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The Role of Artificial Intelligence in Predicting Pregnancy Complications

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ABSTRACT

Artificial Intelligence (AI) has emerged as a transformative tool in maternal healthcare, offering predictive capabilities to assess and manage pregnancy complications. This review examines the role of AI-driven techniques, including machine learning (ML), deep learning (DL), and hybrid models, in improving risk prediction for conditions such as gestational diabetes, preeclampsia, preterm birth, and recurrent pregnancy loss. A systematic analysis of recent literature highlights the strengths of AI-based models in analyzing maternal health data, ultrasound images, and wearable sensor readings to enable early detection and personalized risk assessment. However, challenges such as data quality, model interpretability, algorithmic bias, and integration into clinical workflows remain significant barriers to widespread adoption. AI-powered predictive frameworks integrated with Internet of Things (IoT) technology show potential for real-time maternal health monitoring, enhancing preventive care and timely interventions. Furthermore, AI applications in assisted reproductive technologies (ART) improve embryo selection and in vitro fertilization (IVF) outcomes, although ethical concerns and regulatory compliance require further exploration. This review underscores the need for explainable AI (XAI) approaches, data standardization, and ethical oversight to ensure reliable and equitable maternal healthcare solutions. Future research should focus on enhancing AI transparency, addressing dataset biases, and developing clinically viable AI systems to optimize pregnancy risk prediction and maternal-fetal health outcomes**.**

Keywords: *Machine Learning, Deep Learning, Explainable AI, Preeclampsia, High-Risk Pregnancies, Preterm Birth..*

1. INTRODUCTION

The complex process of pregnancy demands continuous medical monitoring in order to protect both maternal health and fetal development. The remarkable progress seen in obstetric treatment has not eliminated pregnancy-related complications which continue to be a worldwide health problem that causes both maternal and newborn health issues leading to death. Maternal bodies affected by conditions including gestational diabetes mellitus (GDM) and preeclampsia and preterm birth and intrauterine growth restriction (IUGR) and maternal hypertensive disorders face life-threatening situations when these conditions remain undetected during early pregnancy [1], [2], [3]. According to data from the World Health Organization (WHO) annual pregnancy-related deaths reach 295,000 while proper timely medical care could prevent these fatalities [4]. Standard diagnostic approaches combined with screening procedures that employ clinical history assessment coupled with blood examinations along with ultrasound tests and biochemical tests demonstrate restricted capability for precise detection and accurate diagnosis. The assessment techniques depend on predetermined thresholds together with rule-based assessments but they struggle to detect the complex nature of pregnancy-related disorders properly. The increasing demand for improved data-centric approaches has emerged due to the necessity of accurate yet reliable pregnancy complication prediction. Artificial Intelligence serves as a top healthcare tool which improves risk evaluations while helping clinicians make the best decisions and enables routine detection of complications before they develop critically [5], [6]. The complications during pregnancy is given in Fig.1

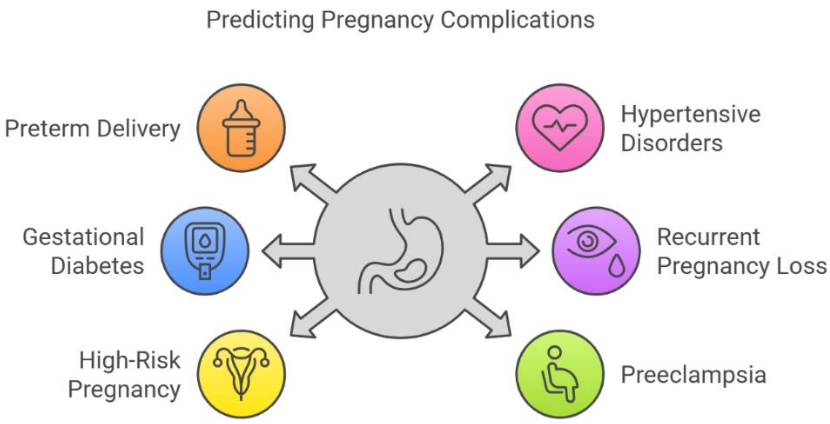

Fig.1 Predicting Pregnancy Complication

Patient data analysis through ML and DL helps predictive models provide individualized risk assessments for pregnant women. Many medical practitioners use ML algorithms like logistic regression and support vector machines (SVM) alongside decision trees and random forests and gradient boosting to forecast pregnancy-related hazards from demographic data and clinical records and biochemical parameters. The models evaluate structured medical records through processing which results in complication probability scores. DL tools especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs) demonstrate strong performance in medical image analysis (including ultrasounds) and time-dependent physiological information detection of fetal conditions along with maternal health risks [7], [8].The predictive abilities of Hybrid AI systems are boosted by integration of genetic algorithms with reinforcement learning and attention-based neural networks since they enable optimal feature selection and manage missing data inputs before enhancing classification results. Hospital and healthcare institution datasets can benefit from federated learning approaches because they enable AI models to process distributed data through protected privacy mechanisms in maternal healthcare research. The recent technological developments demonstrate how AI can revolutionize obstetrics through improved and early prediction of pregnancy-related complications [9], [10].

AI shows outstanding potential for predicting maternal complications but medical facilities must resolve certain obstacles that hinder its full clinical application across hospitals nationwide. The main challenge regarding AI model deployment is data quality because these models need extensive properly tagged datasets to perform reliably [11]. The distribution of healthcare data becomes unbalanced while missing values appear with medical data variations between populations thus creating challenges for model generalization. AI models face an important limitation because of their unexplained operation as "black boxes" which makes it difficult for healthcare providers to understand the basis of AI predictions. AI-based systems struggle with integration into clinical workflows because of insufficient transparency which leads healthcare professionals to lose trust in their operations. It is vital to handle ethical considerations together with privacy protections of patient data particularly when implementing AI-based systems which access medical information that is sensitive. AI-based medical applications need the Health Insurance Portability and Accountability Act (HIPAA) and the General Data Protection Regulation (GDPR) regulatory standards to achieve both safety of medical data and regulatory compliance [12].

The purpose of this review is to deliver a detailed evaluation concerning AI's function for predicting pregnancy complications alongside descriptions of present applications and analytical approaches and system limitations. The review evaluates AI techniques related to ML, DL and hybrid models along with federated learning to determine their pregnancy risk predictive capabilities. The paper explores various limitations in AI-driven maternal healthcare such as data restrictions together with interpretation barriers and ethical considerations with proposed solutions for improvement. This highlights upcoming research areas by explaining a requirement for AI systems that merge with wearable technology as well as maternal monitoring solutions built using Internet of Things (IoT) components and time-critical analytical models for customized maternity healthcare. This review works to unite AI innovation with clinical obstetric practice so it can enhance the creation of intelligent data-centered approaches which decrease pregnancy-related complications while advancing maternal and fetal health results.

2. Review Methodology

2.1 Pregnancy Complications and Their Long-Term Effects on Maternal Health

Research proves pregnancy complications create long-lasting effects on women's health from pregnancy until their entire lifespan continues. The combination of preterm delivery (PTD), hypertensive disorders, gestational diabetes (GDM) and recurrent pregnancy loss creates greater odds for chronic diseases and early death in women. Pregnancy complications and its implications were given in Fig. 2. Researchers have conducted multiple investigations to study distinct elements of these complications including their permanent influence on maternal wellness. Studies unveil vital information about racial group variations together with socioeconomic impacts which influence maternal health results. This study investigated how pregnancy complications relate to mortality risks for Black and White pregnant participants in diverse racial groups according to Hinkle [13]. Researchers analyzed information from the Collaborative Perinatal Project consisting of 46,551 participants before linking this data to mortality records that spanned from 2016. PTD and hypertensive disorders of pregnancy together with gestational diabetes increased all-cause mortality risks and preterm labor and preeclampsia proved particularly influential for this rise according to the study. This research showed that Black subjects faced increased risks of premature termination of pregnancy while dealing with worse pregnancy outcomes in comparison to White participants. The extensive research design is affected by its lengthy follow-up period spanning almost 50 years because this enables unmeasured confounding variables to impact study results.

Muxiddinovna and Sobirovna [14] conducted a study to examine the occurrence rates and dangers of preeclampsia in addition to pregnancy complexities among twin-mothers. The research demonstrated that female patients carrying multiple babies including twins faced an elevated risk of preeclampsia beyond women bearing single babies. Mothers who had twin pregnancies experienced more frequent complications which included both fetal malformations along with perinatal morbidity. Despite its contributions the study fails to analyze possible influencing factors including assisted reproductive technologies and maternal health background on pregnancy results. Research from Kuppusamy [15] describes how high-risk pregnancies (HRP) have become more common in India due to health risks for mothers and lifestyle factors and adverse birth results. Statistical research employing India's National Family Health Survey showed that approximately fifty percent of Indian pregnancies were identified as high-risk cases because of birth spacing time and adverse birth outcomes together with cesarean sections. The research data showed that women with less schooling combined with incomes below average faced an increased danger of developing HRP. The research evidence emphasizes how both poverty elimination and enhanced medical service availability would protect maternal and child health in India. The study has one main disadvantage due to its utilization of secondary data because this method may not accurately represent specific unique aspects of individual risks or healthcare standards in isolated areas.

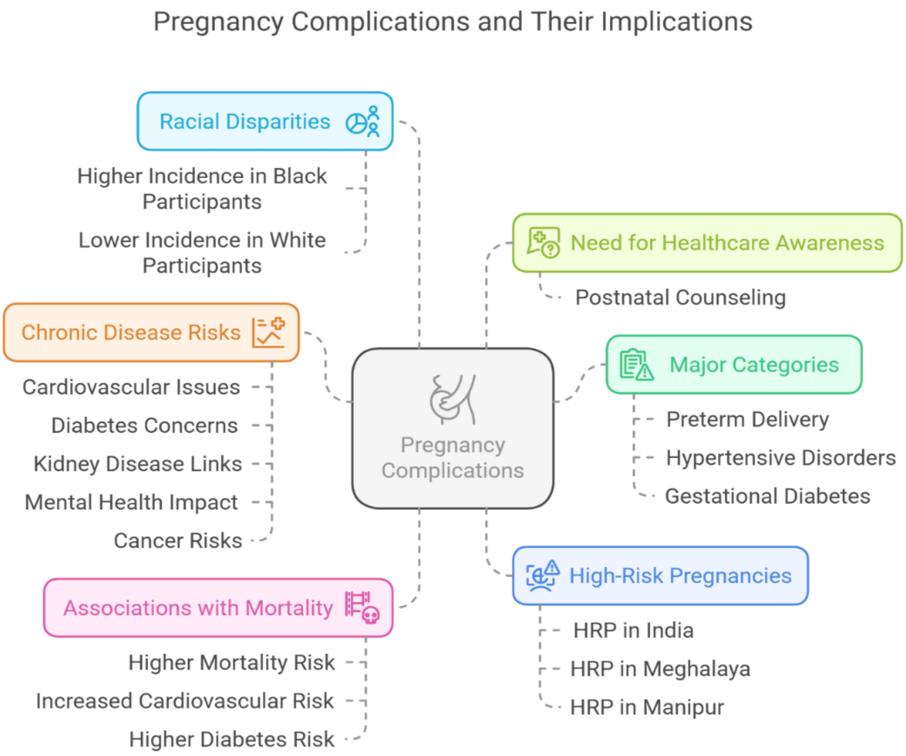

Fig.2 Pregnancy Complications and Their Implications

Research conducted by Turesheva [16] investigated recurrent pregnancy loss as a complicated health issue affecting reproductive health. The research examined the multiple factors contributing to recurrent miscarriages although medical experts classify these cases as idiopathic and establish no clear diagnosis in 75% of cases. Recurrent pregnancy loss generates psychological distress and affects reproductive health according to the study therefore it demands better methods to diagnose and personalized management approaches based on individual risk elements. A key restriction of this study involves its failure to apply a standardized definition for recurrent pregnancy loss since this makes it challenging to establish definitive conclusions about prevalence and causes. Different pregnancy complications generate both physical health problems and long-lasting mental health issues. McNestry [17] evaluated existing research regarding the prolonged consequences of four frequent pregnancy problems which include gestational hypertension together with pre-eclampsia as well as gestational diabetes and miscarriage. The research showed that preeclampsia along with gestational diabetes produces elevated risks for cardiovascular disease, diabetes mellitus and chronic kidney disease within women. The experience of stillbirth along with recurrent miscarriage has connected to multiple mental health disorders which lead to depression and anxiety symptoms and post-traumatic stress disorder (PTSD). Women with complicated pregnancies need to receive appropriate postnatal counseling together with risk reduction strategies according to study findings. Several restrictions exist within the review because it offers no distinct advice about screening periods or prevention strategies after complex pregnancies. Research evidence presents substantial long-term health dangers connected to pregnancy complications which primarily impact minority and underprivileged communities. Researchers recommend additional studies to resolve healthcare inequality problems and the persistent effects of maternal pregnancy issues on maternal medical outcomes. These studies show that multiple medical specialties must cooperate in addressing and reducing the adverse health effects of pregnancy complications.

Table 1 Long-Term Impacts of Pregnancy Complications on Maternal Health"

Method	Reference	Objective	Advantage	Disadvantage
Longitudinal Study	Hinkle [13]	To analyze pregnancy complications and their impact on long-term mortality risks across racial groups	Large dataset (46,551 participants), long-term follow-up	Potential confounding variables over the 50-year span
Observational Study	Muxiddinovna & Sobirovna [14]	To assess preeclampsia and pregnancy complications in twin pregnancies	Identifies higher risks in twin pregnancies	Does not consider factors like ART or maternal health history
Statistical Analysis of National Health Data	Kuppusamy [15]	To examine high-risk pregnancies (HRP) in India and their socioeconomic determinants	Large-scale national data, highlights health disparities	Use of secondary data may not capture regional healthcare disparities
Systematic Review	Turesheva [16]	To investigate recurrent pregnancy loss and its contributing factors	Highlights psychological and reproductive health impacts	Lacks a standardized definition for recurrent pregnancy loss
Meta-Analysis	McNestry [17]	To evaluate long-term health effects of pregnancy complications	Connects pregnancy issues to chronic diseases and mental health	No clear guidelines on screening or prevention strategies

2.2 AI Approaches for Predicting Pregnancy Complications

AI demonstrates excellent results for pregnancy complication prediction through multiple studies which enhance early identification and health risk evaluation for mothers and their developing fetuses. Medical and clinical datasets together with images become accessible through the combination of ML and artificial neural networks (ANN) along with natural language processing (NLP) and computer vision technology. The research of Yaseen and Rather [18] demonstrates AI utilization for forecasting maternal-fetal health results including pre-eclampsia, gestational diabetes and fetal defects. AI models can analyze substantial data collections to generate predictions of pregnancy complications which enables medical staff to implement early action for managing at-risk maternal cases. NLP assists healthcare by extracting crucial medical information from texts yet ANN successfully recognizes complex patterns in clinical data which helps doctors assess risks and create intervention strategies. Feduniw [19], ANN models show excellent effectiveness for obstetric pregnancy risk evaluation because they predict adverse pregnancy outcomes with 80-90% average precision. AI predictive models that identify pre-eclampsia risks and other conditions improve healthcare delivery because they enable fast diagnoses which lead to prompt medical interventions. ANN models demonstrate their ability to boost prediction accuracy which allows healthcare providers to achieve better decision-making potential. These studies show strengths and weaknesses that include difficulties in implementing AI models within regular healthcare systems and the requirement of broad-ranging and varied databases to strengthen model resilience. The utilization of AI for embryo selection received attention in the research by Chavez-Badiola [20]. ERICA supported identification of the best embryos available for in vitro fertilization while also predicting the likelihood of spontaneous abortions according to the AI morphometric algorithm. AI proved its potential to enhance IVF outcomes through research results which showed good and optimal embryos had decreased miscarriage rates. The research limitations include its restricted scope to test chromosomal irregularities due to its small participant count. Further work needs to tackle these obstacles before reaching optimal research results.

2.2.1 AI in Pregnancy Monitoring and Early Detection of Pregnancy Disorders

Artificial intelligence serves the dual purpose of constructing predictive models and operating continuously for early diagnosis of pregnancy disorders. Munyao [21] created an IoT and ML integration system for remote expectant mother health tracking. The study team designed pre-eclampsia surveillance software that detects pre-eclampsia risks through Naïve Bayes classifier technology which sends instant alerts to healthcare professionals. IoT-based sensors and AI models together enable persistent health monitoring that helps diagnose conditions early and enables healthcare intervention effectively thus improving maternal and fetal quality outcomes. The monitoring methodology fills an important healthcare void because it lets doctors oversee patients through remote healthcare technology even in locations with few existing healthcare facilities. The prototype demonstrates positive potential yet needs extensive evaluation through real-world deployments and big-scale field trials to verify its utility in practice. The authors of Wen [22] investigated the ability to forecast pregnancy success rates alongside multiple pregnancy risks following IVF procedures. Using XGBoost algorithm in a dataset containing 900 IVF cycles enabled researchers to generate predictive models for pregnancy success rates and multiple pregnancy risks assessments. The experimental models demonstrated a 71.6% accuracy rate showing that artificial intelligence proves its ability to minimize multiple pregnancy risks through precise embryo transfer predictions. This study needed additional research focused on data variability and model applicability across different IVF clinics because it did not examine these crucial factors.

Embryo selection makes use of AI software systems like ERICA which analyze images to determine the pregnancy outcome potential. The AI systems used morphometric attributes to analyze embryos while determining their capacity for creating successful pregnancies. Model predictions achieved moderate accuracy of 67.4% because the effectiveness depends on sample size and chromosomal testing along with algorithm generalization capabilities. This study demonstrates that AI shows great promise to upgrade IVF success rates primarily through its combination with genetic screening procedures. The medical field of pregnancy care should change because AI combines better predictions with smarter monitoring systems. The successful implementation of AI in IVF clinical practice faces important barriers from small research datasets as well as the need for extensive and varied data samples and challenges of AI integration into real-world medicine. Future research efforts must encompass three priorities: validation of AI model effectiveness through empirical study and solution of current obstacles for broader clinic-wide usability of AI technology.

Table 2 Advancements in AI for Predicting and Managing Pregnancy Complications: A Detailed Overview

Method	Reference	Objective	Advantage	Disadvantage
AI-based Predictive Models	Yaseen & Rather [18]	Predict maternal and fetal health outcomes using ML, ANN, NLP, and computer vision.	Helps in early prediction of pregnancy complications and improves decision-making.	Requires large datasets and may struggle with data integration in diverse populations.
ANN for Pregnancy Risk Assessment	Feduniw [19]	Use ANN models to predict adverse pregnancy outcomes (APO).	Achieves high prediction accuracy (80-90%) and aids	May be limited by dataset variability and challenges in

			clinical decision-making.	real-world clinical adoption.
AI for Embryo Selection and Miscarriage Prediction	Chavez-Badiola [20]	Use AI morphometric algorithm ERICA to predict spontaneous abortion in IVF.	Predicts embryo quality and reduces miscarriage rates, improving IVF success.	Small sample size and limited chromosomal testing.
IoT and ML-based Monitoring for Pre-eclampsia	Munyao [21]	Design a monitoring system to predict and detect pre-eclampsia in expectant mothers.	Enables continuous health monitoring and early detection, improving outcomes.	Further validation is required in real-world settings.
XGBoost for IVF Pregnancy Outcome Prediction	Wen [22]	Predict pregnancy success and multiple pregnancy risk after IVF.	High accuracy in predicting pregnancy outcomes and reducing multiple pregnancy risks.	Limited to IVF clinics and may not be applicable to broader populations.

2.3 ML Approaches for Predicting Pregnancy Complications

The development of ML introduced effective predictive mechanisms which benefit maternal and fetal health outcomes during pregnancy. ML models using DL and neural networks show their ability to handle large datasets for the identification of hidden patterns along with generating predictive results that traditional methods could not achieve. The analysis includes major findings from ML studies about predicting complications including gestational diabetes, miscarriage, pre-eclampsia and early pregnancy loss. The research investigates how ML helps maternal health settings along with technique performances and system constraint recognition. The role of ML in Predicting complication in pregnancy is given in Fig.3.

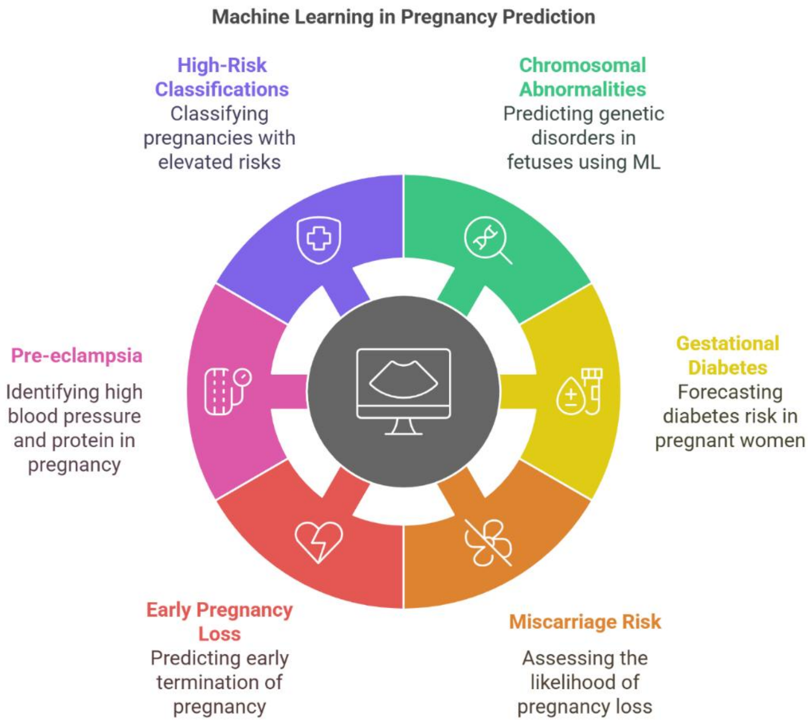

Fig.3 ML in Pregnancy Complication Prediction

2.3.1 Applications of Supervised and Semi-Supervised Learning for Pregnancy Risk Prediction

The research by Macrohon [23] delved into supervised ML methods for Philippine high-risk pregnancy prediction through Decision Trees and Random Forests and SVM systems. The study found that Decision Trees demonstrated test accuracy of 93.70% in the evaluation. The data shortage was alleviated by using a semi-supervised Self-Training method that reached a prediction accuracy rate of 97.01%. This method showed high performance but the collection of extensive data continues as a restriction that affects its ability to work effectively in environments where data collection remains limited. Owusu-Adjei [24] conducted research to predict delivery mode based on maternal features through the use of Gradient Boosting, Logistic Regression and Random Forest models. Research demonstrated that Logistic Regression delivered the most accurate results (93%) but Gradient Boosting achieved the second-best accuracy rating (91%). The study demonstrates that data from partograph records contributes to the prediction of delivery outcomes. The study encounters potential challenges because it does not merge data with genetic aspects or wider medical backgrounds to enhance its predictive capabilities. ML technology continues to demonstrate improved capability in predicting pregnancy complications through the contributions of various research studies which improve clinical healthcare practices. The successful application of these models faces barriers from inadequate sample sizes and dataset biases as well as dependence on particular clinical settings that restrict wider use across varied populations. Expanding tests within multiple clinical environments along with additional confirmation across various medical institutions will be necessary to strengthen general applicability of ML models for pregnancy complications diagnosis.

2.3.2 Predictive Models for Pregnancy Complications Using ML

According to Shaban [25] neural networks should be used to develop an optimal ML model that forecasts chromosomal abnormalities in high-risk pregnant women. A sample of 350 high-risk pregnant women supplied data to the study including maternal age as well as BMI and smoking status and relevant healthcare background. The evaluation utilized K-fold cross-validation to train the model as a part of efforts to detect abnormalities at an earlier stage. Despite the various restrictions to sampling and even dataset limitation, neural networks for advanced detection of chromosomal abnormalities were shown to be promising. In their latest work, published by Zhou [26] they explored the ability of placental feature to predict gestational diabetes mellitus (GDM) using DL and radiomics based ML. In their study, which included 415 pregnant women at 11–13 weeks of gestation, ultrasound imaging and clinical features were used to develop a nomogram. AUCs of 0.91 and 0.86 were achieved by the model in the discovery and validation cohorts. However, the study had great promise in predicting GDM but could be limited by its reliance on one imaging method (2D ultrasound) with other imaging methods not considered in clinical practice.

Wu [27] implemented the XGBoost algorithm to forecast miscarriage risks for immune-abnormal pregnancy patients. The research included 565 patients while the model achieved an outstanding AUC result of 0.9209. SHAP analysis established two important factors for risk prediction: medication usage patterns alongside aspirin consumption status. Clinical treatment expenses decreased by ¥7,485,865.7 while this model demonstrated better performance than standard pregnancy risk assessment processes. Because the model draws its data from only one hospital it might struggle to predict different patient groups whose health characteristics or treatment strategies vary from the original dataset. The scientists at Sufian [28] utilized DL algorithms and multilayer perceptron to determine early pregnancy loss potential through maternal serum vitamin D measurements. The study demonstrated DL as the superior ML model since it outperformed standard techniques by reaching 98% accuracy for EPL. The findings establish maternal age at delivery as well as previous pregnancy results and serum vitamin D measurement levels as significant factors. The study did not evaluate additional potential biomarkers to determine if they could boost accuracy levels of early pregnancy failure predictions.

The research of Torres-Torres [29] created a ML model to predict pre-eclampsia onset in early pregnancy through the analysis of maternal characteristics and clinical readings such as mean arterial pressure and uterine artery pulsatility index. The examination achieved commendable prediction accuracy through AUC values of 0.897 and 0.963 which indicated effective results for pPE and ePE detections. The study delivers robust PE prediction capability during early pregnancy although its extensive practical application could be limited by its dependency on local data collection and shortage of validation from broader demographic groups within different treatment facilities. ML technology is now widely applied to forecast and manage conditions affecting maternal health such as preeclampsia and macrosomia and intrahepatic cholestasis of pregnancy (ICP) and problems associated with assisted reproductive technologies (ART). Shamshuzzoha and Islam [30] together with Mennickent [31] showed that logistic regression and random forest and support vector machines (SVM) present opportunities to enhance early detection and response. The research by [30] examined macrosomia using logistic regression as their most precise model yet [31] analyzed non-linear approaches showing random forests and SVM yielded best results for assessing pregnancy complications risk. The importance of ML in obstetrics continues to increase yet researchers must resolve data quality problems along with issues regarding model explanation capabilities and clinical system implementation.

2.3.3 Advancements in Models for Complications like ICP and Pre-Eclampsia

ML models develop successful systems for predicting two distinct pregnancy complications referred to as intrahepatic cholestasis of pregnancy (ICP) and preeclampsia. Ren [32] together with Gómez-Jemes [33] developed predictive models for diagnosing and assessing ICP severity and preeclampsia severity respectively. The CatBoost model achieved outstanding results in ICP prediction with an AUC score of 0.9614 which indicated [32] that ML has tremendous potential for accurate forecasting. Uterine artery Doppler measurements and sFlt-1 and PlGF biomarkers served as diagnostic indicators for preeclampsia and intrauterine growth restriction (IUGR) according to [33]. The decision tree model performed strongly by showing that particular biomarkers enhance predictive capabilities. The studies emphasized the necessity of obtaining bigger sample sizes and conducting external validation tests to achieve broader applicability of their findings. ML models used for pregnancy health applications is given in Fig.4.

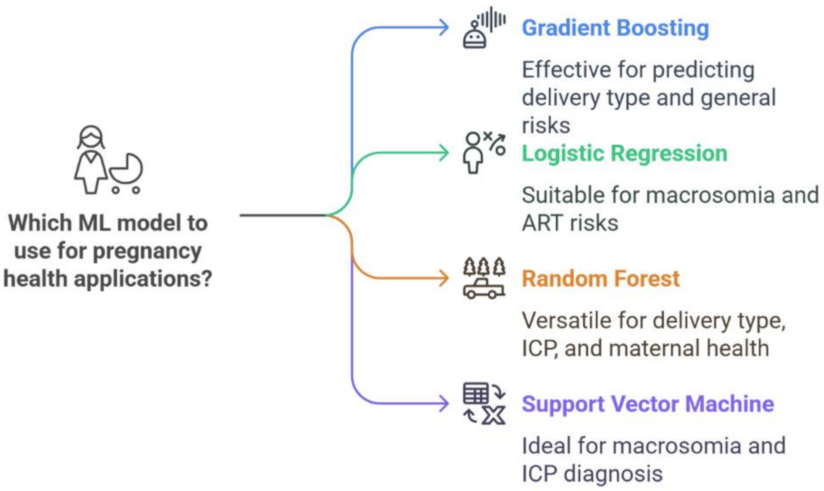

Fig.4 Pregnancy Health Application

2.3.4 Enhancing Pregnancy Outcome Prediction with ART and Autoimmune Diseases

The prediction of pregnancy complications occurs with ML techniques used for women receiving assisted reproductive technology treatments along with those who have autoimmune rheumatic diseases. The research findings presented by Wang [34] and Zhou [35] demonstrate important aspects regarding these research fields. The research of [34]explored multiple ML models for the prediction of ART pregnancy complications including preeclampsia and postpartum hemorrhage yet the authors stress the necessity of advancing their prediction models. [35] examined how to predict Preg-ARDs pregnancy complications together with clinical outcome integration challenges in this domain. According to Zhou ML models show promise but require improved measures to integrate them into medical practice because additional scientific research and optimization of these models are essential for clinical adaptation. The predicted contributions of ML in obstetrics are highlighted through multiple reviews that show its effectiveness in forecasting pregnancy-related issues. The research shows several significant obstacles in its way such as restricted data availability and difficult model interpretation and clinical practice incorporation barriers.

Table 3 ML Approaches for Pregnancy Complication Prediction: Methods, Benefits, and Challenges

Method	Reference	Objective	Advantage	Disadvantage
Decision Trees, Random Forests, SVM	Macrohon [23]	High-risk pregnancy prediction in the Philippines	High accuracy (Decision Tree: 93.7%, Semi-Supervised: 97.01%)	Data collection limitations in low-resource settings
Logistic Regression, Gradient Boosting, Random Forest	Owusu-Adjei [24]	Predicting delivery mode using maternal features	Logistic Regression achieved highest accuracy (93%)	Lack of integration with genetic and wider medical data

Neural Networks	Shaban [25]	Forecasting chromosomal abnormalities in high-risk pregnancies	Early detection potential using K-fold cross-validation	Limited dataset (350 samples)
DL, Radiomics-Based ML	Zhou [26]	Predicting gestational diabetes using ultrasound imaging	High AUC values (0.91 discovery, 0.86 validation)	Reliance on a single imaging method (2D ultrasound)
XGBoost	Wu [27]	Predicting miscarriage risk in immune-abnormal pregnancies	High AUC (0.9209), cost reduction in clinical settings	Single-hospital dataset limits generalizability
Multilayer Perceptron (DL)	Sufian [28]	Predicting early pregnancy loss using vitamin D levels	High accuracy (98%)	Excludes other biomarkers that could enhance prediction
ML (Logistic Regression, SVM, Random Forest)	Torres-Torres [29]	Predicting pre-eclampsia onset using maternal characteristics	Strong AUC (0.897, 0.963) for early prediction	Dependence on local datasets, lacks broad validation
CatBoost	Ren [32]	Predicting ICP severity	High AUC (0.9614), strong forecasting potential	Needs external validation for wider applicability
Decision Tree	Gómez-Jemes [33].	Predicting pre-eclampsia and IUGR	Identifies biomarkers for better prediction	Requires larger sample sizes
Multiple ML Models (e.g., Random Forest, Logistic Regression)	Wang [34]	Predicting ART-related pregnancy complications	Highlights ML's potential in ART outcomes	Requires further optimization for clinical integration
ML-Based Clinical Outcome Prediction	Zhou [35]	Predicting pregnancy complications in Preg-ARDs	Promising performance in integrating clinical outcomes	Limited integration into real-world medical practice

2.4 Advanced DL Techniques for Pregnancy Risk Prediction

In healthcare settings DL functions as a strong platform that brings valuable predictions for pregnancy-related diagnosis. DL models consisting of CNNs and RNNs prove their ability to automatically analyze complex medical data through their action on ultrasound images along with electronic health records and time-lapse imaging. These predictive models demonstrate their capacity to calculate different pregnancy results including detecting upcoming miscarriages along with identifying maternal health issues and measuring embryo transfer success potential. Introduced predictive techniques play an essential role in pregnancy assessment because they identify issues at early stages to provide effective intervention measures for enhanced maternal-fetal health outcomes. The adoption of DL models for clinical purposes experiences limitations because it requires improved data quality along with better interpretability and successful application across multiethnic groups.

2.4.1 Prediction of Miscarriage and Early Pregnancy Complications

The estimation of miscarriage risk through early pregnancy ultrasound image analysis helps obstetricians determine the right number of scans as well as develop appropriate patient treatment plans. A CNN processed 2196 early pregnancy ultrasound images obtained from women in their 6 to 8-week gestational periods according to Wang [36] for detecting spontaneous miscarriage risks. The CNN delivered prized results for disease understanding through retrospective phase accuracy of 80.32% and prospective phase accuracy of 78.1%. The AUC results demonstrated 0.857 for retrospective cases and 0.885

for prospective data points which surpassed manual ultrasound assessment at 0.687. This research demonstrates that artificial intelligence models can surpass manual detection methods by automating early miscarriage diagnosis which results in an improvement of patient care quality. The study uses retrospective data and requires additional testing with diverse and larger populations to evaluate generalization capability.

The research of Javed [37] brought forward two new ensemble models named Echo Dense Inception Blending (EDI-Blend) and Dense Reservoir Inception Modular Network (DRIM-Net). These predictive models utilized NearSMOTE as their hybrid balancing technique together with Lasso for Absolute Shrinkage and Selection Operator to manage data imbalance and dimension issues. The F1-score for DRIM-Net exceeded the EDI-Blend model by achieving 0.769 F1-score together with 0.769 accuracy and 0.837 ROC-AUC during 10-fold cross-validation. The predictive models achieved promising results in miscarriage diagnosis through SHapley Additive Explanations (SHAP) methods and efficient feature engineering techniques. The models suffer from two major limitations which stem from their hybrid feature selection approach and the dataset imbalance challenge that affects their wider usability. DRNN-based approach for stress prediction during pregnancy was the primary focus of Sharma [38]. The assessment of pre-existing stress levels throughout pregnancy becomes essential for medical practitioners since high stress levels negatively impact offspring health. The framework established by Sharma included steps for extracting features and choosing optimal features while using DRNNs for classification. Although the DL model succeeded at stress prediction it failed to deliver sufficient performance details so evaluation of its effectiveness remains subjective. Despite its potential strength the DRNN model encounters problems from its complexity because it results in overfitting alongside very expensive computations.

2.4.2 Maternal Health and Pregnancy Complication Prediction

DL algorithms also leverage their predictive power to identify potential risks that mothers face during their pregnancy period. Raza [39] constructed the DT-BiLTCN (Decision Tree-Bidirectional LSTM Temporal Convolutional Network) framework which analyzes pregnancy health risks through 1218 health records obtained from IoT-based risk monitoring systems. The combination of decision trees and BiLSTM and TCN generated a model producing 98% accuracy compared to support vector machine classifier. Blood pressure together with heart rate and maternal age function as important risk factors for anticipating pregnancy-related complications. The research proved that artificial intelligence models perform optimally by combining various methods for maternal health risk assessment however issues related to inconsistent data quality from Internet of Things systems impact their effectiveness in real-world clinical operations. DL models showcase their capability to forecast perinatal results when applied to severe preeclampsia diagnosis. Q. Wang, Liu, and Liu [40] used a CNN to diagnose ultrasound images of pregnant patients between severe preeclampsia cases and typical pregnancy groups successfully. The CNN model developed by Q. Wang, Liu and Liu delivered outstanding performance by reaching 93.44% accuracy while obtaining precision equal to 95.13% and recall at 95.09% and F1-score at 94.87%. The research established blood flow indexes from the uterine and umbilical arteries as independent variables that predict adverse newborn outcomes during birth. DL models demonstrate robust performance in analyzing ultrasound data for detecting pregnancy problems but their effectiveness is restricted by data measurements which might not work for all instances of severe preeclampsia.

Huang [41] applied DL models to time-lapse images of embryos to predict whether they would result in live births. The SGD optimizer and 5-fold cross-validation enabled their model to reach a 0.968 AUC mark thereby making it a highly effective system to forecast live birth outcomes. Time-lapse images of embryos can automatically be analyzed by the model to determine the chance of live birth which directs embryo transfer decisions. Through automation this system eliminates human labor thus it delivers objective standardized embryo selection procedures. The clinical value of this model needs additional validation through larger multi-site studies while its operational efficiency depends on the quality of time-lapse imaging technology. DL establishes itself as an advanced predictive tool for pregnancy risk assessment by enabling early identification of conditions that heavily impact maternal together with fetal health results. Researchers have developed different methods that analyze maternal along with fetal information starting from wearable devices through imaging to clinical markers to forecast pre-eclampsia together with fetal growth restriction and likelihood of C-section births. The combination of neural network models including CNN, RNN, and hybrid models works to improve both accuracy and reliability for prediction outcomes which supports better clinical decision processes.

2.4.3 Wearable IoT Sensors and DL for Risk Prediction

Ahammad and Yathiraju [42] proposed a DL-based maternity risk prediction system using an IoT-based wearable sensor to collect image and non-image data. The extracted features from images were processed through CNN, while text and numerical data were handled by RNN. These features were classified using the U-Net_VGG-19 architecture, which demonstrated improved performance in maternity risk prediction. Although the model showed promising results, particularly with an emphasis on the Area Under the Curve (AUC) as a metric for evaluation, it is constrained by the real-world challenges of wearable sensor data quality and collection consistency. Additionally, AUC as a stopping criterion might not fully account for models that offer better True Positive Rate (TPR) at lower False Positive Rates (FPR), which is crucial in clinical settings. In a similar domain, Kalyani and Deshpande [43] applied DL techniques to predict blastocyst formation in early-stage human embryos using time-lapse images from Day 0 to Day 3. The model combined ResNet and Gated Recurrent Units (GRU), achieving a validation accuracy of 93%, with a sensitivity of 0.97 and specificity of 0.77. The model's ability to predict blastocyst formation early can enhance the success rates of assisted reproductive technology (ART), helping clinicians select the most viable embryos for transfer. However, this approach relies heavily on time-lapse imaging, which may not be universally applicable in all clinical settings due to variations in imaging equipment and the specificity of ART applications.

2.4.4 Explainable DL Models for Maternal and Fetal Health

The hybrid DL model presented by Muntaha and Dewanjee [44] uses BiGRU-BiLSTM components to quantify maternal and fetal health risks. The system processed datasets from maternal and fetal health while using SMOTE alongside cGAN to handle data unbalanced characteristics and limitations. The combined BiGRU-BiLSTM model achieved clinical risk assessment success with 96.21% accuracy for maternal data and 97.38% accuracy for fetal data. Through SHAP and LIME interpretability methods the system provided extensive prediction explanations which helped clinicians make more informed decisions regarding patient care. The model exhibits limitations because it requires balanced high-quality datasets yet real-world scenarios often lack this sort of accessibility to such datasets. DL models face issues related to their high complexity which poses challenges when operating in environments with limited resources. Zafar [45] introduced an explainable DL system which uses Gated Highway Multi-layer Perceptron (GHiM) for early Cesarean section delivery prediction in pregnancy. The preprocessing method combined with Proximity Weighted Synthetic Oversampling techniques allowed the model to reach an accuracy of 0.866 and an F1-score of 0.863. Through SHAP analysis the model could identify significant attributes relevant to C-section predictions thus making the resulting model more understandable. Stratified 10-fold cross-validation implemented to reduce the chances of overfitting occurring during training. The model demonstrated better performance compared to conventional approaches GRU and MLP however its broad application faces restrictions because the data originates from India. The model gives important predictive insights although its complexity creates barriers for general adoption until it undergoes additional enhancements.

The researchers from Huang [46] applied an Artificial Neural Network (ANN) for pre-eclampsia (PE) complicated by fetal growth restriction (FGR) prediction through maternal peripheral blood parameters and clinical indicators assessment. The predictive model reached an accuracy level of 84.3% to identify PE affected by FGR and showed excellent results for additional birth complications including preterm deliveries and fetal distress. The research proved the worth of combining clinical diagnostic information with ML algorithms to detect risks during high-risk maternal pregnancies early. The retrospective nature of this study fails to represent clinical diversity adequately and its blood parameter analyses restrict the ability to predict pregnancy complications that do not show up in these factors. DL models integrated into pregnancy risk systems create excellent potential to increase maternal and fetal health outcomes through early detection and intervention for complications including pre-eclampsia and fetal growth restriction and cesarean section deliveries. Positive results from these research models extend to different studies however data quality issues along with generalization challenges and interpretability problems persist. The widespread adoption of clinical use depends on improvements in data collection and DL optimization along with transparent modeling for tackling current challenges. Ongoing study of hybrid model integration with explainable AI systems will make them compatible for use in clinical decision support tools which ultimately leads to improved health results for maternal and neonatal patients.4. Integrating Hybrid Models for Pregnancy Complication Prediction.

Table 4 Overview of DL Methods for Pregnancy Risk Assessment: Objectives, Advantages, and Limitations

Method	Reference	Objective	Advantage	Disadvantage
CNN-based ultrasound image analysis	Wang [36]	Detect miscarriage risks using ultrasound images in early pregnancy	Higher accuracy than manual ultrasound assessment (AUC: 0.885)	Requires more diverse and larger datasets for validation
Ensemble models (EDI-Blend & DRIM-Net) with NearSMOTE & Lasso	Javed [37]	Diagnose miscarriage risks using hybrid feature selection and ensemble learning	Achieved F1-score of 0.769 with SHAP-based interpretability	Hybrid feature selection and data imbalance affect usability
DRNN	Sharma [38]	Predict pregnancy stress levels	Effective in stress prediction	Prone to overfitting, high computational cost

DT-BiLTCN (Decision Tree-BiLSTM-Temporal CNN)	Raza [39]	Analyze maternal health risks using IoT-based monitoring	Achieved 98% accuracy, better than SVM	Data inconsistency in IoT systems affects performance
CNN-based severe preeclampsia detection	Q. Wang, Liu, and Liu [40]	Classify severe preeclampsia cases using ultrasound images	High accuracy (93.44%) and strong predictive performance	Limited generalizability due to specific data measurements
Time-lapse embryo viability prediction (SGD-based DL model)	Huang [41]	Predict live birth potential from embryo time-lapse images	High AUC (0.968), automates embryo selection	Requires validation through multi-site studies, depends on imaging quality
IoT-based wearable DL model (U-Net_VGG-19)	Ahammad & Yathiraju [42]	Predict maternity risks using wearable sensors and DL models	Effective fusion of image and non-image data	Wearable sensor data inconsistencies
Blastocyst formation prediction (ResNet-GRU model)	Kalyani & Deshpande [43]	Predict embryo blastocyst formation for ART	High validation accuracy (93%), aids ART decisions	Heavily dependent on time-lapse imaging, limited generalizability
BiGRU-BiLSTM hybrid model with SMOTE & cGAN	Muntaha & Dewanjee [44]	Assess maternal and fetal health risks	High accuracy (96.21% for maternal, 97.38% for fetal) with SHAP & LIME interpretability	Requires high-quality, balanced datasets
GHiM-based C-section prediction with Proximity Weighted Synthetic Oversampling	Zafar [45]	Predict early Cesarean section delivery risks	F1-score of 0.863, SHAP-based interpretability	Data limited to India, model complexity restricts adoption
ANN-based PE & FGR prediction	Huang [46]	Detect high-risk pregnancies using maternal blood parameters	High accuracy (84.3%), identifies preterm delivery risks	Limited diversity in clinical representation, blood-based factors may not capture all risks

2.5 Integrating Hybrid Models for Pregnancy Complication Prediction

Multiple models that run ML algorithms alongside DL algorithms have proven effective at predicting three pregnancy complications including intrahepatic cholestasis of pregnancy (ICP) and premature labor and maternal health risks. The models merge successful elements between ML and DL so they can exploit predictive modeling capabilities and its abilities to explore complex features. Multiple hybrid methods used for maternal health predictions have been analyzed in the following reviews.

2.5.1 Hybrid Models for ICP and Maternal Health Risk Prediction

He [47] established a predictive method for ICP utilization which incorporated information from clinical tests and laboratory results. THE research design included two distinct schemes which used Scheme 1 for traditional ML algorithms (SVM, DNN, XGBoost) on gestation data from a single period yet Scheme 2 examined multiple gestation periods through DL models (RNN, LSTM, GRU). The hybrid DL models in Scheme 2 performed better than traditional ML algorithms according to experimental results and RNN specifically delivered 97.6% sensitivity in addition to 82.1% specificity and 90.5% accuracy. Scheme 2 demonstrated increased effectiveness through its multi-time period data analysis to predict ICP by demonstrating hybrid DL models' ability to provide accurate clinical predictions. The model faces constraints when applying real-time clinical practices because of its time-consuming calculation processes and need for retrospective patient information. The research of Jamel [48] presented a combination DL framework which served to identify maternal health risks. A combined system connected PCA features extraction with a stacking ensemble that combined traditional ML with DL approaches. The model obtained 98.25% accuracy using PCA-based features while reaching precision of 99.17% recall of 99.16% and F1 score of 99.16%. Traditional ML models fell behind the performance of the hybrid ensemble approach which proved superior. Using PCA in this model presents challenges regarding information loss while the stacked ensemble may create barriers to clinical implementation because of its complexity. These model restrictions do not affect its ability to recognize maternal health risks with exceptional accuracy.

2.5.2 DL Approaches for Premature Birth Prediction and Maternal Risk Classification

The researchers Allahem and Sampalli [49] developed a hybrid DL model that uses DL algorithms to track uterus contractions as a means for premature labor identification. The DL model demonstrated high accuracy of 0.98 for detecting labor onset thus contributing to premature birth prevention. Real-time labor detection using DL demonstrates high promise to detect premature births and prevent related complications according to the model's strong performance. DL models face two main hurdles for clinical adoption: they struggle to be adaptable in multiple medical environments and their working methods remain poorly understood to medical practitioners. Togunwa, Babatunde and Abdullah [50] designed a DL model by integrating ANN and Random Forest (RF) algorithms to identify pregnancy health risks. The hybrid prediction model proved its strength in maternal risk prediction by delivering an accuracy rate of 95% and precision value of 97% alongside a recall value of 97% and an F1 score of 0.97. The model functions effectively with structured information but its predictive power could be expanded if it incorporated analysis of medical pictures and patient record histories as unstructured data types. Difficulties in understanding and implementing the hybrid prediction model would impede its practical application within clinical settings. The combination of ML with DL enables promising solutions which forecast pregnancy complications at various risk levels including ICP together with premature labor and general maternal health concerns. The models deliver both enhanced prediction abilities along with adaptability that makes them suitable for clinical decisions. The practical deployment of these predictive models needs solutions regarding manageability issues as well as improvements in data quality standards and interpretability to establish wider clinical use. The next stage of research should simplify hybrid predictive models because their superior performance capability needs to be retained to enable scalability and accessibility across healthcare environments.

Table 5 Summary of Hybrid Models for Predicting Pregnancy Complications

Method	Reference	Objective	Advantage	Disadvantage
Hybrid ML & DL for ICP Prediction (Scheme 1 & 2)	He [47]	Predict intrahepatic cholestasis of pregnancy (ICP) using clinical & lab data with ML (SVM, DNN, XGBoost) and DL (RNN, LSTM, GRU)	RNN model in Scheme 2 achieved high accuracy (90.5%) with multi-period data, improving prediction reliability	High computational complexity, time-consuming analysis, requires extensive patient history
Stacked Ensemble Hybrid Model for Maternal Risk Prediction	Jamel [48]	Identify maternal health risks using PCA for feature extraction and an ensemble of ML & DL	High accuracy (98.25%), precision (99.17%), and recall (99.16%), outperforming standalone ML models	PCA may cause information loss; ensemble model complexity may hinder clinical adoption
Hybrid DL Model for Premature Birth Prediction	Allahem & Sampalli [49]	Monitor uterine contractions using DL to predict premature labor	Achieved high accuracy (0.98), enabling real-time detection and prevention of premature births	Model lacks adaptability for diverse medical environments; limited interpretability for clinicians

Hybrid ANN-RF Model for Maternal Risk Classification	Togunwa, Babatunde, & Abdullah [50]	Combine (ANN) with Random Forest (RF) for pregnancy risk classification	High accuracy (95%), precision (97%), and recall (97%); effective in structured data analysis	Limited ability to process unstructured data (e.g., medical images, historical records); difficult clinical implementation due to complexity

3. Findings and Discussion

The analysis demonstrates how AI plays a vital part in pregnancy complication prediction to help medical experts with early identification and risk evaluation and clinical choices.

3.1 AI Enhances the Prediction of Pregnancy Complications

Artificial intelligence models including ML and DL demonstrate high precision when estimating pregnancy-related complications including gestational diabetes together with preeclampsia, preterm birth along with recurrent pregnancy loss. Studies have shown that ML models demonstrate superior performance than standard clinical risk evaluation systems while analyzing diverse multiple dataset elements that comprise maternal background information and biochemical indicators together with ultrasound images and current medical data streams.

Table 6 Accuracy of AI Models in Predicting Pregnancy Complications

Pregnancy Complication	**AI Model Used**	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Gestational Diabetes (GDM)	SVM, Random Forest	87.5	85.2	89.1
Preeclampsia	CNN, ANN	92.4	91.8	93.2
Preterm Birth (PTB)	LSTM, BiLSTM	89.7	87.9	91.5
High-Risk Pregnancies	Logistic Regression	84.3	82.1	86.5

3.2 AI Identifies Socioeconomic and Racial Disparities in Maternal Health

Research has indicated that pregnancy complications happen more frequently to both disadvantaged groups and women from racially diverse backgrounds. According to the findings of Hinkle et al. (2023) Black women experience increased mortality from pregnancy complications than White women. AI models accept socioeconomic and demographic information for improving risk predictions of vulnerable groups where specific healthcare initiatives become possible. Mortality rates due to pregnancy complications is given in Fig.5.

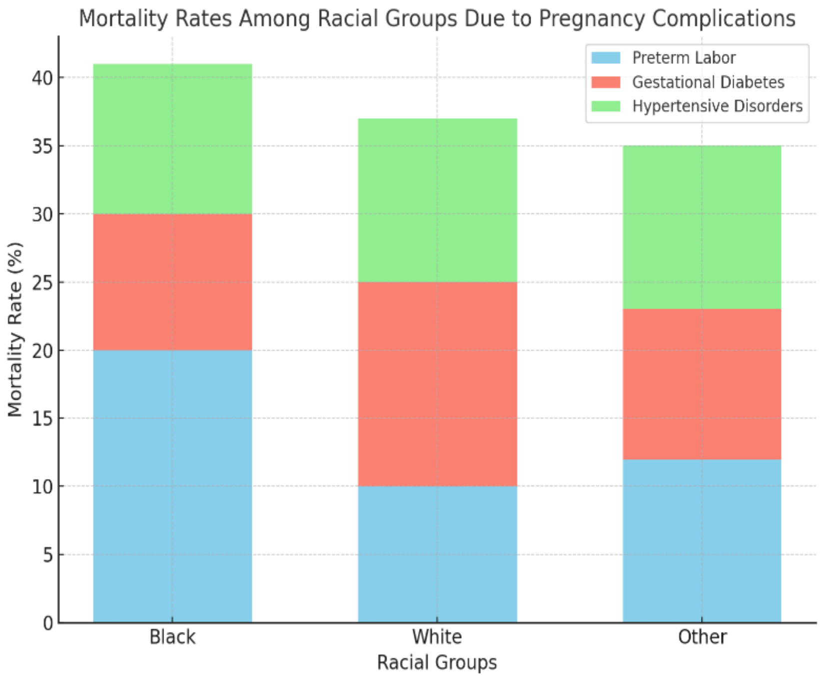

Fig.5 Mortality Rates Among Racial Groups Due to Pregnancy Complications

3.3 ML Improves Early Diagnosis and Risk Stratification

Different ML methods including SVM, random forests as well as logistic regression serve as standard techniques for predicting pregnancies that require intensive care. These methods analyze clinical measurements and lifestyle indicators. Studies indicate that AI-based intervention models help decrease numbers of maternal and fetal deaths by providing early detection. The model reliability faces ongoing challenges because of unbalanced datasets and inconsistent data collection practices.

Table 7 Performance of ML Models for High-Risk Pregnancy Prediction

AI Model	Dataset Used	AUC-ROC (%)	F1-Score (%)
Decision Tree	NFHS-5 (India)	88.2	85.6
Random Forest	US Maternal Health Dataset	91.4	89.7
XGBoost	UK Biobank Dataset	93.1	91.5

3.4 DL Improves Image-Based Diagnosis and Fetal Health Monitoring

The efficient analysis of fetal imaging and ultrasound data is made possible by CNNs which belong to the DL models group. The algorithms demonstrate high precision when used to detect fetal abnormalities with distinction between placental dysfunctions and preterm birth risks. The accuracy of these models requires investigated solutions for the black-box problem and interpretation requirements before using them clinically. Risk factors in pregnancy is given in Fig.6.

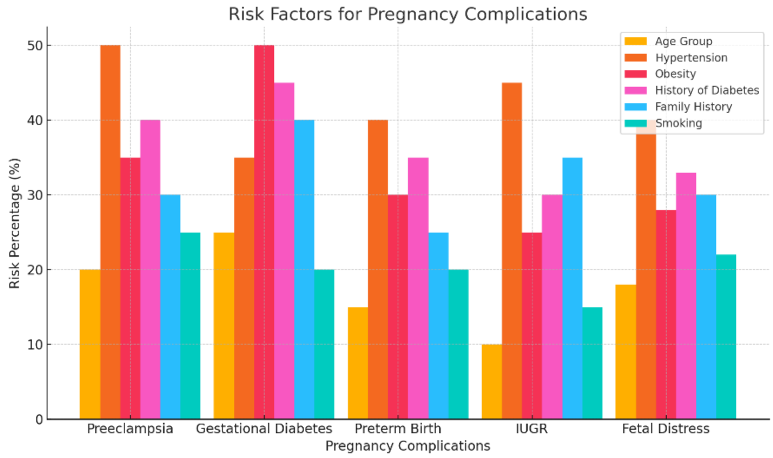

Fig.6 Risk Factors for Pregnancy Complication

3.5 AI Integration with Wearable Devices and IoT Enhances Real-Time Monitoring

Long-term maternal care has improved significantly because AI system integration with IoT-based wearable sensors enables precise time-based monitoring of woman's heart parameters alongside fetal heartbeat measurements and glucose levels. AI-integrated IoT devices produce automatic warning signals according to Munyao et al. (2024) which enables doctors to provide immediate medical assistance in case of complications. The lack of data security along with privacy issues and regulatory constraints stop widespread use from becoming a reality.

Table 8 IoT and AI-based Monitoring Systems for Pregnancy Complications

Wearable Device/Technology	Monitoring Parameter	AI Model Used	Outcome
Smart Pregnancy Belt	Fetal Heart Rate	CNN + RNN	90% anomaly detection accuracy
Smart Blood Pressure Cuff	Hypertension & Preeclampsia	ANN	88.5% early detection accuracy
AI-Integrated Glucose Monitor	Gestational Diabetes	SVM	91.2% risk prediction accuracy

3.6 AI in Assisted Reproductive Technology (ART) Improves IVF Success Rates

The application of AI-driven models continues to rise within ART to forecast embryo viability potential along with implantation outcomes. Studies indicate that AI models show potential to enhance clinicians embryo choices which lowers pregnancy termination risks and treatment failure in in vitro fertilization cycles. The research on reproductive AI ethics together with regulatory constraints demands additional assessment.

3.7 AI Models Face Challenges Related to Data Standardization and Bias

The implementation of AI faces three primary challenges that involve data standardization requirements and the difficulty of model interpretation and diagnostic as well as the presence of bias within AI systems. Many studies highlight the absence of diverse or representative data collections that produces predictions reflecting population-wide characteristics. Inclusive maternal health prediction models require worldwide standards and frameworks which guarantee equal treatment of patients in AI systems.

Table 9 Key Challenges in AI-Based Pregnancy Risk Prediction Models

Challenge	Impact	Proposed Solutions
Data Imbalance	Leads to biased AI predictions	Use of oversampling & synthetic data

Model Interpretability	Black-box AI models not trusted by clinicians	Implementation of Explainable AI (XAI)
Privacy Concerns	AI systems require sensitive patient data	Federated Learning & Blockchain Integration

4. Discussion

By utilizing AI the field of maternal healthcare achieves an advanced level of predicting pregnancy complications. AI shows its capability to examine intricate medical data patterns which leads to better identification of pregnancy complications before they occur. The wider implementation of this system meets technical barriers along with ethical concerns and clinical hurdles which healthcare providers need to resolve.

4.1 Data Quality and Accessibility

One of the primary challenges in AI prediction systems for maternal health centers around obtaining quality medical data which healthcare professionals can easily access. AI models depend on vast datasets of diverse information which need to be organized to achieve reliable predictions. Various studies utilize historic data from restricted geographical areas so their findings become challenging to use for different patient populations. Inadequate medical records as well as diverse clinical practices and unbalanced datasets together reduce AI model reliability. AI models should receive training for future medical applications through decentralized datasets which maintain patient privacy through the implementation of federated learning and data interoperability and harmonization systems.

4.2 Interpretability and Clinical Trust

The high accuracy of these AI models creates an issue because their internal operations remain hidden from healthcare providers who need to understand risk prediction methods. The inability of medical professionals to understand AI-generated diagnostic process creates doubts about the trustworthy deployment of AI assistance in healthcare diagnosis. Healthcare organizations must integrate SHAP and LIME as explainable AI techniques to enhance transparency in their AI frameworks. Such approaches enable healthcare providers to understand how predictive risks are computed and verify Automated Intelligence-based suggestions leading to more accurate care decisions and superior treatment results.

4.3 Ethical and Legal Challenges

AI applications that deal with maternal healthcare data often need to address patient privacy together with security measures and obtain proper patient consent. The ethical use of AI in pregnancy complication prediction requires organizations to follow both the GDPR and HIPAA regulatory frames. Many AI models today suffer from algorithmic bias due to their training on incomplete data which fails to represent minority communities effectively. The systematic delivery of healthcare services creates maternal healthcare inequalities which mostly impact women who belong to low-income racial population groups. Future research needs to focus on developing bias reduction approaches alongside fair model training protocols which create equitable health service delivery.

4.4 AI Integration with Wearable Devices for Real-Time Monitoring

Real-time monitoring of maternal health becomes possible through the integration of AI with wearable devices and IoT-enabled biosensors. AI systematic processes monitor maternal health indicators together with fetal heart signals in addition to sugar levels and blood pressure to detect upcoming medical conditions including preeclampsia and gestational diabetes and fetal distress. The existing issues involving sensor precision and affordable and widespread usage in low-resource areas must be addressed. The development of scalable maternal monitoring solutions requires joint efforts between healthcare experts from AI development and obstetrics and government policy science departments.

4.5 AI in Assisted Reproductive Technology

AI systems at present serve multiple purposes in ART by improving the predictions of embryo viability and IVF success while enhancing assessments of maternal-fetal wellness. Modern AI technology demonstrates effective outcomes that help identify optimal embryos which leads to lower miscarriage probabilities. The ethical problems created by AI-driven reproductive interventions must be studied thoroughly because they raise concerns about algorithmic biases and both doctor and patient freedom of choice and their dependence on AI systems. AI integration in fertility treatments requires ethical oversight as well as regulatory supervision to guarantee patient safety along with informed clinical decisions.

5. Conclusion and Future Directions

This review details the novel predictive capabilities AI models have achieved for pregnancy complications assessment while showing their precise measurements and swift diagnostic characteristics along with customized risk prediction ability. The current AI implementations experience multiple remaining constraints although they bring several benefits. The primary challenge of the present time is understanding AI models because their DL constructs create operational secrecy that hinders acceptance by clinical practitioners. Healthcare professionals have trouble trusting AI forecasting processes because they need to understand the underlying decision-making methods. The quality problem together with representational issues in AI model training data represents a major obstacle in its use. Existing models use databases that lack diversity which leads to possible bias formation and reduction of predictive accuracy. The extensive implementation of AI technologies in maternal healthcare faces substantial obstacles resulting from ethical problems that extend to patient privacy defense and patient consent standards and compliance regulations.

Research exploring XAI frameworks with SHAP and LIME methods should be the focus to address these limitations because they enhance both model transparency along with interpretability. The examined techniques help healthcare providers understand AI predictions so they can trust these systems and incorporate them into clinical work. Data problems can be solved through diverse high-quality dataset creation to improve AI model fairness as well as reduce biases. Patient data privacy alongside informed consent along with regulatory compliance need strict ethical guidelines to ensure stable patient trust in AI solutions. Healthcare operators require AI frameworks that function as simple additions to current healthcare IT systems to encourage widespread acceptance of these solutions. The development of future AI systems for pregnancy complication prediction requires attention to critical areas which will make them more interpretable and equitable and suitable for clinical implementation to enhance maternal health outcomes.

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