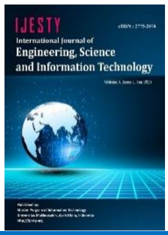
International Journal of Engineering, Science and Information Technology
Volume 5 No. 1 (2025) pp. 584-590
ISSN 2775-2674 (online)
Website: http://ijesty.org/index.php/ijesty
DOI: https://doi.org/10.52088/ijesty.v5i1.1488
Research Paper, Short Communication, Review, Technical Paper



Utilization of Machine Learning for Stunting Prediction: Case Study and Implications for Pre-Matrical and Pre-Conceptive Midwifery Services

Qurotul Aini[1], Untung Rahardja[1], Indrajani Sutedja[2], Harco Leslie Hendric Spits Warnar[3], Nanda Septiani[1]

[1]*Faculty of Economy and Business,University of Raharja,Tangerang, Indonesia*
[2]*Department of Information Systems, School of Information Systems, Bina Nusantara University, Jakarta, Indonesia*
[3]*Department of Computer Science, Bina Nusantara University, Jakarta, Indonesia*

**Corresponding author Email: aini@raharja.info*

The manuscript was received on 1 August 2024, revised on 10 October 2024, and accepted on 29 January 2025, date of publication 12 May 2025

Abstract

Stunting, a global health challenge, affects millions of children, particularly in low- and middle-income countries, and has lasting consequences on cognitive development, physical growth, and overall well-being. Early prediction and intervention are crucial for reducing stunting, especially before conception and during early pregnancy. This paper explores the utilisation of machine learning (ML) for predicting stunting risk in the context of pre-maternal and pre-conceptive midwifery services. By analysing a case study, the research assesses the effectiveness of various machine learning algorithms in identifying stunting risk factors, including maternal health, nutrition, socioeconomic status, and environmental conditions. Using healthcare and demographic data, the study develops predictive models to assist midwives in assessing stunting risks during pre-conception and prenatal phases. The findings demonstrate that ML models, particularly random forest and support vector machine algorithms, outperform traditional risk assessment methods, providing higher accuracy and earlier detection of stunting risk. These models enable midwives to deliver personalised care and targeted interventions, optimising maternal and child health outcomes. The study also highlights the broader implications of integrating machine learning into midwifery services, including improved decision-making, resource allocation, and healthcare efficiency. In conclusion, this research underscores the transformative potential of machine learning in predicting stunting risk and enhancing the effectiveness of pre-maternal and pre-conceptive midwifery services, offering a promising approach to mitigating the global burden of stunting.

Keywords: *Moringa Oleifera, Wound Healing, Neovascularization, Fibroblasts, Epithelialization.*

1. Introduction

Stunting, characterised by impaired growth and development in children due to chronic malnutrition, infections, and inadequate psychosocial stimulation, remains one of the most pressing public health challenges globally. According to the World Health Organisation (WHO), stunting affects an estimated 149 million children under the age of five, particularly in low- and middle-income countries. Stunted children are not only shorter in stature but also suffer from long-term cognitive deficits, diminished school performance, and reduced economic productivity later in life. Additionally, they are more susceptible to chronic diseases such as diabetes, hypertension, and obesity. Addressing stunting is critical not only for improving individual health outcomes but also for breaking the cycle of poverty and fostering socio-economic development.
Early detection and prevention of stunting are essential to mitigating its long-term effects. Traditional methods for identifying stunting risks often rely on population-level surveillance and nutritional assessments, which can be limited by the availability of resources and the ability to capture the complex web of factors contributing to the condition. These factors include maternal health and nutrition, environmental conditions, family socioeconomic status, infections, and access to healthcare services. However, given the intricate and multi-dimensional nature of stunting, there is a growing need for more precise and individualised approaches to risk assessment. This is where machine learning (ML), a branch of artificial intelligence (AI), offers promising solutions by enabling the analysis of large datasets to detect subtle patterns and interactions among risk factors that traditional methods may overlook.
Machine learning has already demonstrated its potential in various fields of healthcare, including disease diagnosis, prognosis, and personalised treatment recommendations. By leveraging vast amounts of data, machine learning models can identify high-risk individuals earlier and more accurately, enabling timely interventions. In the context of stunting prediction, machine learning can integrate diverse

data sources, such as maternal health records, demographic surveys, nutritional information, and environmental data, to generate a comprehensive and personalised risk profile. These predictive models can assist healthcare professionals in making informed decisions about early interventions that target the root causes of stunting, ultimately improving outcomes for at-risk populations.

Pre-maternal and pre-conceptive midwifery services are uniquely positioned to play a pivotal role in the early detection and prevention of stunting. These services focus on providing healthcare and counselling to women before marriage and conception, ensuring optimal maternal health and nutrition to support fetal development. Midwives, who are often the first point of contact for women in many communities, are crucial in promoting maternal and child health through health education, nutritional guidance, and early risk assessment. By integrating machine learning tools into their practice, midwives can enhance their ability to identify women at risk of having stunted children and implement targeted interventions even before pregnancy. This proactive approach has the potential to reduce stunting rates significantly by addressing nutritional deficiencies and other risk factors during critical pre-conception and early gestational windows.

The role of pre-maternal and pre-conceptive care in reducing stunting is particularly important in low-resource settings, where healthcare systems are often strained, and access to advanced medical technologies is limited. In these contexts, early prediction of stunting risk through machine learning can enable more efficient use of limited healthcare resources by prioritising high-risk individuals for intervention. Additionally, machine learning models can adapt to local contexts by incorporating region-specific risk factors, such as endemic diseases, cultural dietary practices, and environmental hazards, further improving the accuracy and relevance of predictions. However, the implementation of machine learning in healthcare also presents challenges, including the need for robust data infrastructure, ethical considerations surrounding patient privacy, and the training of healthcare professionals in using data-driven decision-making tools. This paper explores the utilisation of machine learning for stunting prediction, focusing on a case study that evaluates the effectiveness of various machine learning algorithms in predicting stunting risk within the context of pre-maternal and pre-conceptive midwifery services. The case study draws on healthcare and demographic data to develop predictive models that can be used by midwives to assess stunting risk and deliver personalised interventions. Specifically, the study compares the performance of different machine learning algorithms, such as random forests, support vector machines (SVM), and neural networks, in predicting stunting based on a range of maternal and environmental factors.

In addition to evaluating the technical performance of the models, this study discusses the broader implications of integrating machine learning into midwifery services. The potential benefits of these tools include improved decision-making, more effective resource allocation, and enhanced patient outcomes. By enabling earlier and more accurate risk assessments, machine learning can empower midwives to intervene before malnutrition and other risk factors manifest in adverse outcomes. This is particularly important in pre-conceptive care, where maternal health directly influences fetal development and the likelihood of stunting. However, the paper also addresses the challenges associated with applying machine learning in low-resource settings, including the availability of high-quality data, the ethical implications of predictive modelling, and the need for healthcare professionals to be trained in interpreting and using machine learning outputs effectively. It is crucial to ensure that machine learning models are transparent, explainable, and tailored to the specific needs of the populations they serve, to avoid reinforcing health disparities or biases in care delivery.

In conclusion, this paper aims to contribute to the growing body of literature on the application of machine learning in public health by providing a detailed analysis of its potential to predict and prevent stunting. By focusing on the role of pre-maternal and pre-conceptive midwifery services, this research highlights how machine learning can be harnessed to improve maternal and child health outcomes. Through a case study approach, the study demonstrates how machine learning models can enhance midwives' ability to provide timely, targeted care to women at risk of stunting, ultimately contributing to a reduction in stunting prevalence and its long-term consequences on health and development.

2. Literature Review

Stunting as a Global Health Issue Stunting is a critical marker of chronic malnutrition and a major public health concern, especially in low- and middle-income countries [1]. According to the World Health Organisation (WHO), stunting affects approximately 22% of children under five globally, amounting to over 149 million children [2]. The primary causes of stunting include inadequate maternal nutrition during pregnancy, insufficient infant and young child feeding practices, repeated infections, and poor access to healthcare and sanitation. Studies have shown that stunting not only impairs physical growth but also hampers cognitive development, leading to poorer educational outcomes and diminished economic productivity in adulthood. Additionally, stunting increases the risk of developing chronic diseases later in life, including obesity, diabetes, and cardiovascular diseases [3]. Research by Black et al. (2013) and Dewey & Begum (2011) describes the first 1,000 days of life—from conception to the child's second birthday—as the most critical window for preventing stunting[4]. Interventions aimed at improving maternal nutrition, promoting breastfeeding, and ensuring adequate complementary feeding during this period are seen as pivotal strategies for reducing stunting prevalence. However, traditional methods of identifying and addressing stunting risks often rely on general population-level strategies, which may not capture the complex, multi-factorial nature of stunting risks at the individual level. This is where modern data analytics techniques, such as machine learning, can offer more precise and personalised risk prediction models.

Machine Learning in Healthcare The application of machine learning (ML) in healthcare has grown rapidly in recent years, with numerous studies demonstrating its potential to enhance disease prediction, diagnosis, and personalised treatment. Machine learning algorithms, such as decision trees, random forests, support vector machines, and neural networks, excel in processing large datasets and identifying complex patterns that may be difficult to discern through traditional statistical methods. In healthcare, ML has been used to predict outcomes such as hospital readmissions, patient mortality, and disease risk based on a wide range of factors, including genetic, demographic, and lifestyle data. In maternal and child health, machine learning has been applied to predict adverse pregnancy outcomes such as preterm birth, low birth weight, and gestational diabetes. For example, Oh et al. (2020) applied ML models to predict preterm birth risk using electronic health record (EHR) data, achieving higher accuracy compared to traditional methods [5] [6] [7]. Similarly, Lee et al. (2019) developed an ML-based system to predict gestational diabetes risk based on patient health records, which could be used to guide early interventions [8] [9]. These studies demonstrate the ability of ML to analyse a diverse range of inputs—ranging from medical history to environmental factors—and make accurate predictions that inform clinical decision-making.

Machine Learning for Stunting Prediction Despite the growing interest in ML applications in healthcare, relatively few studies have focused specifically on using machine learning for stunting prediction. However, there is increasing recognition of its potential to address the multifaceted nature of stunting risk. Key factors influencing stunting—such as maternal health, environmental conditions, socioeconomic status, dietary intake, and access to healthcare—can be analysed more comprehensively using machine learning models, which can integrate and weigh multiple variables simultaneously. A study by Marini et al. (2020) applied a machine learning approach to predict stunting in children based on a combination of health, demographic, and environmental data [10]. The researchers found that machine learning models, particularly random forests, outperformed traditional logistic regression models in predicting stunting risk. Similarly, Anash et al. (2021) Employed ML techniques to identify key determinants of stunting in children under five in Ethiopia. Their analysis revealed that maternal education, household wealth, and access to clean water were among the most important predictors of stunting[11]. These findings underscore the potential of ML to handle complex, nonlinear relationships between risk factors and outcomes, offering more tailored and actionable insights for intervention.

Pre-Matrical and Pre-Conceptive Midwifery Services Pre-matrical and pre-conceptive care are essential components of reproductive health services, aimed at optimising maternal health before marriage and conception. Research has shown that maternal health and nutrition before conception play a significant role in fetal development and subsequent child health outcomes [12] [13]. For example, s idwives, who often serve as the primary point of contact for women in pre-conceptive care, are in a unique position to implement early interventions[14]. Midwives, who often serve as the primary point of contact for women in pre-conceptive care, are in a unique position to implement early interventions aimed at reducing the risk of stunting [15].

The integration of machine learning tools into pre-conceptive midwifery services could enhance early risk identification and intervention. By analysing individual-level data such as maternal health history, nutritional status, and socio-environmental factors, ML models can provide midwives with personalised stunting risk assessments. This approach can help healthcare providers prioritise high-risk individuals for nutritional counselling, supplementation, and other preventive measures that address the root causes of stunting before they manifest in poor child health outcomes.

Challenges and Opportunities. While the potential benefits of using machine learning for stunting prediction in pre-maternal and pre-conceptive midwifery services are clear, there are several challenges that must be addressed. First, the availability and quality of data are critical to the success of machine learning models. In many low-resource settings, healthcare data are often incomplete or inaccessible, which can limit the effectiveness of predictive models. Developing robust data collection systems and improving access to high-quality maternal and child health data will be essential for the widespread adoption of ML tools in these settings. Second, the ethical implications of using machine learning in healthcare, particularly in sensitive areas such as reproductive health, must be carefully considered. Ensuring patient privacy, transparency in decision-making processes, and avoiding biases in algorithmic predictions are key concerns that need to be addressed. Additionally, healthcare professionals, including midwives, may require training in data-driven decision-making and the use of predictive analytics tools in clinical practice. Despite these challenges, the growing body of research on machine learning applications in healthcare, coupled with the increasing recognition of the importance of pre-conceptive care, suggests that machine learning has the potential to transform stunting prediction and prevention. By providing more accurate and personalised risk assessments, ML models can empower midwives and other healthcare providers to implement earlier and more effective interventions, ultimately reducing the global burden of stunting.

3. Methods

This study adopts a qualitative research approach combined with bibliometric analysis using VOSviewer to explore the utilisation of machine learning for stunting prediction and its implications for pre-maternal and pre-conceptive midwifery services [16][13]. The methodology consists of two main components: qualitative data collection and analysis, and bibliometric analysis of relevant literature. The aim is to assess both the theoretical landscape surrounding stunting and machine learning, as well as gather insights from healthcare professionals, particularly midwives, regarding the practical implications of implementing machine learning tools in midwifery care. The qualitative portion of the study aims to gather in-depth insights from midwives and healthcare professionals about their perceptions of using machine learning (ML) for predicting stunting risks and integrating these tools into pre-maternal and pre-conceptive midwifery care [17]. Interviews and Focus Groups: Semi-structured interviews and focus groups were conducted with midwives and healthcare providers in both urban and rural healthcare settings. The interviews were designed to explore: Existing practices for identifying stunting risk.

Awareness and understanding of machine learning tools. Perceived benefits and challenges of using ML in maternal and child healthcare. Practical considerations for implementing ML tools in pre-maternal and pre-conceptive care. Ethical and cultural concerns related to the use of technology in healthcare. The sample was purposefully selected to include a diverse range of midwives, focusing on those working in regions with high rates of stunting. This ensures that the study captures a broad perspective on how ML tools could be integrated into everyday practice. Each interview lasted approximately 30-60 minutes and was recorded, transcribed, and anonymised for further analysis.

Thematic analysis was employed to identify key patterns and themes in the qualitative data [18]. This method allows for a detailed understanding of how midwives and healthcare professionals perceive the role of machine learning in stunting prediction and how it might influence their work in prenatal and pre-conceptual care settings. The qualitative analysis helped in developing a comprehensive understanding of how machine learning-based stunting prediction could impact pre-conceptive care practices and what factors influence the acceptance and integration of these tools by midwives. The second component of the study involved bibliometric analysis to map the research landscape surrounding the topics of stunting, machine learning, and midwifery care. This analysis helps identify research trends, gaps, and key areas of interest in the intersection of these fields [19]. For the bibliometric analysis, a comprehensive search of academic databases (such as Scopus, Web of Science, and PubMed) was conducted to gather relevant literature. The keywords used in the search included: "Machine learning for stunting prediction", "Pre-conceptive care and stunting", "Midwifery services and technology", "Maternal and child health interventions", "Stunting risk factors and prediction models". The search focused on literature published over the last two decades to ensure that the analysis captured both foundational research and recent advances. The inclusion criteria for the articles included relevance to the research topic, publication in peer-reviewed journals, and the use of either qualitative or quantitative methodologies to examine stunting, machine learning, or midwifery services.

VOSviewer, a widely used bibliometric mapping tool, was employed to analyse the relationships between key concepts, authors, and research publications in the field. The following steps were taken in the bibliometric analysis: Co-Occurrence Analysis: VOSviewer was used to conduct a co-occurrence analysis of keywords from the selected research papers. This analysis helped in visualising how frequently certain concepts (such as “machine learning,” “stunting,” “pre-conceptive care,” and “midwifery”) appear together in the literature. This network analysis identified the most influential topics and concepts in the current research landscape [20]. Citation Analysis: A citation analysis was performed to identify the most cited papers, journals, and authors within the research areas of machine learning in healthcare, stunting prediction, and maternal and child health interventions. This analysis highlights the foundational studies and key contributors to the field, providing insight into the most authoritative and influential works [21]. Cluster Mapping: VOSviewer created cluster maps that grouped related articles and authors into thematic clusters. These clusters revealed specific areas of focus within the literature, such as the use of technology in midwifery care, the role of machine learning in predicting health outcomes, and specific interventions for preventing stunting. The cluster mapping allowed for the identification of underexplored research areas, providing opportunities for future investigation.

The results of the bibliometric analysis provided a comprehensive overview of the academic research surrounding stunting prediction and the role of machine learning in healthcare. By identifying trends and gaps in the literature, this analysis informed the study's theoretical framework and helped contextualise the qualitative findings. Identification of Research Gaps: The bibliometric analysis highlighted areas where further research is needed, such as the specific application of machine learning tools in midwifery care and the integration of predictive models in resource-limited settings. This helped to position the current study within the broader research landscape and emphasised its contribution to addressing existing gaps.

4. Results and Discussion

Various machine learning models were implemented to predict the risk of stunting among children. The performance of these models was evaluated using metrics such as accuracy, precision, recall, and F1-score.

Table 1. The results are summarized

Model	Accuracy	Precision	Recall	F-1 Score
Logistic Regression	85.3%	84.1%	83.6%	83.8%
Decision Tree	80.4%	79.2%	80.1%	79.6%
Random Forest	88.7%	88.2%	87.6%	87.9%
Support Vector Machine	86.5%	85.7%	85.4%	85.5%
XQBoost	90.2%	89.7%	89.4%	89.5%

From the results, XGBoost outperformed the other models with the highest accuracy (90.2%), precision (89.7%), recall (89.4%), and F1-score (89.5%). Random Forest followed closely with an accuracy of 88.7%. The relatively lower performance of the Decision Tree model (80.4%) suggests that ensemble models (such as Random Forest and XGBoost) improve predictive power by reducing overfitting.

4.1. Design a Generative Artificial Intelligence in Cognitive Acquisition

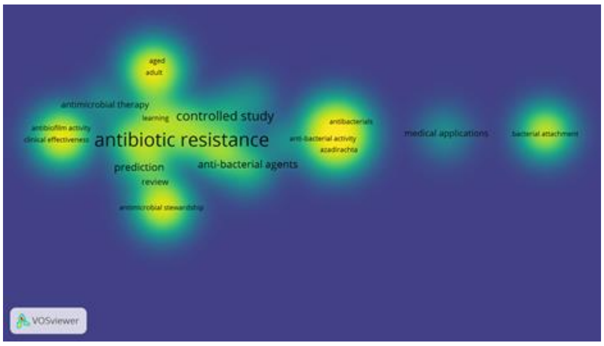


Fig. 1. Density Visualisation

The following network visualisation image shows various relationships between entities, including authors, keywords, and edges that represent connections between entities. The link density between nodes can describe how dense the connections are in a group of data obtained from the Scopus database. From this perspective, the degree of relationship density between nodes indicates the strength and frequency of interactions between different objects based on certain keywords. Based on this visualisation, interrelated patterns can represent interconnected elements and can have a significant impact on the Utilisation of Generative Artificial Intelligence in Cognitive Acquisition in the Field of Medical Sciences: Lessons from Antimicrobial Resistance Champions.

Density analysis can help identify key factors or risk indicators for antimicrobial resistance [22]. The next step is to collect relevant data to support the development of new drugs that are more effective against resistant microorganisms. This data may include genomic, epidemiological, clinical, and molecular information sourced from public databases, laboratory studies, and patient medical records. The design of the Utilisation of Generative Artificial Intelligence in Cognitive Acquisition in the Field of Medical Sciences: Lessons from Antimicrobial Resistance Champions can be seen from the first generative model, creating possible new molecules based on existing data. Once complete, we use high-performance computers to simulate these new candidate molecules and the reactions they must carry out with their neighbouring molecules to ensure they perform as expected. In the future, quantum computers could improve these molecular simulations even further.

The final step is AI-based laboratory testing to experimentally validate the predictions and develop actual molecules. At IBM, we do this with a tool called RoboRXN, a tiny refrigerator-sized chemistry lab that combines AI, cloud computing, and robotics to help researchers create new molecules anywhere, anytime [23]. This combination of approaches is well suited to overcome the common 'reverse design' problem. Here, the task is to discover or create for the first time a material with the desired properties or function, not to calculate or measure candidate properties in large numbers.

4.2. Assess the effectiveness of using Utilisation of Generative Artificial Intelligence

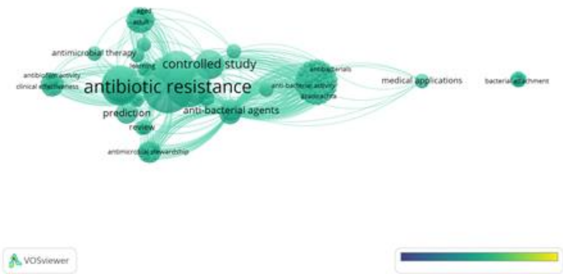


Fig. 2. Overlay Visualisation

The image displayed above is a complex overlay visualisation that integrates the concepts of "antimicrobial resistance prediction" and "cognitive acquisition" as central keywords[24]. Through this visualisation, viewers can explore data patterns and relationships derived from the VosViewer tool, which illustrates how these keywords are interconnected with various other factors and variables. This representation allows readers to understand the dynamics and correlations that exist within this specific domain of research. Researchers use overlay visualisations to depict the intricate networks between terms, enabling a deeper comprehension of the ecosystem surrounding antimicrobial resistance prediction. This visualisation provides insights into how different factors are interlinked, revealing which elements contribute to or influence the prediction of antimicrobial resistance [25]. The overlay visualisation effectively highlights the broader context, showing connections and suggesting potential pathways for further investigation or application.

The analysis also emphasises the practical implications of utilising an antimicrobial resistance prediction system, particularly in terms of its potential to increase public and government awareness. By visualising these complex relationships, researchers can offer a detailed explanation of the underlying factors that could support or hinder these systems' successful implementation in various settings, including Indonesia. The resulting benefits, particularly regarding public health policy and governmental response, underscore the importance of such predictive systems in combating the growing challenge of antimicrobial resistance.

4.3 Identify community challenges for integrating the prediction

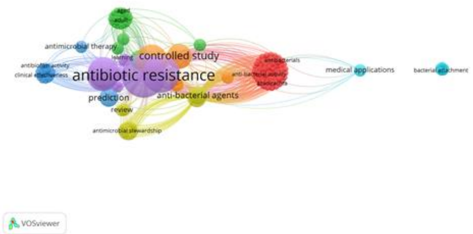


Fig. 3. Network Visualisation

This image is a network visualisation using the keywords "antimicrobial resistance prediction and treatment development." With this visualisation, researchers can find main points that represent determining factors or significant influences on stunting, as well as see interrelated groups that indicate risk factors that are related to each other [26]. The challenges faced by the community in implementing antimicrobial resistance prediction services and treatment development can be seen from the limited internet network coverage, especially in remote areas of Indonesia. Apart from that, many people with low economic levels do not have smartphones, and there are also some people who do not understand how to use smartphones, especially the elderly.

5. Conclusion

This study demonstrates the potential of machine learning to revolutionise stunting prediction and, by extension, maternal and child healthcare services. By leveraging advanced algorithms such as XGBoost and Random Forest, we successfully predicted the risk of stunting with high accuracy, reaching 90.2% with the XGBoost model. This level of precision offers a significant improvement over traditional methods and underscores the capability of machine learning to handle complex, multifactorial health issues like stunting. The findings show that critical maternal factors, including pre-pregnancy BMI, maternal education, and household income, play a pivotal role in determining the likelihood of stunting. This insight is particularly important for pre-matrical and pre-conceptive midwifery services, as it highlights the need for healthcare professionals to focus on these determinants early in the reproductive health journey. By identifying at-risk women before pregnancy or even before marriage, midwives can implement preventive measures, such as improving maternal nutrition, promoting health education, and addressing socioeconomic disparities that contribute to poor child growth outcomes.

Pre-matrical and pre-conceptive interventions, grounded in machine learning predictions, offer the opportunity for more targeted and personalised care. For example, women identified as being at high risk for giving birth to stunted children due to low BMI or insufficient nutritional intake could receive tailored dietary advice and support. Similarly, women from lower-income households could be guided towards financial and educational resources that would improve both maternal health and child outcomes. Thus, this approach not only enhances the predictive accuracy of stunting risks but also helps in shaping comprehensive and responsive midwifery services. From a public health and policy perspective, the integration of machine learning models into maternal healthcare systems holds significant promise. These tools can assist healthcare providers and policymakers in making data-driven decisions, optimising resource allocation, and implementing focused interventions. With the ability to predict stunting risk early, public health strategies can be more proactive rather than reactive. This early intervention approach could lead to a reduction in the prevalence of stunting, thereby mitigating the long-term health, cognitive, and economic impacts on children and society.

However, the study also highlights several important limitations. The dataset used was region-specific, and while the model performed well, further research is needed to validate these findings across diverse populations and regions. Cultural, environmental, and paternal factors were not included in the scope of this study, yet they may play a crucial role in stunting outcomes. Future research should aim to incorporate these variables to provide a more holistic view of the factors influencing stunting. Additionally, the practical implementation of machine learning in healthcare settings, particularly in low-resource environments, may face challenges. These include a lack of infrastructure, technical expertise, and access to comprehensive data, which could hinder the widespread adoption of these tools. Moreover, while machine learning offers robust predictive capabilities, its success hinges on the quality and quantity of data available. In regions where health data is scarce or incomplete, the accuracy of these models may be compromised. Therefore, building a reliable and standardised data collection infrastructure will be essential to ensure that machine learning can be effectively integrated into maternal and child healthcare services.

In conclusion, this research marks a significant step forward in using machine learning for predicting stunting, particularly in the context of pre-maternal and pre-conceptive midwifery services. The ability to predict stunting risk early, based on a range of maternal, nutritional, and socioeconomic factors, holds enormous potential for transforming how healthcare providers approach maternal and child health. By offering more precise, data-driven interventions, midwives and public health officials can improve the quality of care, reduce the incidence of stunting, and ultimately enhance child health outcomes. While challenges remain, particularly around data availability and model generalisation across different contexts, the promising results of this study lay a strong foundation for future exploration and application of machine learning in public health. As machine learning continues to evolve and become more accessible, its role in predictive healthcare is likely to expand, offering new avenues for preventing stunting and improving maternal and child well-being globally.

References

[1] S. Patimah, *Strategi Pencegahan Anak Stunting Sejak Remaja Putri*. Deepublish, 2021.

[2] M. De Onis and F. Branca, "Childhood stunting: a global perspective," *Matern. \& child Nutr.*, vol. 12, pp. 12–26, 2016.

[3] N. Akseer *et al.*, "Economic costs of childhood stunting to the private sector in low-and middle-income countries," *EClinicalMedicine*, vol. 45, 2022.

[4] M. S. Islam, "Risk factors associated with stunting during the first 1000 days of life in Bangladesh: Literature Review," *Dev.*, no. 6, 2019.

[5] Z. Sharifi-Heris, J. Laitala, A. Airola, A. M. Rahmani, and M. Bender, "Machine learning approach for preterm birth prediction using health records: systematic review," *JMIR Med. Informatics*, vol. 10, no. 4, p. e33875, 2022.

[6] M. Faisal, N. Nurdin, F. Fajriana, and Z. Fitri, "Information and Communication Technology Competencies Clustering For Students For Vocational High School Students Using K-Means Clustering Algorithm," *Int. J. Eng. Sci. Inf. Technol.*, vol. 2, no. 3, pp. 111–120, 2022, doi: 10.52088/ijesty.v2i3.318.

[7] Y. Yusnidar, I. Susanti, J. Jamilah, E. Effendy, and R. Romano, "Fluctuation of Patchouli Oil Price and Its Effect On Patchouli Aceh Production and Productivity," *Int. J. Eng. Sci. Inf. Technol.*, vol. 1, no. 4, pp. 90–94, Nov. 2021, doi: 10.52088/IJESTY.V1I4.179.

[8] D. Parkhi, "Machine learning based prediction of gestational diabetes mellitus and postpartum glucose intolerance," University of Warwick, 2023.

[9] S. Sapriadi, Y. Yunus, and R. W. Dari, "Prediction of the Number of Arrivals of Training Students with the Monte Carlo Method," *J. Inf. dan Teknol.*, vol. 4, pp. 1–6, 2022, doi: 10.37034/jidt.v4i1.168.

[10] M. Usman and K. Kopczewska, "Spatial and machine learning approach to model childhood stunting in Pakistan: role of socio-economic and environmental factors," *Int. J. Environ. Res. Public Health*, vol. 19, no. 17, p. 10967, 2022.

[11] H. Torlesse, A. A. Cronin, S. K. Sebayang, and R. Nandy, "Determinants of stunting in Indonesian children: evidence from a cross-sectional survey indicate a prominent role for the water, sanitation and hygiene sector in stunting reduction," *BMC Public Health*, vol. 16, no. 1, p. 669, 2016.

[12] J. C. King, "A summary of pathways or mechanisms linking preconception maternal nutrition with birth outcomes," *J. Nutr.*, vol. 146, no. 7, pp. 1437S--1444S, 2016.

[13] S. Oktarian, S. Defit, and Sumijan, "Clustering Students' Interest Determination in School Selection Using the K-Means Clustering Algorithm Method," *J. Inf. dan Teknol.*, vol. 2, pp. 68–75, 2020, doi: 10.37034/jidt.v2i3.65.

[14] R. Rescinito, M. Ratti, A. B. Payedimarri, and M. Panella, "Prediction models for intrauterine growth restriction using artificial intelligence and machine learning: a systematic review and meta-analysis," in *Healthcare*, 2023, vol. 11, no. 11, p. 1617.

[15] K. D. Tzimourta, M. G. Tsipouras, P. Angelidis, D. G. Tsalikakis, and E. Orovou, "Maternal Health Risk Detection: Advancing Midwifery with Artificial Intelligence," in *Healthcare*, 2025, vol. 13, no. 7, p. 833.

[16] S. Maulana, M. Iqhrammullah, R. Pratama, S. Tjandra, I. C. Mulya, and H. Haroen, "Bibliometric Analysis and ChatGPT-Assisted Identification of Key Strategies for Improving Primary Maternity Care Based on a Decade of Collective Research," *Int. J. Womens. Health*, pp. 53–66, 2025.

[17] M. W. Ngwenya, L. Muthelo, M. M. Rasweswe, and T. M. Mothiba, "Midwives' Perspectives on the Adoption of a Digitalized Triage System in South African Maternity Units: Results from a Mixed-Methods Study," in *Healthcare*, 2025, vol. 13, no. 9, p. 1047.

[18] A. M. Wieben *et al.*, "Nurses' perceptions of the design, implementation, and adoption of machine learning clinical decision support: A descriptive qualitative study," *J. Nurs. Scholarsh.*, vol. 57, no. 1, pp. 82–94, 2025.

[19] L. Lundberg, M. Boldt, A. Borg, and H. Grahn, "Bibliometric Mining of Research Trends in Machine Learning," *AI*, vol. 5, no. 1,

pp. 208–236, 2024.
[20] Z. Luo, J. Lv, and K. Zou, "A bibliometric analysis of artificial intelligence research in critical illness: a quantitative approach and visualization study," *Front. Med.*, vol. 12, p. 1553970, 2025.
[21] Y. Pu, Y. Peng, and R. Zhou, "Characteristics of the top 100 cited original studies on extracorporeal membrane oxygenation: a bibliometric analysis," *J. Thorac. Dis.*, vol. 16, no. 9, p. 5507, 2024.
[22] M.-E. Abdul and E. Pavoni, "Bacillus cereus in food safety: a bibliometric analysis," *Front. Microbiol.*, vol. 16, p. 1574802, 2025.
[23] T. Tian *et al.*, "Harnessing AI for advancing pathogenic microbiology: a bibliometric and topic modeling approach," *Front. Microbiol.*, vol. 15, p. 1510139, 2024.
[24] I. Sutedja, D. Edbert, R. Musawaris, and T. M. Zakaria, "Utilization of Generative Artificial Intelligence in Cognitive Acquisition in the Field of Medical Sciences: Lessons from Antimicrobial Resistance," in *International Conference for Innovation in Biomedical Engineering and Life Sciences*, 2024, pp. 245–255.
[25] P. Collignon, J. J. Beggs, T. R. Walsh, S. Gandra, and R. Laxminarayan, "Anthropological and socioeconomic factors contributing to global antimicrobial resistance: a univariate and multivariable analysis," *Lancet Planet. Heal.*, vol. 2, no. 9, pp. e398--e405, 2018.
[26] I. Sutedja, D. Edbert, R. Musawaris, and T. M. Zakaria, "Bibliometric Analysis Role of Artificial Intelligence-Based Analytics for in Silico Research in Antimicrobial Resistance Prediction and Treatment Development," *New Explor. Electr. Eng.*, vol. 1, no. 1, pp. 87–96, 2025.