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AN INTELLIGENT SYSTEM FOR FETAL HEALTH ANALYSIS USING AI APPROACHES

Prof.Shivayogi Ullagaddi, Priyanka Pujar, Neeta Patil, Aishwarya Badawadagi, Krutika Angadi

Professor, Students of Final Year BE, Dept. Of Computer Science and Engineering
Dept. Of Computer Science and Engineering,
Angadi Institute of Technology and Management, Belagavi, Karnataka, India

Abstract: *Ensuring optimal fetal health during pregnancy is essential for the well-being of both mother and child, requiring constant monitoring and timely intervention. This proposal presents a tuned Support Vector Machines and Additive Tree Ensemble (ETSE) model to monitoring fetal health. The model includes various data processing techniques which includes preprocessing, segmentation and several classifiers for machine learning. The study identifies health issues of the women during pregnancy, particularly in developing countries, and uses cardiotocography (CTG) data and machine learning algorithms to identify fetal health conditions. The study highlight the scope of the proposed ETSE model with accuracy parameters like recall and F1 scores and 99.66% precision. This shows prominent potential of AI-based models to make accurate and effective predictions about fetal health, encouraging timely intervention and better outcomes for both mother and child.*

Index Terms: Cardiotocography (CTG) , Fetal health , Grid search , Ensemble learning

I. Introduction

Artificial intelligence (AI) has become an integral part of our daily life, affecting many aspects and improving efficiency in various fields. From personalized recommendations on streaming platforms and virtual voice assistants like Siri or Google Assistant that understand and respond to natural language, to predictive text recommendations and spam filters, AI is seamlessly woven into our digital experience. In healthcare, artificial intelligence helps with diagnostics and personalized treatment plans, while in finance, fraud detection systems and algorithmic trading. Smart home devices like thermostats and security cameras use artificial intelligence to automate and improve security. AI navigation apps optimize routes based on real-time traffic data, and social media platforms use AI algorithms to curate content and deliver targeted advertising. As AI applications expand, its impact on everyday life becomes increasingly evident, simplifying processes and providing personalized, efficient and often predictive solutions.

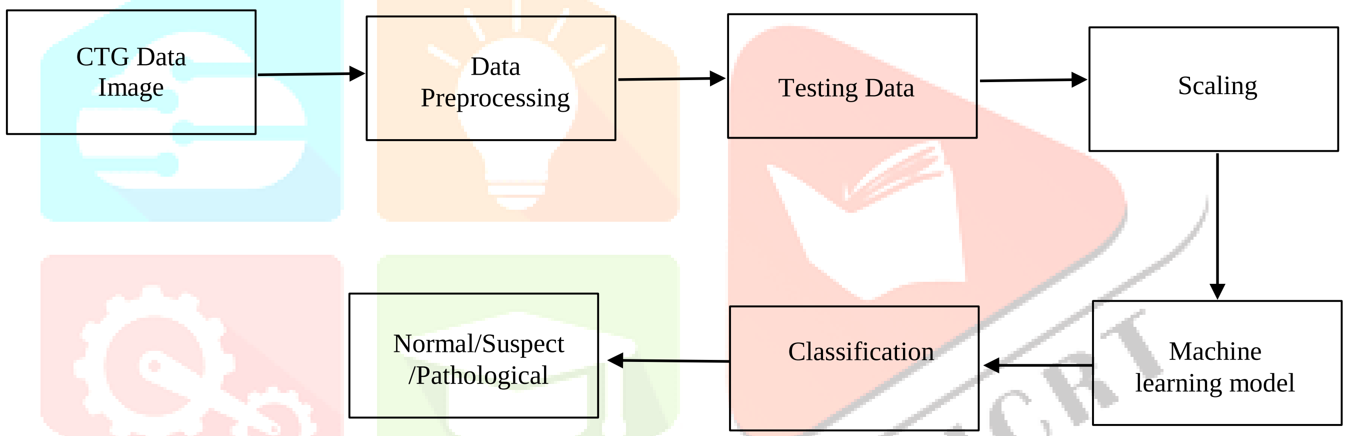
Machine learning (ML) is a subset of artificial intelligence .It is deeply integrated into our daily lives, quietly influencing and optimizing various aspects, making tasks more efficient and personalized. In online services, ML algorithms use recommendation systems, recommending movies, music, products, and even news articles based on individual preferences. Social media platforms use ML to curate content and display content to users based on their interests. Search engines like Google use machine learning to refine and make search results more relevant. ML is prevalent in virtual assistants, allowing them to understand and intelligently respond to voice commands. In healthcare, ML is involved in diagnosis, treatment personalization and predictive analytics. Financial institutions use ML to detect fraud and assess risk. Autonomous vehicles rely heavily on machine learning for navigation and decision making. As these examples show, machine learning is quietly disrupting everyday life by making technology more adaptive and tailored to individual needs.

Machine learning (ML) plays a central role in the medical field. It is transforming various aspects of healthcare to improve diagnosis, treatment and overall patient care. In medical imaging, ML algorithms analyze radiological images, which helps in the early detection of diseases such as cancer. ML is also involved in personalized medicine, analyzing patient data to create a personalized treatment plan based on individual characteristics and genetic makeup. Predictive analysis produced by ML helps to predict diseases and identify high-risk patients for preventive measures. Natural Language Processing (NLP) enables the extraction of valuable insights from unstructured medical data such as electronic health records and clinical notes. In addition, ML applications help optimize hospital operations, streamline administrative processes, and improve resource allocation. Despite the enormous potential, ethical considerations and privacy issues remain important in the integration of ML into the medical field

Pregnancy is a volatile and complex journey characterized by the physical and emotional changes a woman experiences as she grows a new life. Although this time is often filled with anticipation and joy, it also brings with it various challenges and potential complications. From common ailments like morning sickness, fatigue and mood swings to more serious problems like gestational diabetes, preeclampsia and premature labour, the spectrum of challenges faced during pregnancy is diverse. Each woman's experience is unique, influenced by factors such as maternal health, genetics and lifestyle. Access to pregnancy care, healthy lifestyles and emotional support are critical to addressing these challenges. This introduction sets the stage for a deeper exploration of the complex destinations, joys and potential obstacles encountered on the difficult journey of pregnancy. According to the World Health

Organization (WHO), abnormal fetal growth poses a significant threat to maternal health, causing approximately 810 pregnancy-related deaths per day. The difference in maternal mortality rates between developed and underdeveloped countries underscores the urgent need for careful fetal monitoring. Medical professionals support regular evaluation, and cardiotocography (CTG) is emerging as a widely used method to assess fetal and maternal health [2]. In CTG, fetal heart rate (FHR) and uterine contractions (UC) are continuously monitored with a maternal and abdominal ultrasound transducer [3]. A comprehensive set of CTG data, including 21 attributes, helps obstetricians assess fetal health and allows early detection and intervention of potential distress [4, 5]. Despite significant advances in fetal health monitoring facilitated by artificial intelligence [6–11], accurate prediction of fetal health remains a major challenge in the field of machine learning. Monitoring fetal growth during pregnancy is particularly difficult because preventable measures are often missed, resulting in 810 cases per day among pregnant women according to WHO (2021). Maternal mortality is significantly lower in developed countries, highlighting the critical importance of proper monitoring in underdeveloped areas. Common complications that cause high maternal mortality include preeclampsia, inadequate monitoring of the unborn child and mother, and gestational diabetes [National Institutes of Health, n.d.]. Effective medical care, especially in the third trimester, includes fetal monitoring, a process that is critical to the health of the unborn child. Fetal growth is closely related to maternal well-being, and continuous monitoring, especially with cardiotocography, is essential. Performed in the last trimester, this technique focuses on monitoring fetal and heart rate and measuring uterine contractions, a cost-effective and easy-to-understand approach. Developed by medical experts, it aims to detect fetal abnormalities early to reduce fetal mortality. Cardiotocography (CTG) results provide insight into uterine contractions, fetal heart rate, acceleration events, deceleration sets and other complex fetal measurements [Ingemarsson, 2009]. Several machine learning (ML) techniques are available to classify fetal stages – normal, apparent and pathological. The results highlight the potential of ML techniques as a widely applicable framework for automated systems analyzing early fetal health [Jezewski et al., 2010].
The following sections discusses various ML algorithms and their effectiveness in fetal development , and presents a comprehensive study of CTG data for fetal health prediction using various ML techniques.

II. PROPOSED METHODOLOGY



1. **CTG Data Image :** Our experiment used a publicly available cardiotocography (CTG) dataset from the UCI Machine Learning Depony [21]. This dataset of 2126 records contains features extracted from cardiotocography studies, carefully divided into three categories based on the evaluation of three experienced obstetricians using 23 different features. These attributes are specifically related to fetal heart rate (FHR) and uterine contraction (UC) measurements during CTG studies, as described in Table 2. In particular, the dataset has an unbalanced distribution: 1655 records are classified as normal, 295 as suspicious, and 176 as pathological.

2. **Data Preprocessing :** Data processing plays a key role in improving model performance, especially when dealing with real-time data sets that may contain missing values and noise. In our study, a thorough examination did not identify any missing data. To effectively manage outliers, we used the standard deviation method to remove them. However, we faced the challenge of unbalanced data, which can lead the model to overlook minority classes. To solve this problem, we applied the Random Over Sampler (ROS) technique [22], which strategically doubles the data of the minority class to balance the data. This approach helps to reduce biased cluster atrophy and improves model performance. After standardization, we split the dataset into training and testing sets, using 70% for training and 30% for testing.

3. **Testing Data :** In AI-based fetal health assessment, test data play a key role in evaluating the performance and generalization of trained machine learning models. This dataset differs from the training dataset and consists of examples that the model did not encounter during the training phase. Similar to training data, test data contain input features derived from cardiotocography studies, such as fetal heart rate and uterine contractions, as well as corresponding output records that reflect the actual health status of the fetus. Using test data, researchers and practitioners can assess how well a trained model generalizes to new, unprecedented cases and whether it can accurately predict fetal health beyond those present in the training set. Model performance is measured by comparing its predictions from experimental data with actual results, which provides insight into the model's performance and potential application in real-world scenarios.

4. **Scaling :** Scaling fetal health using machine learning involves collecting extensive data sets that include medical data, ultrasound images, genetic data, and maternal health data. After preprocessing and feature selection, appropriate machine learning models are trained and validated using the shared dataset. Emphasis on model interpretability, continuous monitoring, ethical considerations and health system integration ensures responsible implementation. In addition, creating feedback and training healthcare professionals completes the approach, which aims to use machine learning to improve fetal health monitoring at a scalable and efficient level.

5. **Model :** The Electric Thermal Energy Storage (ETES) model fitting methodology includes a comprehensive approach to parameter estimation and validation to accurately characterize the performance of the ETES system. The process usually begins with the collection of test data, including measurements of electrical and thermal output under various operating conditions. Mathematical models, often based on thermodynamics and heat transfer principles, are then constructed to represent the dynamic behavior of the ETES system. The model parameters are then optimized with sophisticated optimization algorithms, such as genetic algorithms or gradient-based methods, to minimize differences between model predictions and experimental data. Model validation is critical to ensure the accuracy and reliability of the fitted parameters and is achieved by comparing the model and predictions with other independent experimental data sets. The iterative nature of this process allows the model to be refined and improved, resulting in a robust and validated ETES model that can be used for system analysis, design optimization, and performance prediction**.**

6. **Classification :** When classifying fetal health using machine learning, the method involves a systematic approach from data collection to model implementation. Initially, different datasets are collected, which include variables such as maternal health data, ultrasound images and genetic information. Appropriate functions are selected after rigorous data processing to handle missing values and to normalize functions. Next, an appropriate classification algorithm, such as logistic regression or neural networks, is selected and trained on part of the dataset where the model and performance are analyzed on a separate test set. Interpretation and validation of the model using methods such as cross-validation are essential to ensure reliability. Continuous monitoring, updating and integration into clinical workflows will contribute to successful implementation of the model. Ethical considerations, a feedback loop for improvement and training of health professionals complete the method, providing a solid framework for using machine learning to classify fetal health.

III. SURVEY OF PERFORMANCE OF MODELS

Model	Precision	Recall	F1-Score	Accuracy
[2] SVM	99	99	99	99.39
[2] Decision Tree	97	97	97	97.24
[2] Random Tree	98	98	98	98.45
ETSE Model	100	100	100	99.66
K-Neighbors	97	97	96	96.51
XGM	99	99	99	99.39
LGBM	99	99	99	98.52
Extra Trees	99	99	99	98.79
XGM+LGBM	99	99	99	98.86

To improve classification accuracy, we created combined models by combining the most efficient classifications.

We explore various machine learning approaches from the mapping literature, some of which are mentioned in the table above. Various algorithms include decision tree, random tree, ETSE model, K-neighbors, XGM, LGBM, Extra Trees, XGM+LGBM, etc. The accuracy of SVM and XGM models improved to 99.39%. But for another layout model like decision tree, K-Neighbors showed accuracy of 97.24%, 96.5%. The proposed tuned SVM and Extra Tree Ensemble (ETSE) model showed significant improvement in precision, recall and F1 score, reaching 100% precision, recall and F1 score and 99.66% precision.

7. SUMMARY OF LITERATURE REVIEW

REFERENCES	MODELS	DATASET	ENSEMBLE LEARNING	ACCURACY
[3]	**ANFIS**	**Normal, suspect, pathological**	**No**	**91.6**
[4]	**SVM and GA**	**normal and abnormal**	**No**	**98**
[5]	**RF**	**Normal, suspect, pathological**	**No**	**93.6**

Artificial intelligence (AI) has gained a significant position in health automation, especially in the analysis and prediction of heart diseases. Amzad Hossein et al. [6] conducted a study comparing the performance of three supervised machine learning models—Random Forest (RF), Decision Tree (DT), and Logistic Regression (LR)—and found that LR achieved the highest accuracy of 92.10%. Notably, this study did not examine other conventional forms of machine learning. Sundar [8] focused on heart disease prediction using Random Forest (RF) and XGBoost (XGB) without relying on commonly used clustering methods such as k-means. Although Sundarand's method was not satisfactory, Sundar et al. [9] involved the implementation of a model-based cardiotocography (CTG) classification system using a supervised artificial neural network (ANN). This approach demonstrated significantly improved efficiency and highlighted the potential of AI to improve diagnostic capabilities and predict fetal health outcomes.

IV. CONCLUSION

This study acknowledges several limitations that deserve attention. First, the lack of real-time testing in a clinical setting limits the model and#039; generalizability and practical application. In addition, the lack of validation of different datasets prevents the evaluation of their robustness and reliability. Another limitation is due to the scarcity of sources in the field, which can affect research and coverage. Finally, the deployment aspect of the model has yet to be explored, and potential technical and logistical challenges have not been addressed. Despite these limitations, the use of machine learning to classify fetal health is promising. In particular, the use of support vector machine (SVM) models on cardiotocography (CTG) data is a cost-effective and widely available approach, especially in areas with limited health resources. The simplicity and efficiency of the SVM model allows easy integration with CTG devices, enabling classification and contributing to the reduction of child mortality. In addition, the model and its user-friendly nature will promote the wider use of CTGs, providing a viable solution for the early diagnosis of various fetal conditions, even in areas where access to qualified obstetricians may be difficult. To overcome the identified limitations, future studies should prioritize large-scale validation in different patient populations from nearby hospitals and clinics, addressing potential challenges of implementation in practice.

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