Capstone Project

Maternal Health Risk Prediction with AI: Literature, data and technology Review

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Literature Review

Introduction

Problem Statement: Maternal health risks remain a significant global health challenge, contributing to high maternal mortality and morbidity rates. Maternal mortality is a critical issue, especially in low-resource settings, with the majority of deaths occurring in developing countries. [3]
Research Gap: There's a need for improved tools for early detection of maternal health risks, particularly in contexts where access to care and quality of services are limited. Artificial intelligence (AI) holds promise for enhancing diagnostic accuracy, improving patient monitoring, and expanding access to care in maternal healthcare. [2]
Purpose of the Review: This review aims to explore the transformative role of AI in maternal healthcare, focusing on its applications in early detection of pregnancy complications, personalized care, and remote monitoring. It will examine effective algorithms, data types, and the success of AI applications in this field.
Outline: The review is structured to provide background on maternal health risks, followed by a thematic organization of the literature, a summary and synthesis of individual studies, a cross-study analysis, and a conclusion highlighting key takeaways and future research directions.
Background

- Key maternal health indicators and common risks include maternal mortality, pregnancy-related complications, and factors affecting access to and utilization of maternal healthcare services. [1],[3]
- Traditional risk assessment methods face challenges in low-resource settings, where access to high-quality emergency obstetric care is often limited. [3]
- There is a need for improved prediction and monitoring strategies to address maternal health risks and reduce maternal mortality.[9]

Organization

This literature review is organized thematically, focusing on key areas: machine learning applications in maternal health, clinical data usage, wearable technology integration, and psychosocial indicators.

a. AI and Machine Learning in Maternal Health

- Studies have explored the use of machine learning models for maternal health risk prediction. [5][6]

- For example, Mondal et al. (2023) developed a machine learning-based maternal health risk prediction model for an Internet of Medical Things (IoMT) framework. [6]
- Mutlu et al. (2023) also utilized traditional machine learning methods to predict maternal health risk. [5]
- These studies often involve analyzing medical parameters such as maternal age, heart rate, blood pressure, and other vital signs to estimate risk intensity. [5]

b. Deep Learning and Wearable Tech

- The integration of IoT devices and wearable technology allows for the collection of real-time health data, enabling continuous monitoring and analysis in IoMT environments. [6]
- This approach facilitates the tracking of crucial signs like heart rate, blood pressure, fetal movements, and temperature, which can be used to predict abnormalities and assess risk levels during pregnancy.[10]

c. Clinical vs. Socio-Demographic Data Use

- AI and machine learning models in maternal health utilize various types of data, including clinical parameters and socio-demographic factors.[5]
- For instance, studies may analyze medical parameters like maternal age, heart rate, blood oxygen level, blood pressure, and body temperature.[5]
- Additionally, socio-demographic factors such as access to care, quality of services, and healthcare policies can also play a role in maternal health risk assessment.

d. Psychosocial and Behavioral Indicators

- Psychosocial and behavioral factors also influence maternal health. [7][8]
- The World Health Organization (WHO) has identified several behavioral health priorities as risk factors for noncommunicable diseases in maternal populations, including tobacco use, harmful alcohol use, poor nutrition, and lack of physical activity.[8]
- These risk factors can significantly affect pregnant and postpartum mothers, increasing health risks and economic burden. [8]
- Additionally, psychosocial and environmental factors can affect the utilization of maternal healthcare services. [7]

Summary and Synthesis

Study Summaries:

- **Mondal et al. (2023):** This study developed a machine learning-based maternal health risk prediction model for an IoMT framework, utilizing IoT devices to collect real-time health data. [6]

- **Mutlu et al. (2023):** This research explored the use of traditional machine learning methods to predict maternal health risk by analyzing medical parameters.[5]
- **Mapari et al. (2024):** This review discussed the transformative role of AI in maternal healthcare, focusing on its applications in early detection, personalized care, and remote monitoring. [2]
- **Kane et al. (2014) and Sweeting et al. (2014):** These studies focused on the prediction and prevention of specific maternal health conditions, such as pre-eclampsia and gestational diabetes, using screening and risk assessment methods.[9][4]
- **Goodarzi et al. (2020):** This scoping review aimed to enhance the understanding of risk selection in maternal and newborn care, identifying key dimensions and themes related to risk selection practices.[10]
- **Moran et al. (2016):** This paper outlined a common monitoring framework for ending preventable maternal mortality, focusing on global targets and indicators.[1]
- **Mavalankar et al. (2005):** This commentary analyzed healthcare policies that restrict access to life-saving emergency obstetric care in resource-poor settings. [3]
- **Washio & Humphreys (2018):** This research discussed maternal behavioral health, focusing on risk factors such as tobacco use, harmful alcohol use, poor nutrition, and lack of physical activity.[8]
- **Sialubanje et al. (2014):** This qualitative study explored the psychosocial and environmental factors affecting the utilization of maternal healthcare services in Zambia.[7]

Comparison:

- Methodologies vary across studies, with some focusing on machine learning models, others on clinical screening, and some employing qualitative research methods. [10]
- Data sources also differ, with some studies utilizing real-time health data from IoT devices, others relying on clinical records, and some gathering data through surveys and interviews.

Critique:

- Some studies may have limitations such as small datasets, lack of generalizability, or a limited focus on real-world application.
- For example, Goodarzi et al. (2020) highlighted the methodological challenges of contextual diversity in risk selection. [10]
- Mavalankar et al. (2005) focused specifically on policy barriers to care in resource-poor settings, which may limit its broader applicability. [3]

Cross-Study Analysis

- **Common trends:** Several studies emphasize the importance of early detection and risk prediction in improving maternal health outcomes.[9]
- AI and machine learning are increasingly being explored as tools to enhance maternal healthcare. [2]
- **Conflicting results or gaps:** There is a need for more research on the integration of diverse data sources, including clinical, socio-demographic, and psychosocial factors, to provide a comprehensive understanding of maternal health risks.
- **Emerging opportunities:** Combining wearable technology and clinical data with AI-driven analytics offers opportunities for continuous monitoring and personalized care in maternal health.

Conclusion

Existing literature shows promise in AI for maternal health but lacks integration of diverse, real-world data such as wearable and psychosocial inputs. Our project will contribute by combining clinical, wearable, and psychosocial data in a practical, mobile-accessible solution—expanding the research frontier and potential for real-world impact.

- **Synthesis of Key Takeaways:** The literature highlights the potential of AI and machine learning in transforming maternal healthcare by improving risk prediction, enhancing care delivery, and addressing disparities in access to care.[2][10]
- However, challenges remain in terms of data integration, contextual diversity, and the need for a comprehensive understanding of risk selection.
- **Your Contribution:** Our project aims to build upon existing literature, especially in terms of data diversity and user accessibility.
- **Future Research Directions:** Future research could focus on developing more robust and generalizable AI models, integrating diverse data sources, addressing ethical considerations, and evaluating the real-world impact of AI interventions on maternal health outcomes.

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Data Research

Introduction

Addressing maternal health requires rich and diverse data. Our objective is to develop a data-driven risk prediction model to detect high-risk pregnancies. A thorough exploration of data sources ensures the accuracy and reliability of our model.

Organization

This section is structured by dataset source and its relevance to clinical, wearable, and psychosocial indicators.

Data Description

Maternal Health Risk Dataset (UCI):

- Format: CSV
- Features: Age, BP, Blood Sugar, Risk Labels
- Size: ~1,000 records
- Chosen for its labeled risk data to train classification models.

Safe Motherhood Case Studies (WHO):

- Format: Regional reports and tabular datasets.
- Features: Local maternal health indicators.
- Chosen to contextualize model predictions by region.

MIMIC-III Clinical Database:

- Format: SQL/CSV
- Features: Pregnancy-related hospital admissions
- Size: 60,000+ admissions
- Useful for feature expansion and validation.

RMNCH+A Dataset (India):

- Format: CSV

- Features: Socio-demographics, maternal health services
- Chosen for integrating socio-economic context into the model.

National Survey of Family Growth (NSFG):

- Format: Survey data
- Features: Socio-demographic, behavioral, and reproductive health information.
- Chosen to provide detailed insights into factors influencing maternal health.

Pregnancy Risk Assessment Monitoring System (PRAMS):

- Format: Survey data.
- Features: Maternal attitudes and experiences before, during, and shortly after pregnancy.
- Chosen to capture psychosocial factors affecting maternal health outcomes.

World Health Organization (WHO) Global Health Observatory:

- Format: Statistical data
- Features: Maternal mortality ratios and other key health indicators.
- Chosen for benchmarking and global contextualization.

Demographic and Health Surveys (DHS):

- Format: Household survey data
- Features: Maternal health service utilization, socio-economic status, and health outcomes.
- Chosen to analyze the impact of socio-economic factors on maternal health.

Wearable Sensor Data:

- Format: Time-series data
- Features: Heart rate, activity levels, sleep patterns (collected from wearable devices).
- Chosen to provide real-time physiological data for continuous monitoring.

Electronic Health Records (EHRs):

- Format: Structured and unstructured data
- Features: Comprehensive patient information, including diagnoses, treatments, and lab results.

- Chosen to obtain detailed clinical information for model training and validation.

Data Analysis and Insights

- UCI Dataset: Shows correlation between high BP/sugar and maternal risk. Clean and ready-to-use.
- WHO Data: Reveals regional disparities in maternal care, useful for tailoring interventions.
- MIMIC-III: Needs filtering but offers in-depth clinical features.
- RMNCH+A: Indicates strong influence of access to care on outcomes.
- NSFG: Provides detailed socio-demographic and behavioral insights.
- PRAMS: Captures crucial maternal attitudes and experiences.
- WHO Global Health Observatory: Enables global benchmarking and trend analysis.

- DHS: Helps in understanding socio-economic determinants of maternal health.
- Wearable Sensor Data: Offers potential for personalized and real-time risk assessment.
- EHRs: Provides comprehensive clinical data for accurate modeling.

Conclusion

Combining clinical, contextual, socio-demographic, and real-time physiological data improves prediction accuracy and equity. Our model is designed to leverage multiple data sources to enhance maternal healthcare, especially for underserved populations.

Technology Review

Introduction

Technology selection is vital to the success of our AI model and delivery system. This review discusses the tools and frameworks that will support our development of an accurate, accessible maternal health risk prediction platform.

Tools and Frameworks

Scikit-learn:

- A machine learning library in Python for regression, classification, and model evaluation. [4]
- Widely used for medical data modeling. [1]

XGBoost:

- Ensemble model known for speed and performance. [5]
- High accuracy on structured data. [2]

SHAP/LIME:

- Explainable AI tools for interpreting model decisions. [6][7]

Streamlit/Flutter/React:

- Frameworks for developing interactive web/mobile applications. [8][9]

FastAPI/Django/Flask:

- Lightweight backend for ML model integration. [10][11]

Docker:

- Containerization tool for running apps. [12]

Kubernetes:

- Container Orchestration tool for handling many containers. [13]

Relevance to Our Project

These tools are selected for their ability to:

- Handle tabular data. [1]
- Support real-time inference.
- Enhance model transparency—critical for clinical adoption.

Comparison and Evaluation

- Scikit-learn is easier for prototyping; XGBoost excels in performance. [1]
- SHAP offers global interpretability, while LIME excels at local explanations.
- Flutter enables cross-platform development, while Streamlit is more suited for web-based dashboards.
- React.js offers rich web UI capabilities; Django/Flask provide robust backend development options.
- Docker/Kubernetes facilitate efficient deployment and management

Use Cases and Examples

- XGBoost is used in maternal health risk prediction. [2]
- Flutter is used in mobile symptom-checker apps globally.

Identify Gaps and Research Opportunities

- Few maternal health apps use wearable data.
- Existing platforms lack model transparency, reducing trust.
- Need for culturally localized apps. [3]

Conclusion

Our tech stack balances performance, interpretability, and accessibility. These tools will help us create a scalable, transparent, and impactful solution for predicting maternal health risks.

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