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A Comprehensive Review On Artificial Intelligence Based Approaches For Prenatal Depression Detection

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Abstract: Prenatal depression is a critical health condition that may have significant consequences not only on the maternal health but also on the outcomes of fetal health. Early intervention is crucial as it helps to prevent the potential long-term effects and avoid them. This survey paper provides an in-depth analysis of various Artificial Intelligence (AI) methods used for the detection of prenatal depression based on different data sources, including clinical interviews, questionnaires and physiological data. The paper highlights their effectiveness, strengths and limitations of these AI-based approaches. This review analyzed the various performance metrics in the detection of prenatal depression. This study aims to provide a comprehensive insight into existing methodologies and identify the scope for future research, ultimately aiming to improve both the mother's mental health and the child's growth.

Keywords - Prenatal depression, Artificial Intelligence (AI), Clinical interviews, Questionnaires and Physiological signals.

I. Introduction

Prenatal (Antenatal) depression is the mood disorder that occurs during pregnancy. It is characterized by persistent feelings of depressions, anxiety and hopelessness. It frequently happens as a result of combination of hormonal changes, psychological stress and personal or environmental factors impacting the expectant mother. Unlike the occasional mood swings, symptoms of prenatal depression are more persistent and severe and may lead to the interference with the daily functioning and the well-being. Prenatal depression may result in serious health problems for both the mother and the fetus. Figure 1 shows various factors leading to prenatal depression during pregnancy. For mothers, it can result in the lack of self-care, poor nutrition, sleep disturbance and even suicidal thoughts in severe situations. From a child's point of view, prenatal depression can cause an increase in premature birth, low birth weight and delayed development. Moreover, prenatal depression that is left untreated can harm mother-infant bonding and can lead to the development of postpartum depression.

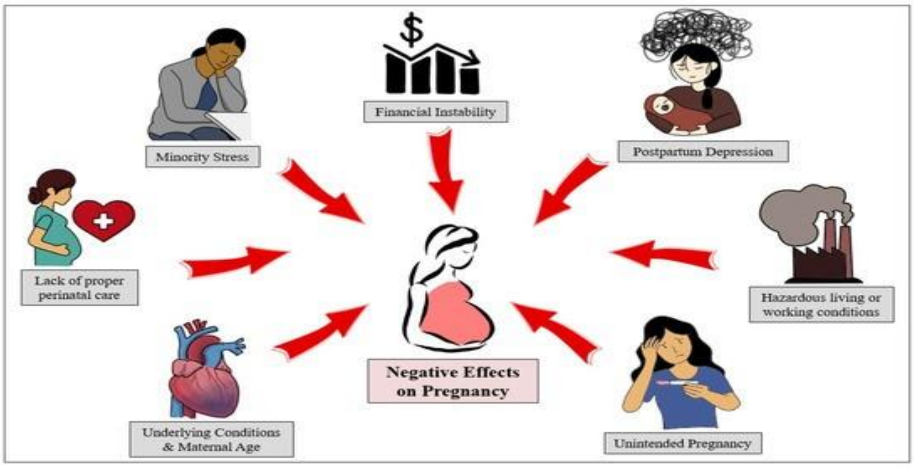

Fig. 1. Various factors leading to Prenatal Depression during pregnancy [26]

Artificial intelligence (AI) is the new revolution in the healthcare industry. It offers novel solutions in the early detection and treatment of prenatal depression. Multiple AI methods have demonstrated strong potential in detecting depression-related patterns using multimodal sources of data and these developments could benefit maternal mental healthcare by enabling continuous monitoring and early intervention strategies.

1.1 CONTRIBUTIONS FOR THIS SURVEY

This study provides an in-depth analysis of various Artificial Intelligence techniques for the detection of prenatal depression, covering various Artificial intelligence methods such as Recurrent Neural Network, Long Short-Term Memory, Support Vector Machine and Logistic regression. These methods utilize various data sources, including clinical interviews, questionnaires and physiological data. The effectiveness, strengths and limitations of different AI techniques are systematically analyzed with reference to recent studies (2020-2025), offering an updated perspective for researchers and practitioners. Performance metrics used in prior work are critically discussed to identify the main gaps for future research and highlights some challenges and provides clear future research direction to guide the development of AI-based systems for improving the maternal and fetal healthcare.

The paper is organized as follows. The second section briefs on the related works on prenatal depression detection using multiple data sources. The third section explains the various performance metrics used for the evaluation of the methods. The fourth section gives the analysis of the discussed methods. Fifth section discusses the inference obtained from the related study. The last section gives the conclusion of this study.

II. RELATED STUDY

This section focuses on a comprehensive study on detection of prenatal depression using various techniques.Garbazza et al. [1] used ML on multimodal health and demographic data to predict perinatal depression (PND); PSG variables had limited impact on model performance. Huang et al. [2] analyzed EMR data using ML to detect antenatal depression, focusing on interpretability and fairness. Zafar et al. [3] employed hybrid deep learning on mental health and socio-demographic data, using oversampling for class imbalance; generalizability was limited by dataset scope.

Krishnamurti et al. [4] applied a Machine Learning on self-reported data to predict moderate-to-severe prenatal depression. The study assessed the performance of each model using relevant evaluation metrics, demonstrating the effectiveness of their predictive approach. Bao et al. [5] applied ML to physiological data for prenatal anxiety detection; nonlinear relationships were poorly captured. Terrone et al. [6] used regression models on self-reported data to assess prenatal depression, limited by sample size. Peng et al. [7] proposed EEG-based feature extraction to identify prenatal depression; small sample size impacted statistical significance. Wong et al. [8] analyzed EHRs with ML for PND prediction; highlighted fairness and bias concerns.Raghavan et al. [9] applied regression to psychosocial and clinical data to detect prenatal depression and analyze risk factors.Ogur et al. [10] used feature selection and ML models on perinatal mental health data for depression classification. However, it faced limitations such as potential biases, high computational demands and limited generalizability across different populations.

Gopalakrishnan et al. [11] assessed antenatal depression using EDA data via deep learning; reliance on time-domain features was a limitation.Preis et al. [12] predicted prenatal depression using physiological data and feature selection; limited regional generalizability.Hu et al. [13] built ML models using mental health and demographic data; lacked external dataset validation. Wegbom et al. [14] detected depression, anxiety, and stress using regression on prenatal assessment data. The study applied statistical and regression models to identify factors contributing to depression, stress, and anxiety, and they also estimated predictive values for levels of depression, stress and anxiety.Zuo et al. [15] applied regression to biological samples to detect prenatal depression.

Wang et al. [16] used questionnaires and regression to detect third-trimester antenatal depression; convenience sampling posed bias concerns. Zhang et al. [17] employed regression on depression assessment data; small sample size limited generalizability. Khan et al. [18] used regression on mental health data to assess prenatal depression in second and third trimesters. Faisal-Cury et al. [19] applied regression on mental health and demographic data to predict depressive symptoms.

Liu et al. [20] used statistical models on questionnaires to assess prenatal and postnatal depression and analyzed the key risk factors influencing these conditions. Barszcz et al. [21] analyzed questionnaire data during a socioeconomic crisis to detect prenatal depression. Li et al. [22] studied the impact of social status on stress-induced prenatal depression using regression and stratification. Han et al. [23] utilized embedding techniques to identify prenatal depression using survey data. Rodriguez-Munoz et al. [24] conducted a psychological self-report data among pregnant women to predict prenatal depression. The study utilized a regression model to assess depression in both nulliparous and multiparous women.Zhan et al. [25] conducted a study to identify prenatal depression during different stages of pregnancy by analyzing dietary habits and depression assessment data and employed statistical modeling techniques to distinguish between depressed and non-depressed individuals and further examined the occurrence of depression across the first, second and third trimesters.

III. EVALUATION CRITERIA FOR MODEL PERFORMANCE

For evaluating the performance of the Artificial Intelligence (AI) models in the process of detecting prenatal depression, a series of measures is utilized. These measures can offer an insight into the classification accuracy of the model and allow an equalized analysis of the strengths and weaknesses concerning prediction. These metrics are:

Accuracy: Accuracy gives the percentage of accurate prediction of the model developed for the application, as defined in Eq. (1).

$$\text{Accuracy}=\frac{TP+TN}{TP+FN+TN+FP} \quad (1)$$

Sensitivity: Sensitivity indicates how good the model is at finding that the positive actually do have a condition. It is defined in Eq. (2).

$$\text{Sensitivity}=\frac{TP}{TP+FN} \quad (2)$$

Specificity: Specificity means how well the model classifies the negative cases, as shown in Eq. (3)

$$\text{Specificity}=\frac{TN}{TN+FP} \quad (3)$$

Precision: Precision is the number of the positive results predicted that turn out to be true (Eq. (4)).

$$\text{Precision}=\frac{TP}{TP+FP} \quad (4)$$

F1-Score: F1-score balances both precision and recall. It is like a combined score that tells how good the model is when both false positives and false negatives matter.It is defined in Eq. (5).

$$\text{F1 score}= 2.\ \frac{\text{Precision .recall}}{\text{Precision +recall}} \quad (5)$$

AUC / AUROC (Area Under the Receiver Operating Characteristic Curve): AUC quantifies the capability of a model to differentiate positive from negative cases at varying decision thresholds, as shown in Eq. (6).

$$\text{AUROC}=\int_0^1 \text{TPR}(\text{FPR})d(\text{FPR}) \qquad (6)$$

An overview of the discussed studies is presented in Table 1, summarizing the methodologies and results for prenatal depression detection.

Table 1 Overview of the discussed study.

Author	Year	Methods	Results
Garbazza et al. [1]	2024	Supervised Learning Algorithms	AUROC-77%, Specificity-0.82 and Sensitivity-0.51
Huang et al. [2]	2024	Random Forest, Elastic Net, and XGBoost model	AUROC-61%
Zafar et al. [3]	2025	RNN-LSTM Model	Accuracy-95%
Krishnamurti et al. [4]	2024	Causal discovery with KCI and ML algorithms	AUC of 0.93
Bao et al. [5]	2024	Support Vector Machine	Accuracy-69.3%
Terrone et al. [6]	2023	Hierarchical Regression models	Accuracy-27.2%
Peng et al. [7]	2024	Spatial patterns	Accuracy-87.88%
Wong et al. [8]	2024	Logistic and ML Models	AUROC values of 60% for LR,62% for RF and 60% for XGB
Raghavan et al. [9]	2021	Logistic Regression	Prevalence of PND (23.9%)
Ogur et al. [10]	2023	Machine learning algorithms and Deep Feed Forward Neural Network.	Accuracy -90.8%
Gopalakrishnan et al. [11]	2025	Stacked Ensemble based deep learning	Accuracy- 93.79%
Preis et al. [12]	2022	Random Forest Algorithm	Accuracy-80%
Hu et al. [13]	2025	Random Forest models	AUC- 0.710
Wegbom et al. [14]	2023	Ordinal Logistic Regression Models.	Prevalence of prenatal depression (9.5%), anxiety (26.6%) and stress (17.3%)
Zuo et al. [15]	2025	Logistic Regression Models	AUC-0.75
Wang et al. [16]	2024	Multiple Linear Regression analysis	Antenatal depression -19.4% and healthy control -80.6%
Zhang et al. [17]	2021	Binary Logistic Regression	Prevalence of PND (19.1%)
Khan et al. [18]	2021	Generalized Linear Model (GLM) with Logistic Regression.	Prevalence of PND (27%)

Faisal-Cury et al. [19]	2021	Logistic Regression Models	Prevalence of PND (82.3%)
Liu et al. [20]	2023	Regression analysis and Linear Mixed Modelling	Prevalence of PND (36.70%)
Barszcz et al. [21]	2025	Statistical Methods	Prevalence of PND (31.6%)
Li et al. [22]	2021	Logistic Regression Models and stratification	Prevalence of PND (28.2%)
Han et al. [23]	2024	Semantically enhanced option embedding models	F1 Score-0.8
Rodriguez-Munoz et al. [24]	2024	Linear Regressions methods	Prevalence of PND: Multiparous women (20.1%) and nulliparous women (15.6%).
Zhan et al. [25]	2022	Generalized Estimating Equation Models	Prevalence of PND: first trimester-23.89%, second trimester -21.12% and third trimester-22.42%.

IV. RESULTS ANALYSIS

This section discusses the results analysis from the survey paper and compares various AI techniques for detecting prenatal depression. Figures 2 and 3 shows the performance metrics of different Artificial Intelligence techniques and Figure 4 presents the percentage of prenatal depression prevalence detected using statistical and machine learning models.

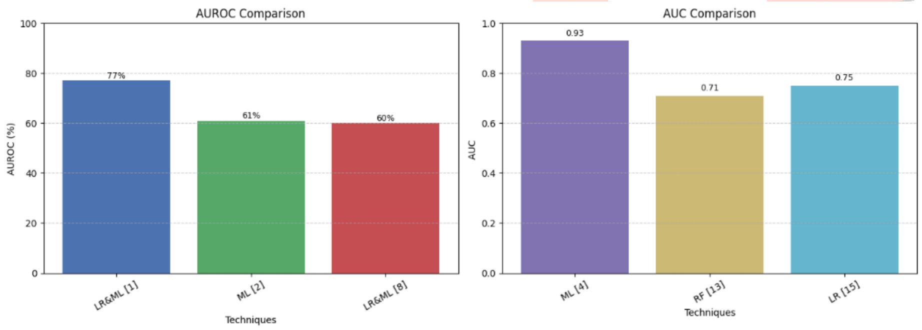

Fig. 2. and **3.** AUROC and AUC comparison of different Artificial Intelligence (AI) models for prenatal depression detection

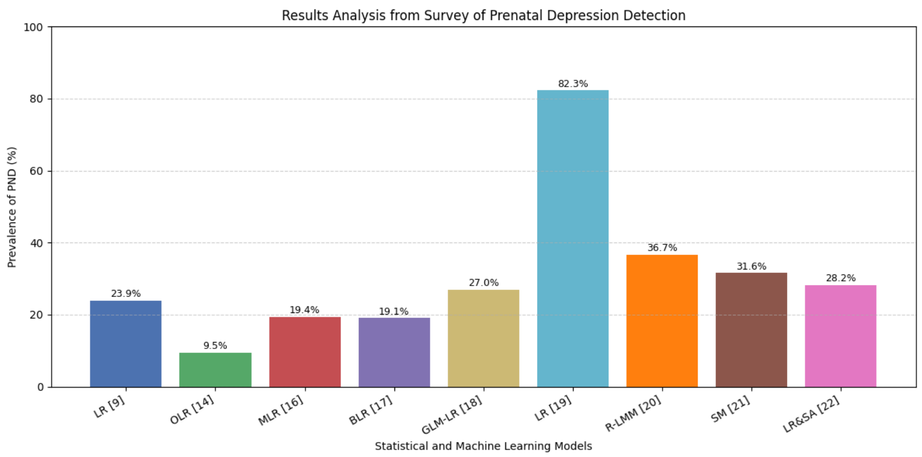

Fig. 4. Prevalence of PND (%) comparison across Statistical and Machine Learning Models

V. INFERENCE FROM THE SURVEY

This survey discussed various AI-based methods for detecting prenatal depression, with most existing methods focusing on the important steps in the detection process. Although the existing techniques demonstrated promising results, revealed key risk factors of prenatal depression detection. several limitations were identified. The use of small sample sizes was one of the major issues that can affect the generality of the findings. Also, certain studies were not sufficiently validated on a wide range of datasets and had limitations in their model interpretability and computational complexity. Despite these limitations, this survey provides important insights into the current state of AI-based approaches for detecting prenatal depression. The results indicate the necessity of improved detection accuracy and the integration of multimodal approaches to enhance the reliability and applicability of these AI-based models.

VI. CONCLUSION

This survey outlined a detailed analysis of various AI-based methods for prenatal depression detection, highlighting the strengths and limitations. The current AI-based approaches have demonstrated a scalable performance over different data sources including clinical assessments, questionnaires and physiological data. However, several limitations have been identified, such as small sample sizes, inconsistencies in evaluation metrics and limited generalizability. Moreover, their models are associated with computational complexity and model interpretability issues that must be examined in order to enhance the reliability of AI-based models.

Despite these challenges, the study provides meaningful insights into the role of Artificial intelligence in identifying prenatal depression. To improve the model accuracy, as a potential area of future research, integrating multiple data sources and validating results across diverse real-world datasets to improve clinical applicability should be investigated. The further development of these AI approaches will make it possible to improve the early intervention strategies, ultimately promoting better mental health care for both pregnant women and their children.

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