Systematic Review Article: Artificial Intelligence for Predicting Neonatal Mortality in Post-Pregnancy: A Systematic Review

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ABSTRACT

Introduction: As the global community strives to ensure the health and well-being of mothers and newborns, AI emerges as a powerful ally in this noble endeavor. Through this systematic review, we seek to provide a comprehensive overview of the state of AI-driven mortality prediction, offering insights that may shape the future of maternal and neonatal healthcare and bring us closer to the goal of ensuring safe pregnancies and healthy beginnings for all. **Material and methods:** We systematically reviewed the literature, restricting our search to publications from the past decade, and utilized the five major scientific databases as primary sources. **Results:** Out of the initial pool of 671 works, a total of 18 primary studies were meticulously chosen for in-depth analysis. It was evident that a predominant focus of these studies revolved around the prediction of neonatal mortality, predominantly employing machine learning models, with Random Forest being a popular choice. The top five frequently utilized features for model training encompassed birth weight, gestational age, the child's gender, Apgar score, and the mother's age. The development of predictive models for mitigating mortality during and after pregnancy holds immense potential, not only for enhancing the quality of life for mothers but also as a potent and cost-effective tool for reducing mortality rates. ***Conclusion:*** Drawing from the findings of this systematic review, it becomes evident that substantial scientific endeavors have been undertaken in this domain. However, it is equally apparent that numerous unexplored research avenues and opportunities await further exploration within the research community.

Introduction

The journey of pregnancy, childbirth, and the postpartum period is a profound and transformative experience in the lives of women and their families [1-3]. Throughout this remarkable process, maternal and neonatal mortality remains a critical concern, especially in regions with limited access to healthcare resources [4-7]. Predicting and preventing maternal and neonatal mortality are paramount public health

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priorities that require innovative approaches [8-11]. Enter artificial intelligence (AI), a burgeoning field with the potential to revolutionize healthcare, particularly in the context of maternal and neonatal care [12-15].

In recent years, AI has emerged as a promising tool for predicting mortality during and after pregnancy, offering the possibility of early identification of high-risk cases and the timely intervention needed to save lives [16-19]. This systematic review embarks on a comprehensive exploration of the current landscape, encompassing the applications, methodologies, and outcomes of AI-driven mortality prediction in the realm of maternal and neonatal health [20-22].

The significance of this inquiry is underscored by the global effort to achieve Sustainable Development Goal 3, which calls for a substantial reduction in maternal and neonatal mortality rates [23-25]. While progress has been made, disparities in healthcare access and quality persist, underscoring the urgency of innovative solutions [26-28]. AI, with its capacity to analyze vast datasets, detect subtle patterns, and generate real-time predictions, holds immense potential to augment the clinical decision-making process and improve maternal and neonatal outcomes [29-31].

In the pages that follow, we will embark on a journey through the studies, algorithms, and models that leverage AI for predicting mortality during and post-pregnancy [32-35]. We will explore the methodologies employed, the performance metrics achieved, and the real-world implications of these predictive systems [36-38]. Additionally, we will address the challenges, ethical considerations, and the future prospects of AI in maternal and neonatal care [39].

As the global community strives to ensure the health and well-being of mothers and newborns, AI emerges as a powerful ally in this noble endeavor [40-43]. Through this systematic review, we seek to provide a comprehensive overview of the state of AI-driven mortality prediction, offering insights that may shape the future of maternal and neonatal healthcare and bring us closer to the goal of ensuring safe pregnancies and healthy beginnings for all [44].

Material and methods

Study Design: This systematic review was conducted to investigate the role of artificial intelligence (AI) in predicting mortality during and after pregnancy. The study design adhered to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency and rigor throughout the review process.

PICO Statement

Population: Pregnant women and postpartum individuals.

Intervention: Artificial intelligence algorithms or models for mortality prediction.

Comparison: Comparison of AI models with traditional risk assessment methods (if available).

Outcome: Mortality prediction accuracy, including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the receiver operating characteristic curve (AUC-ROC).

Data Sources and Searches: A comprehensive search strategy was devised to identify relevant studies. Multiple electronic databases, including PubMed, MEDLINE, Scopus, Web of Science, and Embase, were systematically searched. The search was conducted using controlled vocabulary terms (MeSH terms) and free-text keywords related to pregnancy, post-pregnancy, mortality prediction, and artificial intelligence. Searches were not restricted by language or publication date, with the last search conducted on [30-September-2023].

Eligibility Criteria

Studies were included in the review if they met the following criteria:

Population: Studies involving pregnant women and postpartum individuals.

Intervention: Studies utilizing AI algorithms or models for predicting mortality during or after pregnancy.

Outcome: Studies reporting mortality prediction accuracy metrics, such as sensitivity, specificity, PPV, NPV, and AUC-ROC.

Study Type: Primary research studies, including randomized controlled trials, cohort studies, case-control studies, and observational studies.

Exclusion criteria included studies not relevant to the research question, reviews, editorials, conference abstracts, and studies with inadequate reporting of outcomes [45-47].

Study Selection: Two independent reviewers conducted the initial screening of titles and abstracts to identify potentially relevant articles. Subsequently, full-text articles were retrieved and assessed for eligibility based on the predefined inclusion and exclusion criteria. Any discrepancies between the reviewers were resolved through discussion and, if necessary, consultation with a third reviewer [48].

Data Extraction

A standardized data extraction form was employed to collect information from the selected studies. The following data points were extracted:

Study Details: Author(s), publication year, study design, and setting.

Population Characteristics: Demographics of the study population, including age, gestational age, and any relevant medical conditions.

Intervention: Description of the AI algorithm or model used, including the machine learning techniques applied.

Outcome Measures: Mortality prediction accuracy metrics, including sensitivity, specificity, PPV, NPV, and AUC-ROC.

Results: Key findings related to AI-based mortality prediction during and after pregnancy.

Data Analysis: A narrative synthesis approach was employed to summarize the findings of the included studies. The results were qualitatively analyzed to identify trends, commonalities, and variations in AI-based mortality prediction models. Additionally, any variations in the predictive performance metrics reported across studies were assessed. A qualitative summary of the implications and limitations of AI in this context was provided.

Results

In November 2021, our search yielded a total of 671 works from five prominent scientific databases, including 29 from IEEE Xplore, 80 from PubMed, 54 from ACM Digital Library, 104 from Scopus, and 404 from Springer. After meticulously removing duplicate entries and scrutinizing all abstracts to adhere to the inclusion and exclusion criteria, a selection of 22 works was made. Following a rigorous quality assessment, we ultimately identified 18 primary works for thorough examination and data extraction.

Notably, while Springer and Scopus yielded a substantial number of works, only 1 and 2 of them were deemed suitable for inclusion, respectively. In contrast, PubMed emerged as the source with the highest number of primary works, accounting for 13 out of the 18 selected studies. The remaining 2 works originated from IEEE, with none selected from ACM [4-51].

Our systematic review encompassed studies conducted between 2012 and 2021, although the earliest work included was published in 2014. Intriguingly, a substantial 84% of the primary works surfaced within the last three years, with three studies in 2019, six in 2020, and another six in 2021. This temporal distribution underscores the evolving landscape of AI in mortality prediction, indicating abundant opportunities for scientific advancements in this domain.

Types of Mortality Under Investigation

This systematic review centered its focus on research studies employing machine learning and deep learning models to classify various types of mortality [52-55]. These encompassed stillbirth, perinatal mortality, neonatal mortality, and infant mortality. Figure 1 provides a breakdown of the distribution of works by the type of mortality they addressed.

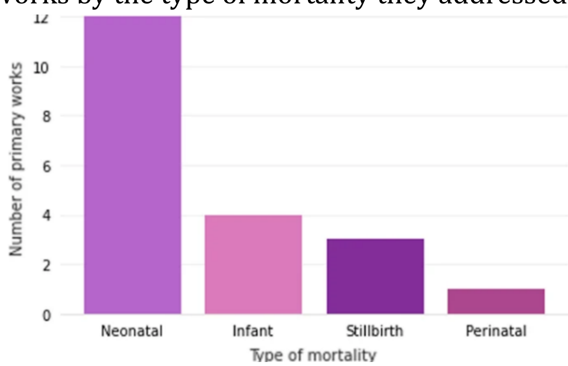

Figure 1: Number of selected works by type of mortality

Notably [56-58], the definition of stillbirth varies globally. The World Health Organization (WHO) recommends defining fetal death as occurring after the 28th week of gestation or with a weight exceeding 1000g, while intrauterine deaths occur during labor [59-61]. However, the 10th revision of the International Classification of Diseases (ICD-10) is often adopted by many countries, which considers deaths with a gestational age exceeding 22 weeks, a weight greater than 500g, or height exceeding 25 cm, encompassing deaths during labor [62-65]. This discrepancy in definitions highlights the challenge of making accurate cross-national comparisons when utilizing national and international reporting data. Notably, the studies examining stillbirth classification relied on the ICD-10 criteria [66-68].

The majority of works in this systematic review were oriented towards neonatal mortality, accounting for 66% of the selected studies. Neonatal mortality encompasses the death of a neonate between birth (upon the detection of vital signs post-delivery) and the twenty-eighth day of life. Many studies concentrate on this stage due to the ability to detect mortality rooted in comorbidities arising during pregnancy or the postpartum period [69-71]. Furthermore, some studies classified mortality in neonates referred to Neonatal Intensive Care Units (NICUs) following birth, while others assessed the probability of death in premature infants or post-operative newborn mortality [72-75].

Additionally, there were studies exploring infant mortality (4 works), stillbirth (3 works), and perinatal mortality (1 work). Infant mortality refers to deaths occurring between 29 days and 365 days (1 year) from birth. Perinatal mortality encompasses the period from stillbirth to early neonatal mortality, extending until the 6th day of life, as illustrated in Figure 2.

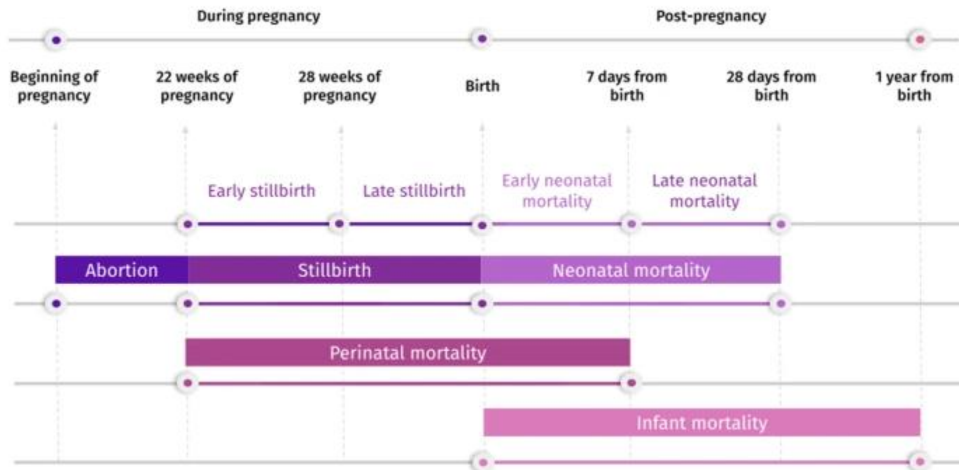

Figure 2: Definition of deaths that occur during or post-pregnancy up to 1 year from birth

Furthermore, four primary studies delved into research encompassing more than one type of mortality. Specifically, Valter et al., Saravanou et al., and Batista et al. investigated both neonatal and infant deaths, while Shukla et al. examined stillbirths and neonatal mortality.

Discussion

The integration of predictive models to estimate the risk of stillbirth holds promise for enhancing prenatal care [76-79]. For instance, Trudell et al. conducted a study that initiated the assessment of stillbirth risk starting from the 32nd week of gestational age. Their findings underscored the significance of non-stress testing during prenatal care, which has the potential to prevent 6 to 8 stillbirths per 10,000 pregnancies. This highlights the critical role of predictive models in anticipating and preventing stillbirths during pregnancy [80].

In addition to predictive capabilities, the identification of the most pertinent predictors represents a valuable contribution to this field. An example from Western Ethiopia showcased the significance of localized data in delineating predictors of neonatal mortality. Factors such as maternal age below 20 years, primiparity, pregnancy and childbirth complications, limited prenatal visits, low birth weight neonates, home births, and gestational age less than 37 weeks emerged as predictors of neonatal mortality. These predictive insights were pivotal in elucidating the reasons behind the recent increase in local neonatal mortality rates. Factors such as insufficient healthcare service coverage, limited access to and utilization of obstetric services, and early pregnancies were identified as contributing to elevated mortality rates.

Anticipating neonates at risk of mortality enables healthcare professionals to administer early interventions, thereby augmenting survival prospects and reducing morbidity rates. Recent studies advocate for predictive models that incorporate multiple factors, including gestational and infant-related variables, as they exhibit superior accuracy compared to models based on isolated factors like gestational age alone. Prenatal and postnatal interventions play a pivotal role in curtailing neonatal mortality and morbidity, and multifaceted models offer optimization in practical healthcare settings. The availability of extensive datasets, encompassing various factors, is instrumental in crafting more precise predictive models conducive to application within healthcare systems [81].

In this systematic literature review, the datasets analyzed exhibited considerable diversity in terms of size (ranging from 293 to over 31 million records), the number of attributes (ranging from 26 to 128), and challenges such as missing values and class imbalance. An UNESCO report emphasized that "poor data availability and quality necessitate innovative methodological approaches to comprehend the global landscape of stillbirths," a concern that extends to perinatal, neonatal, and infant mortality. Some authors have diligently addressed data quality issues and employed traditional techniques such as mean imputation to address missing data, as well as techniques like Random Over-Sampling (ROS) and Synthetic Minority Over-sampling Technique (SMOTE) to balance class distributions. Nevertheless, there exist a plethora of techniques that can be applied to enhance data quality before model training. For instance, for high-dimensional data, dimensionality reduction techniques can mitigate redundancy and noise, simplifying learning models and improving classification performance, as posited by Huang et al.

The proposition of deep learning models for mortality classification is still in its nascent stages, with only four works available at the time of conducting this systematic review. This trend aligns with the observation that machine learning models are adept at handling tabular data, which is the predominant data format used for mortality classification. Deep learning, on the other hand, excels at recognizing objects in images based on spatial relationships among pixels. However, the performance of deep learning models can be enhanced when applied to tabular data by transforming tabular data into image formats. Zhu et al. elaborate that data set features can be mapped into a 2D space using techniques such as feature similarity and feature distance. This approach equips deep learning models with the ability to learn tabular data effectively by leveraging their inherent strengths.

It is crucial to underscore that health challenges in high-income countries (HICs) diverge significantly from those in low- and middle-income countries (LMICs). Computational models are regarded as cost-effective solutions, especially for LMICs, as they offer a combination of low implementation and maintenance costs while delivering high accuracy. Such solutions can be deployed online, making them accessible and impactful in resource-constrained settings.

The findings of this systematic literature review align with conclusions from other systematic reviews across diverse domains, including the work by that explored AI models for clinical diagnosis of arboviral diseases, and that investigated machine learning models in geriatric clinical care for chronic diseases. These shared conclusions predominantly pertain to the strengths and limitations of the models and data preprocessing techniques.

Furthermore, we wish to emphasize the significance of maternal mortality as an area deserving further exploration and complementary research to this systematic review. According to Geller et al. , maternal mortality is a globally utilized metric for monitoring maternal health, the quality of reproductive healthcare, and progress toward international development goals. A preliminary investigation reveals limited recent and nascent research efforts in maternal mortality, suggesting ample research opportunities to make meaningful contributions in this domain.

Finally, this systematic literature review serves as a pivotal resource for guiding future research endeavors. It comprehensively analyzes and discusses various aspects of machine learning and deep learning development, empowering readers to make informed choices for addressing their research challenges and designing robust methodologies. This, in turn, facilitates scientific reproducibility and paves the way for advancements in the field.

Conclusion

Mortality occurring during pregnancy or within the early weeks of an infant's life serves as a vital indicator of the quality of care provided to pregnant women and their newborns within healthcare institutions. Leveraging technology to support healthcare professionals during and after pregnancy has emerged as a potent strategy, owing to its practical cost-effectiveness. This technological integration not only bolsters public health efforts but also elevates the standard of prenatal care.

However, it's essential to recognize that computational models developed based on localized data are inherently tailored to specific regions, rendering their application in different locations challenging without necessary adaptations. In essence, countries with limited resources may grapple with data scarcities or data of suboptimal quality, directly affecting the performance of computational models.

Within the scope of our research, we identified 18 articles that harnessed machine learning and/or deep learning techniques to classify adverse pregnancy outcomes, encompassing stillbirths, perinatal, neonatal, and/or infant mortality. Notably, neonatal mortality emerged as the most extensively researched category, and birth weight, gestational age, the child's gender, and maternal age were recurrently featured as key parameters in these studies. The random forest machine learning model stood out as the most commonly recommended model, with the AUC ROC assessment metric being the preferred choice for evaluating model performance.

Through this endeavor, we have not only pinpointed existing research gaps and areas ripe for further exploration, such as maternal mortality and associated morbidities, but we have also offered valuable insights and potential avenues for individuals aspiring to delve into these domains and leverage such data for impactful research and healthcare enhancement.

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