatal mortality, encompassing stillbirths and infant deaths within the first seven days of life, remains disproportionately high in low- and middle-income countries, accentuating the imperative for effective monitoring and intervention strategies. While technological advancements such as CTG have significantly mitigated perinatal mortality rates in high-income countries, challenges persist, including birth-related complications such as prematurity, birth asphyxia, maternal hypertension, and septicemia.

The core objective of intrapartum fetal monitoring is early recognition of fetal risks to enable timely intervention. While CTG stands as a cornerstone in fetal monitoring, concerns arise regarding its overuse, leading to unnecessary interventions and cesarean sections. International guidelines advocate judicious CTG use, particularly for high-risk pregnancies, emphasizing the need for refined monitoring strategies to optimize outcomes while minimizing interventions.

Project Brief

Our project endeavors to harness the power of machine learning techniques to revolutionize fetal health assessment, contributing to global initiatives aimed at reducing child and maternal mortality rates.

Main Objectives:

Data Preparation and Understanding:

Implement techniques for Data Cleansing, Feature Engineering, and Data Visualization to gain initial insights into the fetal health data.

Machine Learning Analysis:

Utilize a variety of machine learning algorithms to analyze and classify Cardiotocography (CTG) data into three fetal health states: Normal, Suspect, or Pathological. Parameters such as fetal heart rate, movements, and uterine contractions will be key features in this classification process.

Other Objectives:

Exploring Model Performance:

Understand the limitations and advantages of different machine learning models under conditions of lower computing power. This involves contrasting the performance of various models and architectures trained with smaller datasets ranging from 1000 to 10000 examples.

Deep Learning Implementation:

Investigate the best techniques to implement deep learning models for practical medical solutions, focusing on enhancing fetal health assessment. This involves exploring architectures and methodologies that optimize performance while considering resource constraints and practicality in medical settings.

Through this project, we aim to create a scalable and impactful solution that empowers healthcare professionals with timely and accurate information for prenatal care. By leveraging machine learning and artificial intelligence, we envision a future where parents are equipped with critical insights into fetal health, enabling proactive and efficient prenatal care, while providing physicians with invaluable assistance for diagnosis and decision-making processes. This initiative not only stands to elevate the standards of medical technology but also holds the potential to significantly improve the quality of life and life expectancy for generations to come.

Previous Research and Algorithms

The field of fetal health classification has seen significant advancements in recent years, driven by the application of various machine learning (ML) algorithms and techniques. These innovations aim to predict fetal health outcomes based on features extracted from Cardiotocogram (CTG) exams, which are crucial in preventing fetal and maternal mortality. Let's delve into the background of ML algorithms and research methodologies utilized in this domain.

Logistic Regression (LR):

LR is a standard algorithm used for interpreting labeled outputs of mortality. It's a fundamental classification technique employed in many medical predictive models.
LR operates by estimating the probability of a binary outcome based on one or more predictor variables. In the context of fetal health classification, LR may be used to predict the likelihood of fetal anomalies or pathologies.

K-Nearest Neighbors (KNN):

KNN is chosen for its robustness in similarity function, especially when dealing with datasets where class splits are separable based on distance for many attributes.
It operates by assigning a class label to an input data point based on the majority class among its k nearest neighbors in the feature space.

Random Forest Classifier:

Random Forest is favored for its ease of generalization and handling limitations in class imbalance. It's an ensemble learning method that constructs multiple decision trees during training and outputs the class that is the mode of the classes of the individual trees.

Support Vector Machine (SVM):

SVM is a powerful algorithm known for its effectiveness in high-dimensional spaces.
It works by finding the hyperplane that best separates data points of different classes while maximizing the margin between them.

Principal Component Analysis (PCA):

PCA is utilized for dimensionality reduction, especially in conjunction with deep learning models like Convolutional Neural Networks (CNNs). It identifies the most important features in a dataset and creates new variables (principal components) that capture the variability of the data while reducing its dimensionality.

Convolutional Neural Networks (CNNs):

CNNs have shown promise in image identification and classification applications, making them suitable for analyzing CTG data. They excel at recognizing patterns and inherent characteristics in images or sequential data like CTG recordings.

Opportunities for Improvement and Identified Gaps

While the application of machine learning algorithms has shown promising results in fetal health classification, there are still several areas for improvement and identified gaps that could enhance the effectiveness and reliability of these models:

Feature Engineering and Selection:

- Despite the utilization of advanced algorithms like Random Forest and Convolutional Neural Networks (CNNs), the process of feature engineering and selection remains crucial. There is an opportunity to explore additional features or derive new ones from the existing dataset to improve model performance.
- Incorporating domain knowledge from obstetrics and gynecology experts could help identify relevant features that may not have been considered in the initial analysis.

Handling Imbalanced Data:

- Imbalanced datasets, where one class significantly outweighs the others, can pose challenges in model training and evaluation. While techniques such as oversampling and undersampling were mentioned, more sophisticated methods like SMOTE (Synthetic Minority Over-sampling Technique) or ensemble approaches could be explored to address this issue effectively.
- Moreover, evaluating model performance using metrics tailored for imbalanced datasets, such as F1-score or area under the precision-recall curve, would provide a more accurate assessment of classification performance.

Algorithm Selection and Comparison:

- The project mentions the use of Logistic Regression, K-Nearest Neighbors, Random Forest, and SVM among others. While these algorithms are commonly employed, there could be an opportunity to explore alternative approaches such as gradient boosting algorithms (e.g., XGBoost, LightGBM) or deep learning architectures specifically designed for sequential data like Long Short-Term Memory (LSTM) networks.
- Conducting comprehensive comparative studies to assess the performance of different algorithms on the same dataset under standardized conditions would provide valuable insights into their relative strengths and weaknesses.

Interpretability and Explainability:

- While advanced models like CNNs may offer superior performance, they often lack interpretability, making it challenging for medical professionals to understand the rationale behind predictions.
- Exploring techniques for model interpretability, such as SHAP (SHapley Additive exPlanations) values or LIME (Local Interpretable Model-agnostic Explanations), could facilitate the understanding of model decisions and enhance trust in predictive models among healthcare practitioners.

Robustness and Generalization:

- Ensuring the robustness and generalization of predictive models across diverse patient populations and healthcare settings is critical for real-world deployment.
- Performing external validation on independent datasets from different sources or geographical regions could assess the generalizability of models and identify potential biases or limitations.

In summary, while machine learning algorithms offer promising avenues for fetal health classification, addressing the identified gaps and opportunities for improvement is essential to develop robust, reliable, and interpretable models that can effectively support medical decision-making and ultimately contribute to reducing fetal and maternal mortality rates.

Applied Roadmap

ETL (Extract, Transform, Load)

Data Extraction

The dataset utilized in this study comprises 2,126 records sourced from Cardiotocogram (CTG) exams, a pivotal tool in assessing fetal health during pregnancy. The data was meticulously collected and annotated, with a focus on feature extraction to aid in the classification process.

Each record in the dataset encompasses an array of features extracted from CTG exams, capturing essential parameters indicative of fetal well-being. These features have been meticulously curated to encompass a comprehensive understanding of fetal health dynamics.

To ensure the accuracy and reliability of the dataset, three expert obstetricians meticulously classified the records into three distinct classes:

- Normal: Records in this category denote instances where fetal health parameters fall within the expected range, indicating a healthy status.

- Suspect: This class encompasses records where certain fetal health indicators display deviations or abnormalities, suggesting potential concerns that warrant further medical attention or monitoring.

- Pathological: Records classified under this category indicate significant deviations from normal fetal health parameters, signaling potential pathological conditions that require urgent medical intervention or specialized care.

The dataset serves as a valuable resource for researchers, practitioners, and stakeholders involved in maternal-fetal healthcare, facilitating exploratory analysis, predictive modeling, and the development of decision support systems aimed at enhancing prenatal care and mitigating adverse pregnancy outcomes.

For further exploration and analysis, the dataset is publicly accessible on Kaggle via the following link: Fetal Health Classification Dataset.

Data Preprocessing

In order to explore and verify the features and challenges within the dataset, the following steps were undertaken:

1. Importing Libraries:

Necessary libraries such as pandas, matplotlib, numpy, seaborn, and sklearn were imported for data manipulation, visualization, and preprocessing.

2. Handling Duplicate Rows:

Initially, the dataset containing 2126 rows and 22 columns was checked for duplicate rows. Thirteen duplicate rows were identified and subsequently removed, resulting in a dataset with 2113 rows and 22 columns.

3. Handling Missing Values:

No missing data was found in the dataset, thus no imputation or handling of missing values was required.

4. Scaling:

Due to the significant scale differences among variables, scaling techniques were applied to ensure uniformity before model training. This step is crucial for maintaining model performance.

5. Identifying Skewness:

Examination of variable distributions revealed skewness, particularly right skewness, among certain variables. Skewness can impact model performance; hence, it was noted for further consideration.

Exploratory Data Analysis (EDA):

1. Histogram Visualization:

Histograms were created to visualize the distribution of variables. Skewness and normal-like distributions among features were observed.

2. Class Imbalance Check:

Class imbalance within the target variable (fetal_health) was identified, with a substantial difference in instances among the "normal," "suspect," and "pathological" categories. Addressing this imbalance is crucial for model training.

3. Boxplot Analysis:

Boxplots were utilized to compare variable distributions across different classes. Significant differences were observed, especially concerning histogram variables, accelerations, and mean_value_of_long_term_variability.

4. Correlation Analysis:

Correlation between the target variable and other features was examined. Features such as acceleration, histogram mode and mean, prolonged decelerations, and abnormal short-term variability showed higher correlations with fetal_health. This analysis aids in feature selection for model development.

5. Feature Range Observation:

Charts depicting the ranges of features were generated to identify scaling differences and variations in feature ranges. Notably, histogram variances exhibited major variability, while features related to accelerations, contractions, and fetal movement showed limited variation.

6. Feature Correlation Analysis:

Correlation between sets of features was explored to assess the necessity of using all features for model training. Understanding feature correlations helps in optimizing model performance and reducing redundancy.

7. Target Variable Transformation:

Labels of the fetal_health variable were mapped to meaningful categories (1: normal, 2: suspect, 3: pathological) for better interpretation and understanding of the target variable.

These preprocessing steps lay the foundation for building robust machine learning models for fetal health classification, ensuring data quality, uniformity, and relevance.

Model Selection

Selected Metrics

In line with our objective of constructing a sickness prediction model, priority is given to identifying instances indicative of sickness. Therefore, special emphasis is placed on the recall metric for classes representing or indicating sickness, namely 'suspect' and 'pathological'.

Balanced accuracy assumes significance owing to the challenge of imbalanced classes. It computes the average recall obtained on each class, serving as our primary metric for model optimization.
Macro-averaging is employed as the method for combining metrics across classes, assigning equal importance to all labels regardless of their distribution.

Hyperparameter Optimization in ML models

The hyperparameters of ML models such as Logistic Regression and Random Classifier undergo optimization based on their balanced accuracy to maximize performance. The most optimal model is preserved for further rigorous evaluation.

Parameter grids are meticulously selected, taking into account training time (approximately 20 minutes), feasible parameter combinations (fewer than 500), and metric maximization. The final choice of parameter grids results from extensive research, expert recommendations, and experimentation to ensure optimal performance.

Model Evaluation

Evaluation Approach

The ultimate evaluation of the performance of selected ML models is conducted through ten-fold cross-validation with the test data partition. This approach ensures precise model evaluation independent of random data partition configurations that may skew scores. These results serve as the basis for final model comparison.

Baseline Metric Estimation

We commence the evaluation process by preparing the dataset specifically for training the dummy classifier to establish baseline metrics. This phase encompasses the standardization of features using StandardScaler and the definition of metrics to assess model performance, taking into account the imbalanced nature of the target variable.

Model Training

Hyperparameters are fine-tuned using GridSearchCV to optimize our models, conducting an exhaustive search over specified parameter values while prioritizing balanced accuracy. The best performing model is chosen based on the results of this evaluation.

Evaluation

A thorough evaluation of the selected model is conducted using cross-validation, ensuring precise performance assessment independent of random data partitions that may influence metrics. Baseline metrics are established using a dummy classifier that predicts the most frequent class.

Saving the Best Model

Finally, the best-performing model is serialized using the pickle library for future deployment and utilization.

Artificial Neural Network Architecture

The final model evaluated is an Artificial Neural Network (ANN) implemented with the TensorFlow library. It features an architecture comprising three hidden layers with a Rectified Linear Unit (ReLU) activation function. Several techniques, including batch normalization, dropout layers, and L2 regularization, are employed to achieve faster convergence and prevent overfitting.

This architectural choice is informed by extensive research on similar projects and expert recommendations. The model undergoes training for a total of 120 epochs. Additionally, the model with the highest recall on the 'Pathological' class is preserved using the ModelCheckpoint callback, ensuring optimal sickness detection.

Deployment, Model Score and Review

Logistic Regression Classifier

The first model employed for Fetal Health Classification is a logistic regression classifier. The model was developed using the scikit-learn library.

Data Preprocessing

The dataset was preprocessed by splitting it into training and testing sets, followed by standard scaling of the features.

Model Training

The logistic regression model was trained using a grid search with cross-validation to find the optimal hyperparameters. The parameters were selected based on their impact on the balanced accuracy metric.

Evaluation

The trained logistic regression model was rigorously evaluated using cross-validation to ensure precise performance assessment. The evaluation results demonstrate the model's ability to accurately classify fetal health conditions.

The model achieved the following performance metrics:

- Balanced Accuracy: Approximately 68.60%
- Precision: Ranges from 60% to 82% for different health classes
- F1-Score: Approximately 69.75%
- Accuracy: Approximately 86.64%

The classification report provides detailed metrics for each class, demonstrating the model's performance across different health categories.

Random Forest Classifier

Our second model employs a Random Forest classifier, a robust ensemble learning technique. The execution of this notebook typically lasts around 20 minutes, primarily due to the Grid Search for hyperparameter optimization.

Importing Libraries

Essential libraries including pandas, numpy, matplotlib, seaborn, and scikit-learn are imported for data manipulation, visualization, and model implementation. The RandomForestClassifier module from scikit-learn's ensemble module is utilized for building the Random Forest model.

Setting Random Seed

To ensure reproducibility, a random seed of 11 is set using the RANDOM_STATE variable.

Model Construction

The Random Forest classifier was constructed following rigorous data preprocessing steps. Initially, the fetal health dataset was imported from the specified path and split into features (X) and target variable (y). To ensure generalization, the data was partitioned into training and testing sets using a stratified split of 80:20, respectively. Subsequently, feature scaling was performed using StandardScaler to standardize the feature values.

Defining Evaluation Metrics

To evaluate the performance of the Random Forest classifier, multiple metrics were defined, including accuracy, balanced accuracy, precision, and F1-score. These metrics were tailored to address the imbalanced nature of the dataset, ensuring comprehensive model assessment across all classes.

The Random Forest classifier underwent hyperparameter tuning using GridSearchCV, a technique that exhaustively searches over specified parameter values to optimize the model's performance metric. In this case, the metric of interest was the balanced accuracy score, which accounts for imbalanced class distributions and calculates the average recall obtained on each class.

The grid search was conducted over a range of hyperparameters including the number of estimators, maximum features, maximum depth, minimum samples per leaf, and minimum samples per split. The best performing model was selected based on the mean test score obtained during cross-validation.

The results of the grid search, including the parameter combinations and corresponding mean test scores, were saved in a dataframe for visualization and analysis. The top-performing parameter combinations were identified based on their mean test scores, which were sorted in descending order.

Evaluation

To precisely assess the performance of the Random Forest classifier, we employed ten-fold cross-validation, ensuring independence from random data partitions that may influence our metrics.

The evaluation results indicate promising performance metrics for the Random Forest classifier:

- Accuracy: The model achieved an **accuracy** of approximately **88.27%**, indicating the proportion of correctly classified instances among all instances.

- Balanced Accuracy: With a **balanced accuracy** of around **71.82%**, the model demonstrated effectiveness in handling imbalanced classes, providing a more accurate representation of overall model performance.

- Precision: The **precision values** for each class ('Normal', 'Suspect', 'Pathological') were approximately **84.46%, 66%, and 87%, respectively**. Precision measures the proportion of true positive predictions among all positive predictions.

- F1-Score: The **F1-scores for each class** were around **75.10%**, indicating a balance between precision and recall. The F1-score is the harmonic mean of precision and recall, providing a single metric to evaluate model performance.

The classification report further elaborates on the model's performance, presenting precision, recall, and F1-score for each class ('Normal', 'Suspect', 'Pathological'). Overall, the Random

Forest classifier demonstrated strong performance, particularly in accurately predicting the 'Normal' class, while maintaining satisfactory performance for the 'Suspect' and 'Pathological' classes.

Neural Network Classifier

The third and final model employed for Fetal Health Classification is a Neural Network developed using the TensorFlow library. The architecture comprises three dense layers with varying numbers of neurons, each followed by activation functions (ReLU), batch normalization, and dropout regularization to prevent overfitting. The model utilizes the softmax activation function in the output layer for multi-class classification.

Data Preprocessing

The dataset was preprocessed by splitting it into training, testing, and validation sets. Standard scaling was applied to normalize the feature values. Additionally, the target variable was one-hot encoded to facilitate multi-class classification.

Model Training

The neural network model was trained using a sequential model architecture. It consisted of three dense layers with varying numbers of neurons, employing batch normalization and dropout regularization to enhance learning and prevent overfitting. The model was compiled using categorical cross-entropy as the loss function and Adam optimizer.

Evaluation

The trained neural network model was evaluated on the test dataset, yielding the following performance metrics:

- Balanced Accuracy: Approximately 92.11%
- Categorical Accuracy: Approximately 92.49%
- F1-Score: Approximately 85.16%
- Loss: Approximately 0.192

The Neural Network model demonstrated robust performance in accurately classifying fetal health conditions, with high accuracy and balanced performance across different health categories. Further analysis of precision, recall, and F1-score for each class ('Normal', 'Suspect', 'Pathological') offers insights into the model's effectiveness in identifying specific health conditions.

Final Thoughts: Performance Comparison of Models

In our endeavor to classify fetal health conditions, we employed three distinct models: Logistic Regression, Random Forest, and Neural Network. Each model underwent rigorous development, training, and evaluation processes, aiming to achieve accurate predictions and robust performance. Let's delve into the comparative analysis of their performance.

Logistic Regression:

The logistic regression classifier demonstrated moderate performance in classifying fetal health conditions. With a balanced accuracy of approximately 68.60%, it exhibited a fair ability to handle imbalanced classes. Precision, recall, and F1-score varied across different health categories, highlighting the model's effectiveness in distinguishing between 'Normal', 'Suspect', and 'Pathological' cases. However, its performance metrics, particularly balanced accuracy and F1-score, were comparatively lower than those of the Random Forest and Neural Network models.

Random Forest:

The Random Forest classifier outperformed the logistic regression model, showcasing robust performance across various metrics. With a balanced accuracy of around 71.82%, it demonstrated effectiveness in handling imbalanced class distributions. The model achieved a notable accuracy of approximately 88.27% and exhibited balanced precision and recall values for each health category. The Random Forest classifier's ability to capture complex relationships within the data contributed to its superior performance compared to logistic regression.

Neural Network:

The Neural Network model emerged as the top performer in our classification task, boasting impressive performance metrics. With a remarkable balanced accuracy of approximately 92.11%, it showcased superior accuracy and predictive capability. The Neural Network model's ability to capture intricate patterns and nonlinear relationships within the data enabled it to achieve high accuracy across all health categories. Additionally, the model demonstrated robustness against overfitting, as indicated by its high F1-score and low loss value.

Comparative Analysis:

Across all three models, the Neural Network model emerged as the most effective in classifying fetal health conditions, followed by the Random Forest classifier and logistic regression model. While logistic regression provided a baseline understanding of the data, its limited capacity to capture complex relationships hindered its performance. On the other hand, both Random

Forest and Neural Network models demonstrated superior predictive capabilities, with the Neural Network model exhibiting the highest accuracy and balanced accuracy scores.

Knowledge Gained and Next Steps:

Through this project, we gained valuable insights into the performance of various machine learning models for fetal health classification. We learned the importance of selecting appropriate evaluation metrics, handling imbalanced datasets, and optimizing model hyperparameters to enhance performance. Moving forward, we can explore advanced deep learning architectures, ensemble methods, and feature engineering techniques to further improve classification accuracy. Additionally, conducting additional experiments with larger datasets and incorporating domain knowledge could provide deeper insights into fetal health assessment and aid in developing more robust predictive models.

Conclusion

Leveraging Machine Learning for Fetal Health Classification

The pursuit of reducing child and maternal mortality rates is an indispensable component of the global health agenda, encapsulated within the United Nations' Sustainable Development Goals. As we approach the target year of 2030, endeavors to eradicate preventable deaths among newborns and children under five underscore the urgency for innovative solutions. Technologies such as Cardiotocography (CTGs) have emerged as invaluable tools in assessing fetal health, providing critical insights into vital parameters such as fetal heart rate, movements, and uterine contractions.

In response to these challenges, our project embarked on harnessing the power of machine learning (ML) algorithms to revolutionize fetal health assessment, thereby contributing to global initiatives aimed at reducing child and maternal mortality rates. Through meticulous data preprocessing, feature engineering, and model selection, we endeavored to develop robust predictive models capable of categorizing fetal health states into normal, suspect, or pathological categories.

Project Outcomes and Milestones Overcome:

Our journey commenced with a thorough exploration of the fetal health dataset, encompassing 2,126 records sourced from CTG exams. Through meticulous data preprocessing, including handling duplicate rows, addressing missing values, and scaling features, we ensured data quality and uniformity. Exploratory data analysis (EDA) revealed insights into feature distributions, class imbalances, and correlations, guiding subsequent model development steps.

The project's main objectives were twofold: to explore and compare the performance of various ML algorithms and to investigate deep learning approaches for fetal health classification. We meticulously implemented techniques such as logistic regression, random forest, and neural networks, rigorously evaluating each model's performance based on metrics like balanced accuracy, precision, recall, and F1-score.

Positive Outcomes and Knowledge Gained:

Through this project, we gained invaluable insights into the application of ML algorithms for fetal health classification and the challenges inherent in this domain. We learned the importance of feature engineering, model selection, and hyperparameter optimization in enhancing predictive accuracy. Furthermore, we explored the practical implications of deploying deep learning models in real-world medical settings, considering resource constraints and interpretability.

The outcomes of our project underscore the potential of ML algorithms in revolutionizing fetal health assessment and prenatal care. While logistic regression provided a baseline understanding, random forest and neural networks demonstrated superior performance, with the neural network model achieving a remarkable balanced accuracy of approximately 92.11%. These findings highlight the efficacy of advanced ML techniques in accurately categorizing fetal health states and empowering healthcare professionals with timely and accurate information for proactive prenatal care.

Future Directions and Societal Impact:

Looking ahead, our project sets the stage for future research and initiatives aimed at further enhancing fetal health classification and prenatal care. Incorporating domain knowledge from obstetrics and gynecology experts, addressing class imbalances, and exploring alternative ML algorithms are avenues for improvement. Moreover, initiatives like ours underscore the transformative potential of technology in healthcare, paving the way for improved maternal and child health outcomes globally.

In conclusion, our project represents a testament to the power of collaboration between technology and healthcare in addressing complex societal challenges. By leveraging machine learning and artificial intelligence, we aspire to usher in a future where every pregnancy is monitored with precision and every child is welcomed into the world with the best possible chance at a healthy life. This initiative not only advances the frontiers of medical technology but also holds the promise of saving countless lives and improving the quality of life for generations to come.