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Advancements And Challenges In Predicting Preeclampsia: A Comprehensive Review Of Machine Learning And Deep Learning Approaches

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ABSTRACT

Preeclampsia is a serious pregnancy complication that poses significant risks to both maternal and fetal health, often leading to severe outcomes if not detected early. Traditional diagnostic methods rely on clinical observations and biomarkers, which may not always provide timely or accurate predictions. In recent years, deep learning models have emerged as powerful tools for analyzing complex, high-dimensional data, offering the potential to enhance preeclampsia prediction by identifying patterns and features not easily discernible by conventional techniques. A review of the literature reveals that different types of ML and DL models for preeclampsia prediction were published between 2018 and 2022 using a variety of input data such as maternal demographics, clinical records, and ultrasound images. Studies demonstrate promising results, with models achieving improved sensitivity, specificity, and overall accuracy compared to traditional methods. However, challenges such as data quality, interpretation of models, and generalizability across populations remain key areas for further research. This literature review highlights the current advancements in deep learning-based preeclampsia prediction and discusses the potential for future improvements in clinical applications.

Keywords: *Preeclampsia, maternal demographics, clinical records, biomarkers, ultrasound images.*

1. INTRODUCTION

Preeclampsia is a multifaceted and severe pregnancy complication characterized by elevated blood pressure and often accompanied by proteinuria, along with other systemic manifestations such as swelling, headaches, and vision changes [1]. Typically occurring after the 20th week of gestation, preeclampsia poses significant risks to both maternal and fetal health, leading to potentially life-threatening conditions. These include eclampsia, which involves seizures, HELLP syndrome (hemolysis, elevated liver enzymes, and low platelet count), preterm birth, and fetal growth restriction. The severity of these outcomes underscores the necessity for early detection and proactive management to improve health outcomes for both mother and child. The complexity of preeclampsia's etiology and its varied presentation make effective prediction challenging. Traditional diagnostic methods, such as monitoring blood pressure and testing urine for protein, are often reactive and may only identify the condition when it has already advanced to a critical stage. This reactive approach can delay necessary interventions, which is why there is a pressing need for more proactive and early detection methods. These models leverage a wide range of data sources, including electronic health records (EHRs), maternal demographics, biometric measurements (e.g., blood pressure, weight, and laboratory test results), genetic data, and medical imaging. By analyzing this high-dimensional data, predictive algorithms aim to uncover patterns and risk factors associated with preeclampsia that may not be evident through conventional diagnostic methods. The integration of artificial intelligence (AI) in preeclampsia prediction has the potential to significantly transform maternal healthcare. By enabling earlier identification of at-risk individuals, these predictive models facilitate timely interventions and personalized monitoring strategies. This proactive approach can lead to better management of preeclampsia, reducing the incidence of severe complications and improving overall pregnancy outcomes. Enhanced predictive capabilities also allow for more efficient use of healthcare resources, optimizing patient care and reducing costs. Ongoing research and advancements in AI technologies continue to refine these predictive models. This study is actively addressing challenges such as data quality, model interpretability, and generalizability across diverse populations. Improved data collection methods, better understanding of disease mechanisms, and advancements in algorithmic techniques are contributing to more accurate and reliable predictive tools. As these models evolve, they promise to provide more precise and actionable insights, paving the way for a more proactive and effective approach to managing preeclampsia and ultimately improving the safety and well-being of both mothers and their babies.

To further elaborate, the subsequent literature review explores the most recent advancements and challenges related to the application of AI and ML models in preeclampsia prediction.

2. LITERATURE REVIEW ON PREDICTION OF PREECLAMPSIA

Based on 12-lead electrocardiogram (ECG) data from the University of Tennessee Health Science Center (UTHSC) and Atrium Health Wake Forest Baptist (AHWFB), this study [1] looks into the ECG-AI model, an AI-based method for finding and predicting preeclampsia . This study trained the CNN model using 904 ECGs from 759 patients at UTHSC and then tested it on 817 ECGs from 141 patients at AHWFB. It was excellent at predicting what would happen, with AUCs of 0.85 in internal validation and 0.81 in external validation. Performance varied depending on the timing of ECGs relative to diagnosis, and the model was particularly effective in predicting PE 30 to 90 days before diagnosis. This study shows a machine learning model that can tell the difference between preeclampsia (PE) and preterm PE by looking at biomarkers and characteristics of the mother. These include Pregnancy Associated Plasma Protein A (PAPP-A), mean arterial pressure (MAP), Placental Growth Factor (PLGF), and Uterine Artery Pulpability Index (UtA-PI) [2]. Tested on a cohort of over 5,000 pregnant women in China, the model employed algorithms such as LR, ETC, and VC, with the Voting Classifier achieving the highest predictive accuracy, particularly for preterm PE. Rigorous validation using 5-fold cross-validation confirmed the model's reliability, while SHAP values provided interpretability. This model offers significant potential for large-scale screening and early intervention in PE management. This study investigates a machine-learning model using XGBoost to predict intensive care needs in women with severe preeclampsia [3]. Analyzing data from 41 ICU patients and 40 controls, the model incorporates routine clinical parameters such as ASAT, uric acid, and BMI. Leaving out some categorical variables reduced the risk of overfitting, and repeated stratified K-fold cross-validation confirmed that the model was stable. This study evaluates four machine learning algorithms, RF, SVM, NB, and DT, to predict preeclampsia and intrauterine growth restriction in singleton pregnancies. Conducted on 210 high-risk pregnancies at a Romanian tertiary maternity hospital [4], the research identified RF as the most effective model, achieving the highest accuracy in predicting both PE and IUGR. Lower levels of biomarkers like PlGF and PP-13 and higher mean arterial pressure were important indicators for predicting ischemic placental disease. This study created a machine-learning model to predict preeclampsia in 3,050 pregnant women in Mexico. The model used maternal characteristics and locally derived MoM for MAP, UtA-PI, and PlGF during the first trimester. It had an AUC of 0.897 for preterm PE and 0.963 for early-onset PE, with detection rates of 76.5% for preterm PE and 88.2% for early-onset PE, and a 10% false-positive rate. These results [5] show how important it is to calibrate local biomarkers to make predictions more accurate across a wide range of populations. This study developed and validated machine-learning models, including LR, CT, and RF, to predict preeclampsia using retrospective data from electronic medical records of 916 pregnant women [6]. The RF model did the best, with an AUC of 0.871. The study found that the most important predictors were a family history of high blood pressure, a high BMI before pregnancy, and early pregnancy blood pressure over 130/80 mmHg. Using a public dataset and data from 95 patients, this study created a machine-learning model that can predict preeclampsia and IUGR [7]. The model was based on Doppler ultrasound and biomarkers such as the sFlt-1/PlGF ratio. Employing a multi-label classification model, the study achieved strong predictive performance with the extra tree classifier, which attained an AUC-ROC of 0.87. Key predictive indicators included the absence of an arterial notch and sFlt-1 levels. Data preprocessing involved removing highly correlated features to enhance model accuracy, precision, and recall. This study developed machine-learning models to predict the timing of delivery and the risk of complications, such as HELLP syndrome or abruptio placentae, in early-onset preeclampsia [8] cases. This study designed two models, one for predicting the need for delivery within seven days and another for assessing the risk of severe complications, using a dataset of 215 This study conducted hyperparameter tuning using Optuna, and the model achieved a high cross-validation accuracy of 0.88 and an AUC of 0.91, demonstrating strong predictive capability. pregnancies. The advanced models were able to make accurate predictions when they used angiogenic biomarkers and ultrasound data. They had an AUC value of 0.79 and high negative predictive values of 76.2% and 90.3%, respectively. This study created a CSDNN model to aid in the early prediction of preeclampsia. It performed better than traditional machine learning algorithms on datasets from Texas, Oklahoma, and MOMI databases. The CSDNN demonstrated strong predictive accuracy with an AUC of 76.5% on MOMI data and effectively addressed data sparsity and racial disparities, especially benefiting African American and Native American women at higher risk. The model used focal loss and weighted cross-entropy to handle data imbalance, improving sensitivity across racial groups. Researchers are studying the effects of LMWH, a blood thinner, on PlGF levels in high-risk pregnancies, particularly in women who don't have much PlGF in the early stages of the second trimester. LMWH administration was associated with increased PlGF levels, delayed delivery, and higher birth weights, suggesting enhanced placental function. Patients receiving LMWH showed improved outcomes compared to controls, with lower rates of adverse events such as stillbirth. [11] This study developed a ML model to predict severe preeclampsia using routine blood examination data from 19,653 pregnant women, including 248 with severe PE, at Sichuan University’s West China Second University Hospital. A study suggests that AST, DBIL-activated partial thromboplastin time ratio (APTT-R), and other markers of blood, liver, kidneys, and coagulation could help in figuring out what will happen. The LightGBM model achieved the highest predictive accuracy, with an AUC of 89.74%, suggesting ML's potential for cost-effective, early detection of severe PE. This study used ML models, including RF, SVM, and XGBoost, to predict preeclampsia by analyzing EHR from 3,759 pregnant women at Shanghai Jiao Tong University [12]. Among the models, XGBoost achieved the highest accuracy, with an AUC of 0.955, identifying fasting plasma glucose, mean blood pressure, and body mass index as key predictors. This study looks into how to use ensemble learning to diagnose PPH and its complications, like DIC. It uses 5G technology to quickly gather data on 3,842 cases. By combining RF, GB, and SVM algorithms, the ensemble model was able to diagnose with 96.7% accuracy for PPH and 90.3% accuracy for DIC, which is better than traditional methods like LR and NN. Clinical metrics related to blood loss were important predictors [13] . This study developed a machine learning model to predict CVD risk in women with a history of preeclampsia, using clinical and demographic data from 907 patients [14]. This study tested five machine learning algorithms, including RF and SVM, and found that RF performed the best, achieving an AUC of 0.711. Key predictors included systolic blood pressure, fasting glucose, urea nitrogen, neutrophil count, and D-Dimer levels. This study investigated how AI could predict HDP through ultrasound placental image texture analysis and biomarkers. Following 429 pregnant women, including 58 who developed HDP, the research employed the deep learning model "resnext101_32x8d," achieving 71% accuracy for early HDP prediction [15]. Researchers found big differences in the texture of the placenta and biomarkers like PAPP-A and PlGF between HDP cases and controls. These differences show that there are already problems with the health of the babies.This study investigates the maternal blood Lep/Cer ratio as an early predictive biomarker for pre-eclampsia, showcasing its superior performance over the sFlt-1/PlGF ratio [16] . The author split it into two parts: retrospective discovery and longitudinal confirmation. The study examined a wide range of populations and discovered that women at risk for PE had a significantly higher Lep/Cer ratio (85% sensitivity compared to 20% for sFlt-1/PlGF). This biomarker, especially effective between 5 and 25 weeks of pregnancy, offers a promising tool for non-invasive early screening, potentially improving prenatal care by identifying high-risk pregnancies more accurately. This study developed a machine-learning model for early prediction of preeclampsia using clinical and laboratory data from routine prenatal visits. Conducted on a cohort of 16,370 births at Stanford's Lucile Packard Children's Hospital [17] , the model utilized elastic net and GB algorithms, identifying hypertension, history of PE, and blood glucose as key predictors. It achieved an AUC of 0.79 for PE and 0.89 for early-onset PE, demonstrating strong predictive performance. This led to the creation of a machine learning model that utilized a CVR method to predict preeclampsia PE and IUGR [18] . The model was based on information from the second and third trimesters about the mother's characteristics, uterine artery Doppler measurements, and biomarkers like sFlt-1 and PlGF. The CVR model demonstrated robust predictive performance, achieving an AUC of 0.97 and effectively addressing class imbalance with a 69% case class size. This study looks at how useful the sFlt-1/PlGF ratio is for diagnosing and treating high blood pressure during pregnancy, especially PE and IUGR. University Hospital Leipzig conducted a study on 283 different singleton pregnancies and found a strong correlation between higher sFlt-1/PlGF ratios and worse placental dysfunction, as well as earlier delivery times [19] . Combining the sFlt-1/PlGF ratio with maternal characteristics enhanced prediction accuracy, though clinical adoption remains limited. This study developed machine learning models to predict late-onset preeclampsia using maternal factors and antenatal laboratory data from 11,006 pregnant women at Yonsei University. This study tested six algorithms, including LR, DT, and SGB, and found that the SGB model achieved the highest performance (C-statistic of 0.924). Key predictors included blood pressure, serum creatinine, AST, ALT, platelet counts, white blood cell count, and serum calcium [20]. This study investigates ML techniques, including DL and PSO, for predicting preeclampsia risk using data from 1,077 patients in Indonesian hospitals. This study evaluated various algorithms, including NB, KNN, and SVM, using Leave-One-Out Cross Validation [21]. Deep Learning achieved the highest accuracy of 95.12%, which improved to 95.68% after PSO feature selection reduced the dataset from 17 attributes to 9. This systematic review and meta-analysis looked at 23 studies that tested 52 prediction models for PE. The study concentrated on the models' ability to distinguish between various situations and their calibration capabilities [22]. The FMF model, which incorporates maternal factors and biomarkers, showed strong predictive performance with an AUC of 0.90, especially for preterm PE. However, many other models demonstrated poor calibration and the risk of overfitting, limiting their applicability across different populations. This article examines the relationship between PE and PPCM, emphasizing how issues with endothelial function, inflammatory responses, and genetic traits contribute to both conditions. The article highlights specific factors such as cytokines, angiogenic imbalance, and markers like PD-L1 and sFlt-1 as contributors to both conditions [23]. This systematic literature review, following PRISMA guidelines, investigates AI and ML techniques for predicting PE through an analysis of 21 studies published between 2018 and 2022. Published in the International Journal of Intelligent Systems and Applications in Engineering, the review [24] identifies maternal demographics, medical history, and laboratory data as key predictors, with SGB achieving the highest accuracy at 97.3%. While the review highlights ML's potential in enhancing PE prediction, it also points out challenges such as data imbalances and the need for consistent validation across populations.This study systematically reviews advancements in ML for predicting PE [26] , emphasizing the importance of feature selection and algorithmic performance. With a focus on maternal health indicators, including age, blood pressure, and protein levels, the review highlights RF and GB algorithms for their accuracy. Using data from a Romanian cohort, this prospective study looks at how well different ML models can predict PE in the first trimester. Analyzing maternal characteristics, MAP, and serum biomarkers, the study tested four models: DT, NB, SVM, and RF. DT and SVM [27] performed well for early-onset PE, while NB and RF achieved high accuracies of 98.6% and 92.8% for all PE types. Statistical tests, such as ANOVA, confirmed how strong these results were. They show that ML has the potential to help find and treat PE earlier, which is beneficial for both the mother and the baby's health. This study looked at how LMWH can help high-risk pregnant women avoid PE and SGA complications. Including 15 studies with 2,795 women, the analysis showed that LMWH significantly reduced PE recurrence, SGA births, and perinatal death, particularly when administered before 16 weeks' gestation. Combining LMWH with LDA provided a stronger effect in reducing PE than LDA alone. Although findings suggest LMWH's potential benefits in specific high-risk groups, methodological biases and study heterogeneity indicate the need for further trials to support broader clinical application [28]. This review discusses advancements in PE prediction and management, focusing on the integration of ML [29] and remote monitoring technologies. It highlights the role of ML-based decision support systems in enhancing early detection of at-risk patients and emphasizes the potential of remote monitoring devices, such as blood pressure and proteinuria assessments, for home-based PE management. The review also underscores the importance of involving various stakeholders to ensure patient-centered care and improve data flow. The review by Konstantinos Giannakou discusses advancements in predicting PE, a complex condition impacting 2%–8% of pregnancies and involving genetic, environmental, and maternal factors [30]. Multiple factors contribute to PE, making a single test unreliable. Multiparametric models include clinical, biophysical, and biochemical markers such as maternal characteristics, MAP, uterine artery Doppler, PAPP-A, and PlGF. These models show promise for early PE detection, but challenges remain with calibration and validation across diverse populations.The systematic review highlights the development of various preeclampsia prediction models over the years, showing a wide range of predictors and model performances. While some models yield promising results with high predictive accuracy, there is substantial variability in performance across studies, largely due to differences in study populations, gestational age at prediction, and the types of predictors used. Additionally, the limited external validation and calibration of models restrict their widespread clinical applicability [31] . This study examines how machine learning models such as LR, SVM, RF, and XGBoost can predict severe PE in women who have never given birth before, using the nuMoM2b cohort from several US clinical sites. The developed bias-free model, PEPrML, demonstrated improved predictive performance throughout gestation, with AUROC scores increasing from 0.72 in the first trimester to 0.77 by the third. Key predictors included BMI, blood pressure, placental analytes, and ultrasound metrics.

The studies reviewed highlight various AI and ML approaches used to predict preeclampsia, showing promising results with high predictive accuracy across multiple datasets. Key predictors often include maternal demographics, clinical parameters, and biomarkers, though challenges remain in model calibration and generalizability across diverse populations. This study recommends further multi-center validation and the integration of advanced techniques to improve clinical utility. Moving on to the machine learning models used in previous studies, the current study explores a range of algorithms and their performance metrics in predicting preeclampsia.

3. MACHINE LEARNING MODELS FOR PREDICTION OF PREECLAMPSIA

[2] The study utilized a prospective cohort design with stringent quality control during data collection to predict PE and preterm PE using ML. This study applied various algorithms, such as LR, ETC, VC, GPC, and SC, on a dataset of 4,644 pregnant women. This study validated the models using 5-fold cross-validation and an 8:2 train-test split, enhancing hyper parameter tuning with Bayesian optimization. The VC achieved an AUC of 0.831, a detection rate of 0.513, and a 10% false positive rate for all types of PE. For preterm PE, the SC achieved an AUC of 0.884, with a sensitivity of 86% and specificity of 83.4%. [3] The methodology in this study involved developing a ML model to predict the need for intensive care in women with severe PE. Among the models developed, the best-performing model employed the XGBoost algorithm, which achieved an AUC of 0.91 with cross-validation and an AUC of 0.85 in internal validation on a test set. [3] The study employed a machine learning methodology, using an XGBoost model to predict the need for intensive care in women with severe preeclampsia (PE). The development of the model involved an iterative process of feature selection, using SHAP values to rank importance and Optuna for hyperparameter optimization. Key clinical parameters included in the model were ASAT, uric acid, and BMI, chosen for their strong predictive relevance. The model achieved a cross-validation accuracy of 0.88 and an AUC of 0.91; internal validation on a test set yielded an AUC of 0.85. The study selected the XGBoost model due to its high predictive performance in identifying high-risk PE cases that require intensive care. [4] This study used a prospective design to create machine learning algorithms that could predict PE and IUGR. The algorithms were trained on clinical and biochemical data from 210 first-trimester pregnant women. This study used DT, NB, SVM, and RF models. These models incorporated maternal characteristics, MAP, and serum biomarkers such as PAPP-A, PlGF, and PP-13. Among the models, the RF algorithm performed best, achieving the highest predictive accuracy for both PE and IUGR, as well as their combined occurrence. [5] The researchers looked at factors like MAP, UtA-PI, and PlGF along with information about the mothers and locally derived MoM. The study used an elastic-net regression model for predictor selection, optimizing it through cross-validation. The elastic-net algorithm was chosen as the model because it was very good at making predictions. It had an AUC of 0.897 for preterm PE, 0.963 for early-onset PE, and 0.778 for all other types of PE. The model had success rates of 76.5% for pPE, 88.2% for ePE, and 50.1% for all PE, with a 10% false-positive rate for each. [6] It employed three ML models LR, CT, and RF using maternal demographic and clinical data such as blood pressure, BMI, and family history of hypertension. This study ultimately selected the RF model for its superior predictive accuracy, achieving an AUC of 0.871, along with high sensitivity and specificity (79.6% and 94.7%, respectively). [7] The study used biomarkers like sFlt-1 and PlGF along with

Doppler ultrasound data to use machine learning to predict PE and IUGR in a group of 95 pregnant women. The dataset included measurements of the uterine artery and relevant biochemical markers to enhance predictive power. Among the models tested, the ETC demonstrated the best performance, achieving an AUC of 0.87. This study selected this model for predicting placental dysfunction disorders with high reliability due to its robust metrics, particularly precision, recall, and F1 score. [8] The researchers applied a mono-objective genetic algorithm for feature selection and developed two primary models. The KNN model did the best job of predicting the baseline, and the SVM algorithm did the best job of making predictions using data that was available at the time of the eoPE diagnosis. This study ultimately selected the SVM model due to its superior predictive performance, achieving sensitivity and specificity rates of approximately 77.3% and 80.1% for delivery prediction, and 66.7% and 82.8% for HELLP or abruptio placentae prediction, respectively. [11] This study evaluated three machine learning model LightGBM, DT, and RF based on 43 blood examination variables. This study selected the LightGBM model due to its superior performance, achieving an AUC of 89.74%, a sensitivity of 88.37%, and a specificity of 77.27% and also identified AST, DBIL, and APTT-R as the key predictive variables that were most influential in predicting severe preeclampsia. [12] The study evaluated the predictive performance of various machine learning algorithms, including LR, RF, SVM, and XGBoost. The study was identified the key predictors as FPG, MAP, and BMI, highlighting their importance. The study ultimately selected the XGBoost model due to its superior predictive performance, achieving an AUC of 0.955 with high accuracy and recall scores. [13] The study utilized ensemble methods, including RF, XGB, GBDT, and SVM as base learners. Ensemble learning combined the outputs of these models through voting and averaging techniques to enhance predictive accuracy. The study was ultimately selected the ensemble learning model due to its high performance, achieving an accuracy of 96.7% for PPH diagnosis and 90.3% for DIC prediction. [14] The researchers applied five machine learning algorithms: LR, SVM, NB, XGBoost, and RF. This study ultimately selected the RF model for its superior performance, achieving an AUC of 0.711. This model demonstrated high accuracy, sensitivity, and specificity, with important predictive variables including systolic blood pressure, glucose levels, urea nitrogen, neutrophil count, and D-Dimer. The RF model's strong calibration and DCA results underscored its suitability for identifying women at elevated CVD risk postpartum. [17] The study applied two machine learning models: (1) Elastic Net, a regularized regression model, and (2) Gradient Boosting, which utilized sequential decision trees. The study ultimately selected the Elastic Net model for its robust predictive performance, achieving an AUC of 0.79 for all PE cases and 0.89 for early-onset PE (before 34 weeks). [18] They utilized Weka's Auto-Weka tool for automated model selection alongside manual comparisons of 23 models, focusing on metrics suited for imbalanced data. The selected model was the "classification via regression" (CVR) approach, which combines a decision tree with multiple linear regression models. This CVR model achieved robust predictive performance, with an AUC of 0.97, high specificity, and a sensitivity of 95%. The study selected it due to its ability to balance class imbalance, using the lowest PI-UtA as a critical feature for identifying placental dysfunction disorders. [20] Among the machine learning models tested, including LR, DT, NB, SVM, RF, and SGB, the SGB model achieved the best predictive performance. It reached a C-statistic of 0.924, with an accuracy of 97.3% and a low false positive rate of 0.009. This study ultimately selected the SGB model due to its superior prediction accuracy and robustness in identifying patients at risk for late-onset PE. [32] This study selected the RF model among the tested machine learning models due to its superior performance. It achieved AUC scores of 0.72, 0.75, and 0.77 across the first, second, and third visits, respectively. The RF model was particularly effective due to its robustness to noise and ability to manage feature importance, which was crucial for fair and accurate predictions across different racial groups. Figure 1 illustrates the bar chart and highlights the evolution of machine learning and deep learning model usage from 2015 to 2024. It shows a consistent focus on traditional models like LR, SVM, and RF, with a growing emphasis on ensemble methods and deep learning models like CNN and XGB in recent years. Advanced architectures, such as ResNet and sophisticated ensembles, will be more prominent from 2022 onward, reflecting advancements in research and application. The trend indicates a shift toward more complex and high-performing models. Overall, the chart illustrates the progression from simpler algorithms to more powerful and innovative techniques over the years. Figure 2 displays bar charts that illustrate the accuracy performance of various models, with values ranging from approximately 0.6 to 0.98. Models like XGB, RF, and ensemble methods show the highest accuracy, close to 0.98, indicating strong predictive performance. Overall, deep learning models and ensemble techniques generally outperform traditional algorithms in terms of accuracy.

The various machine learning models, such as Random Forest, XGBoost, and stochastic gradient boosting, are used for predicting preeclampsia and related conditions. These models demonstrated high predictive accuracy and robust performance in different datasets, with key predictors including blood pressure, biochemical markers, and maternal characteristics. However, the study also noted challenges such as class imbalance and the need for external validation. Next, the study transitions to exploring the application and performance of deep learning models in predicting preeclampsia, focusing on their unique advantages and limitations.

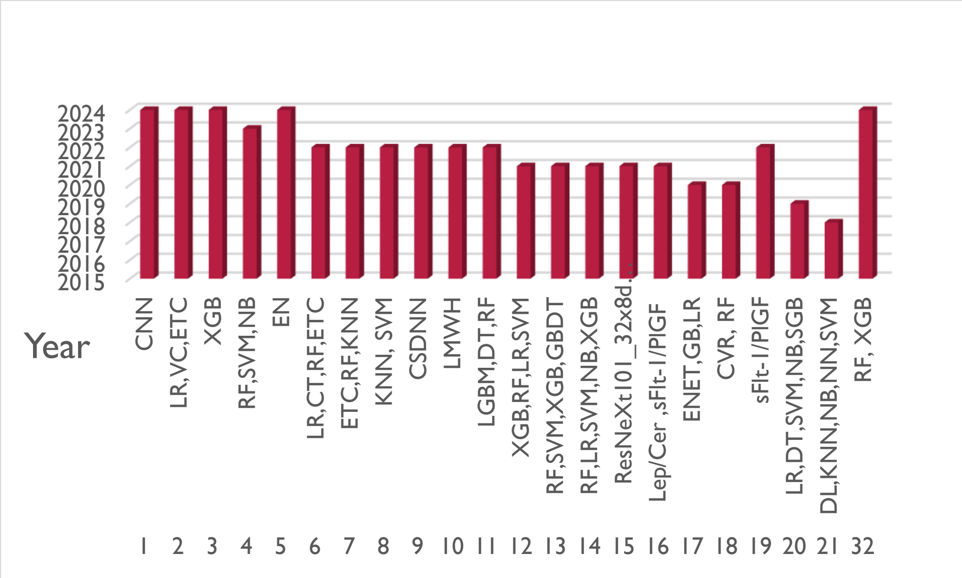

Figure 1: 3D view of reviewed articles

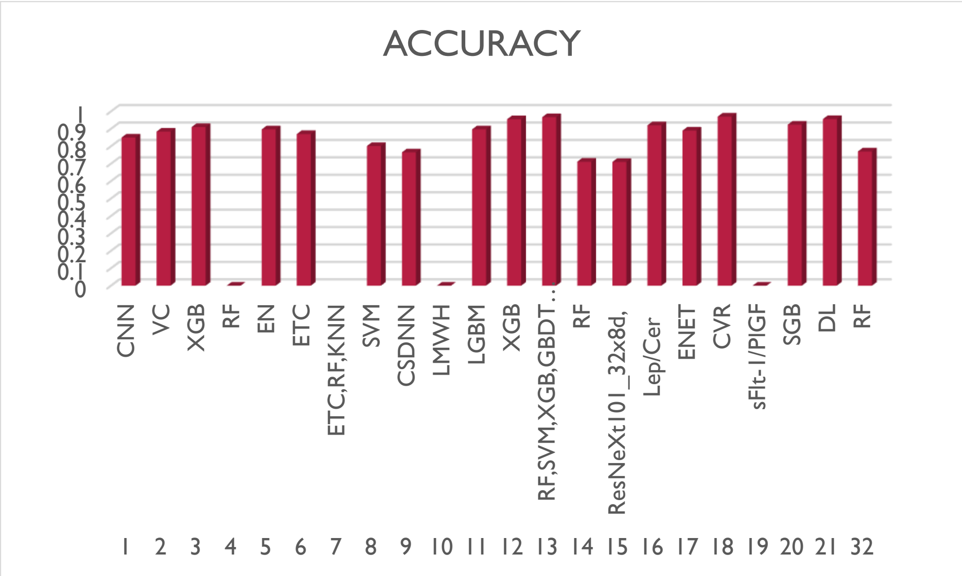

Figure 2: 3D view of selected model and accuracy

4. DEEP LEARNING MODELS FOR PREDICTION OF PREECLAMPSIA

[1] The study specifically employed a modified ResNet CNN to process one-dimensional raw 12-lead ECG signals. The model achieved an area under the curve (AUC) of 0.85 on the UTHSC hold-out set and an AUC of 0.81 on the external validation data from AHWFB. Additionally, this study analyzed the model's performance across various prediction windows, specifically within 30, 60, and 90 days before PE diagnosis, highlighting the model's robustness across different timeframes with the highest accuracy closer to the diagnosis. [9] This study developed an imbalance-aware DNN model specifically to handle the prediction of PE in datasets with high-dimensional, sparse, and imbalanced data. The study employed three hyperparameter optimization algorithms Bayesian optimization, hyperband, and random search to enhance the performance of the model. The study found the best way to use the chosen model, a CSDNN with focal loss and weighted cross-entropy functions, to deal with uneven data. It achieved an AUC of 76.5% on the MOMI dataset, showing strong predictive reliability and adaptability across multiple racial groups. [15] The study processed and analyzed the images using various pre-trained deep learning models, such as "wide_resnet50_2," "wide_resnet101_2," "resnext50_32x4d," "resnext101_32x8d," and "googlenet." These models underwent data augmentation and cross-validation. The study selected "resnext101_32x8d" as the model with the highest performance among the tested models, achieving an accuracy score of 0.71 and a Cohen's kappa score of 0.413. The model demonstrated significant potential for early HDP detection by distinguishing between placental textures differences associated with high blood pressure. [21] The study applied two classification algorithms, NN and DL,

to the optimized dataset. The study ultimately selected the DL model due to its superior accuracy. Using PSO-reduced data, the DL model achieved a performance accuracy of 95.68%, slightly higher than without PSO. This approach proved effective in reducing computational time while maintaining high predictive accuracy, demonstrating DL's utility in preeclampsia risk prediction. Table 1 shows the different views of preeclampsia prediction using deep learning and machine learning technology.

The previous author employed deep learning models, such as modified ResNet CNN and imbalance-aware DNN, to predict preeclampsia, achieve high AUC scores, and address challenges related to data imbalance. The models, which included ResNeXt and deep learning models improved with Particle Swarm Optimization (PSO), showed promise in being accurate and stable when dealing with a wide range of complex datasets. These studies highlight the efficacy of deep learning in capturing nuanced patterns, such as placental texture differences, for early detection of hypertensive disorders. Moving forward, the next section will discuss future implementations, focusing on how emerging technologies and real-time data integration can further enhance predictive models for clinical applications**.**

5. CATEGORIZATION OF AI MODELS FOR PREECLAMPSIA PREDICTION

DL models have been extensively used in maternal health prediction tasks. CNNs are mostly used to look at medical imaging data like ultrasound and ECG signals. For instance, this study uses a modified ResNet CNN to predict preeclampsia based on the ECG. This study analyzes sequential and time-series data using various neural network types, including LSTM, GRU, and transformer-based models. For instance, we can continuously track maternal health indicators over time. DNNs are particularly useful for high-dimensional and imbalanced datasets; an example is the CSDNN, which was designed to address class imbalance in predicting preeclampsia.ML models also play a significant role in maternal health prediction. Tree-based models like RF are frequently used for structured clinical data and feature importance analysis. Gradient boosting techniques, including XGB, LightGBM, and Stochastic Gradient Boosting, have been applied to structured datasets to enhance predictive performance. SVMs are often used to sort and classify biomarkers and indicators of maternal health. LR, on the other hand, is used as a starting point for simple binary classification problems like figuring out the risk of preeclampsia. Furthermore, ensemble learning methods like VC, ETC, and stacking models use more than one algorithm to make predictions more accurate and less variable.

Table 1. Over view of Literature Review

S.No	Journal Name	Year	Data and Variables	Techniques	Pros	Cons
01	Frontiers in Cardiovascular Medicine	2024	759-UTHSC & 141 – AHWFB data	ResNet CNN –AUC(0.85)	High accuracy - even 30 to 90 days before diagnosis- potential for global implementation using smart devices.	Limited diversity in the dataset (mostly African-American and White patients); potential issues with generalizability to broader populations(1 PEP 2024(1)).
02	Frontiers in Endocrinology	2024	4,644 data	LR- AUC (0.82), ETC- AUC(0.81), VC- AUC(0.83)	5-fold cross-validation, ensuring robustness.	Small sample size from a single center.
03	Hypertension in Pregnancy	2024	81 data	XGBoost –AUC(0.91)	High predictability using simple clinical parameters.	Retrospective design, small sample size, potential overfitting concerns, limited generalizability.
04	*Hypertension in Pregnancy*	2023	210 data	RF-acc(96.3),SVM-ACC(95.8),NB-ACC	Predict PE & IUGR.	Limited sample size, imbalanced data, and the need for external

				(94.7)		validation on larger cohorts.
05	Ultrasound in Obstetrics & Gynecology	2024	3050 data	Elastic-Net Model:AUC (0.963)	High accuracy.	Require external validation
06	Annals of Translational Medicine	2022	237 data	LR- AUC(0.77) CT-AUC(0.85) RF- AUC(0.87)	High specificity.	Llimited by a single-center design and a relatively small dataset.
07	Electronics	2022	95 data, 21 variables	ETC-AUC(0.87) ,RF-AUC (0.84), KNN-AUC (0.79)	High performance in predicting pre-eclampsia and intrauterine growth restriction.	Very small data set.
08	Frontiers in Cardiovascular Medicine	2022	215 data,13 varibles	KNN-precision (0.68), SVM- Precision(0.79)	Retrospective data.	Lack of external validation.
09	PLOS ONE	2022	Texas PUDF: 360,943 patients, Oklahoma PUDF: 84,632 patients, MOMI: 31,431 women, 300 variables	CSDNN-AUC (76.5)	Effectively handles imbalanced data, addresses racial disparities, and yields superior predictive .	Performance overfitting, and performance is sensitive to hyperparameter settings and data sparsity issues.
10	American Journal of Obstetrics & Gynecology	Kelsey McLaughlin et all	7 data	LMWH	Increase in placental growth factor (PlGF) levels.	Small sample size.
11	Medicine in Novel Technology and Devices	Xinyuan Zhang et all	19653 data, 43 variables	LGBM: AUC (89.74), DT: AUC(71.41)RF: AUC(89.49)	High predictive accuracy.	Not be generalizable
12	Pregnancy Hypertension: An International Journal of Women's Cardiovascular Health	Yi-xin Li et all	3759 data, 38 varibles	XGBoost: AUC(0.95) RF: AUC(0.914) SVM:AUC(0.915) LR: AUC(0.853)	Potential for early intervention data imbalance.	Model complexity, and the need for external validation to ensure generalizability.

13	IEEE Access	Yawei Zhang et all	3842 data,23 variables	RF,SVM,XGB,GBDT, Ensemble Learning: ACC(96.7)	Reliable for remote healthcare applications.	Data collection is time-consuming and costly, potential for overfitting, and limited external validation.
14	Frontiers in Cardiovascular Medicine	Guan Wang et all	907 data	RF: AUC(0.711) LR: AUC(0.678) SVM:AUC (0.606) NB:AUC(0.629) XGB: AUC (0.683)	Importance of clinical and demographic predictors for postpartum cardiovascular risk.	Single-center study with missing data imputation and needing external validation for broader applicability.
15	The Journal of Maternal-Fetal & Neonatal Medicine	Krishan Gupta et all	429 data	ResNeXt101_32x8d: Acc (71), Wide_ResNet50_2, Wide_ResNet101_2, ResNeXt50_32x4d, GoogleNet –acc(from 58.1% to 70.9%)	Cost-effective prediction.	Small sample size, and the models require external validation.
16	BMJ open	Qianyang Huang et all	55 data	Lep/Cer –AUC(0.92), sFlt-1/PlGF –AUC(0.52)	Early identification, potentially aiding timely intervention.	Need for prospective validation and broader racial representation.
17	AJOG MFM	Ivana Maric et all	16,370,67 variables	ENet: AUC(0.89), GB: AUC(0.89), LR AUC (0.79)	Suitable for high-dimensional data.	Limited external validation.
18	JMIR Medical Informatics	Herdiantri Sufriyana et all	95	CVR: AUC(0.970), RF :AUC(0.976)	High predictive performance.	Potential overfitting risk due to lack of external validation.
19	AJOG	Anne Dathan-Stumpf et all	283	sFlt-1/PlGF	Assessing placental dysfunction and predicting adverse pregnancy outcomes.	May not add significant benefit in predicting outcomes beyond existing clinical practices, and repeat measurements may not always be meaningful.
20	PLOS ONE	Jong Hyun Jhee et all	11006 data, 14 variables	LR Acc(0.862) DT Acc(0.874) NB Acc(0.899) SVM Acc(0.892)	Use of common antenatal data makes it easily applicable in clinical settings.	Limited to second and third trimester data, variability in antenatal evaluation intervals.
21	EMITTER	Muhlis	1077 data,	DL: Acc(95.68),	PSO	Limit generalizability

	International Journal of Engineering Technology	Tahir et all	17 variables	KNN: Acc(93.96) NB: Acc(92.11) NN: Acc(93.78) SVM: Acc(87.65)	effectively reduced the feature set from 17 to 9, improving execution speed and efficiency.	and need for extensive validation.
32	EMITTER International Journal of Engineering Technology	Yun Lin et all	1857 data,57 variables	RF: AUC(0.77), XGB: AUC(0.74)	Explainable features, making them suitable for clinical use.	Limited to nulliparous women.

6. MODEL ROBUSTNESS CHALLENGES

The current studies often face limitations due to single-center designs and retrospective approaches, which restrict the generalizability of the models across diverse ethnic and geographic populations. There is also a significant lack of extensive external validation, necessitating broader multi-center studies to confirm model robustness and applicability. Additionally, the reliance on specific laboratory or Doppler data limits the models' utility in settings without advanced diagnostic capabilities. Comparative studies with traditional clinical assessment methods are required to establish the true clinical value of machine learning approaches. Furthermore, the author's understanding of important biomarkers such as PAPP-A, PlGF, and genetic or environmental factors remains incomplete. This incomplete understanding makes it more challenging for these models to accurately predict the future and identify issues early. Most of the reviewed machine learning and deep learning models for preeclampsia prediction remain in the research stage and have not been widely deployed in clinical settings. Some models, like ECG-AI and LightGBM-based blood test predictors, have shown a lot of promise in retrospective and multi-center studies. However, they still need a lot of outside validation and regulatory approval before they can be used in the real world.

Finally, the study moves on to its conclusion, summarizing the key findings, the impact of machine learning and deep learning models in preeclampsia prediction, and the future directions needed to advance this field.

7. CONCLUSION

The integration of AI and ML has revolutionized the prediction of preeclampsia, showcasing their potential to enhance early detection and improve maternal-fetal outcomes. By analyzing diverse and high-dimensional datasets, including maternal demographics, clinical records, laboratory biomarkers, and medical imaging, advanced models have demonstrated superior predictive accuracy compared to traditional methods. CNNs, RNNs, and ensemble learning algorithms like RF and XGBoost have demonstrated effectiveness in identifying complex, non-linear patterns that often go unnoticed. Despite these advancements, challenges remain in ensuring the robustness and generalizability of these predictive models. The reliance on single-center datasets and retrospective data limits the external applicability of these tools, emphasizing the need for multi-center validation and real-time data integration. The study must address critical hurdles such as data quality, interpretability of models, and fairness across diverse populations. Future research should focus on refining these models by incorporating a broader range of biomarkers, leveraging wearable technology for continuous monitoring, and developing user-friendly clinical decision support systems. Ultimately, AI-driven prediction models hold the promise of transforming prenatal care by facilitating early, personalized interventions. However, ongoing efforts are required to improve model reliability, optimize data integration, and ensure equitable healthcare access. With continued advancements and collaborative research, AI and ML have the potential to significantly mitigate the risks associated with preeclampsia, paving the way for safer pregnancies and healthier outcomes for mothers and their babies.

DATA AVAILABILITY STATEMENT

Data sharing does not apply to this article because no datasets were generated or analyzed in this study.

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ETHICS DECLARATIONS

ETHICS APPROVAL

This article does not contain any studies with human participants or animals performed by any of the authors

COMPETING INTERESTS

The authors declare no competing interests.

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