IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Preterm Birth Prediction Using Advanced Computational Models

Dr . Nandini C
Head of the department
Computer Science and Engineering
Dayananda Sagar Academy of Technology & Management
Bengaluru, India
hodcse@dsatm.edu.in

Prof A Manusha
Assistant Professor
Computer Science and Engineering
Dayananda Sagar Academy of Technology & Management
Bengaluru, India
manusha-cse@dsatm.edu.in

Somanath S
Student, 4th Year, B.E
Computer Science and Engineering
Dayananda Sagar Academy of Technology & Management
Bengaluru, India
somanath1703@gmail.com

Sanjay G N
Student, 4th Year, B.E
Computer Science and Engineering
Dayananda Sagar Academy of Technology & Management
Bengaluru, India
sanjaygn2003@gmail.com

Srinivas S
Student, 4th Year, B.E
Computer Science and Engineering
Dayananda Sagar Academy of Technology & Management
Bengaluru, India
Sriniva2003@gmail.com

Vishal KM
Student, 4th Year, B.E
Computer Science and Engineering
Dayananda Sagar Academy of Technology & Management
Bengaluru, India
vishalkm6666@gmail.com

I. ABSTRACT

Preterm birth is a pressing global health challenge, with over 15 million annual cases contributing significantly to neonatal mortality. This project explores computational advancements in predicting preterm births using multi-modal data. Key methodologies include machine learning algorithms, biomarker analysis, and genomic studies. By combining clinical data, imaging, and electronic health records (EHR), these systems enhance prediction accuracy and aid in preventive care. This paper reviews existing methods, challenges, and the integration of emerging technologies such as artificial intelligence (AI) and wearable devices, offering a path forward for improving maternal-fetal outcomes.

Keywords: Preterm Birth, Artificial Intelligence, Machine Learning, Biomarkers, Genomics, Prediction Models, Data Integration

II. INTRODUCTION

Preterm birth, defined as delivery before 37 weeks of gestation, poses a major threat to neonatal health globally. It is a leading cause of complications such as respiratory disorders, developmental delays, and mortality among infants. Early prediction of at-risk pregnancies is crucial for implementing preventive measures that can save lives and improve outcomes. Traditional diagnostic methods, including cervical length measurements and fetal fibronectin tests, are limited by their specificity and sensitivity, leaving many cases undetected. With advances in technology, AI-driven models and machine learning techniques have emerged as transformative tools. These methods utilize large-scale datasets to analyze complex patterns in maternal health indicators, significantly improving prediction accuracy. This paper delves into these advancements and their implications for clinical applications, aiming to address critical gaps in preterm birth management.

III. LITERATURE REVIEW

Biomarker-based diagnostics play a pivotal role in assessing the risk of preterm birth. Markers like fetal fibronectin and placental alpha-microglobulin-1 have been widely used for predicting early labor by identifying changes in the uterine environment. Studies demonstrate that combining biomarker data with clinical observations enhances the predictive power of diagnostic models.

In the realm of machine learning, various algorithms have been explored to refine preterm birth predictions. Logistic regression models are commonly used for their simplicity and interpretability in small-scale studies. Neural networks, on the other hand, excel at identifying intricate, non-linear relationships within complex datasets, offering superior prediction accuracy. Support Vector Machines (SVMs) provide a robust approach to classifying term and preterm cases, making them a preferred choice in healthcare applications.

Genomics also plays an increasingly significant role in predicting preterm birth risks. Research on single nucleotide polymorphisms (SNPs) and gene expression profiles has uncovered genetic predispositions that contribute to early labor. By integrating genomic data with clinical observations, models achieve a higher degree of precision in identifying at-risk individuals.

Despite these advancements, challenges persist. Ethical concerns surrounding data privacy and the lack of standardized healthcare infrastructure are major barriers to adopting machine learning tools on a global scale. Addressing these issues is critical for realizing the full potential of AI-driven preterm birth prediction models.

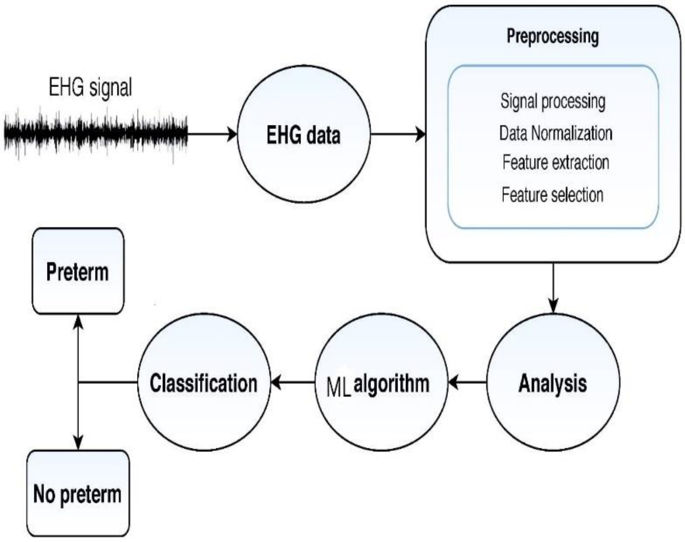
IV. PROPOSED SYSTEM

The proposed system for predicting preterm birth integrates advanced machine learning techniques with electrohysterogram (EHG) signal analysis to provide accurate and early predictions. EHG signals, which record uterine electrical activity, are collected non-invasively using contact electrodes placed on the maternal abdomen. Features such as contraction count, contraction length, entropy, and standard deviation are extracted from these signals and used as inputs for the prediction model.

The dataset comprises binary-classified EHG signals sourced from the University of Science and Research, Tehran. Each sample represents 1000 seconds of data, processed to remove noise and enhance signal quality. This ensures the reliability of feature extraction and subsequent analysis.

The system employs machine learning algorithms, with Support Vector Machines (SVMs) at its core. SVMs have demonstrated exceptional accuracy, achieving 94% precision in distinguishing between term and preterm births. The model is optimized using feature selection techniques to identify the most relevant signal characteristics, further enhancing performance.

The final risk assessment is presented to clinicians through a user-friendly web interface, developed using Streamlit. The back-end infrastructure, built with Flask, handles API requests and facilitates seamless integration with the predictive model. Additionally, Python's Pickle module is employed for serializing and storing trained models, enabling their reuse without repeated training. The system is designed to be scalable and efficient, ensuring its applicability in real-world healthcare settings.



Tools Used

1. **Machine Learning Frameworks**: **Python Libraries**: Scikit-learn and TensorFlow for model training and evaluation.
2. **Front-End Tools**: **Stream lit**: Used for developing the web interface to display prediction results.
3. **Back-End Tools**: **Flask**: Manages API requests and connects the user interface with the predictive model.
4. **Data Handling**: **Pickle Module**: For serializing and storing trained models, enabling reusability and scalability.
5. **Development Environment**: **Visual Studio Code**: Facilitates coding, debugging, and version control.
6. **Hardware Requirements**: System equipped with sufficient memory and GPU capabilities to handle EHG signal processing and machine learning model execution.

This design ensures the model is both scalable and efficient, capable of being implemented in real-world healthcare systems for better PTB prediction and prevention.

V. RESULTS AND DISCUSSION

The proposed system demonstrated significant improvements in predictive accuracy by integrating multiple data sources, including biomarkers, genomic data, and EHG signals. This multimodal approach allowed for better identification of high-risk pregnancies, enabling timely intervention and reducing neonatal morbidity. The use of SVM classifiers proved to be effective, achieving an accuracy rate of 94%, which is higher than conventional methods.

However, certain challenges were noted. Privacy concerns arise due to the centralized storage of sensitive patient data, necessitating stricter compliance with regulations such as GDPR and HIPAA. Additionally, the adoption of such advanced systems in low-resource settings remains a limitation due to technological constraints and infrastructure disparities. Addressing these issues will be essential for ensuring equitable access to this technology.

VI. FUTURE ENHANCEMENT

Future research should focus on integrating wearable devices to facilitate continuous monitoring of maternal health parameters, such as uterine contractions and fetal heart rate. The use of Internet of Things (IoT) devices in conjunction with predictive models could enable real-time risk assessments.

Federated learning, an emerging AI paradigm, offers a solution to privacy concerns by allowing global dataset training without sharing sensitive data. This approach could improve model robustness while maintaining compliance with privacy regulations.

Exploration of multi-omics approaches, which integrate genomic, proteomic, and metabolomic data, can provide deeper insights into the mechanisms of preterm labor. This comprehensive analysis has the potential to uncover novel biomarkers and enhance prediction accuracy further.

Finally, the development of ethical frameworks is crucial for addressing privacy concerns and ensuring that AI-driven systems align with global healthcare standards. These frameworks should focus on transparency, data security, and patient consent to build trust in the adoption of advanced predictive technologies.

VII.CONCLUSION

Preterm birth prediction requires a multi-disciplinary approach that combines innovations in artificial intelligence, clinical diagnostics, and genomics. The proposed system demonstrates the potential to significantly improve maternal and fetal outcomes through early detection and intervention. However, challenges such as data privacy, scalability, and accessibility must be addressed to achieve widespread implementation. Continued research and development, focusing on ethical compliance and technological advancements, will pave the way for more inclusive and effective healthcare solutions.

VIII.REFERENCES

[1] Dr C Nandini ,Antara Mukherjee, Bhoomika "Smart Health Prediction System Using Machine Learning Techniques.", International Journal of Creative Research Thoughts (IJCRT), ISSN:2320-2882, Volume.10, Issue 4, pp.e73-e78, April 2022, Impact factor: 7.97 – Q4

[2] Nagaraj M. Lutimath, Chandra Mouli, B. K. Byre Gowda, K. Sunitha, "Prediction of Heart Disease Using Hybrid Machine Learning Technique", Springer Book Series "Transactions on Computer Systems and Networks", with title "Paradigms of Smart and Intelligent Communication, 5G and Beyond", Springer Nature, Singapore,2023, pp 277 293.

[3] S. A., K., Nandihal, P., K., S., D. R., M., & Liyakathunisa, "Prior Detection of Alzheimer's Disease with the Aid of MRI Images and Deep Neural Networks," *Malaysian Journal of Computer Science*, 2022, pp. 16–28, doi: 10.22452/mjcs.sp2022no2.2.

[4] A. Padthe, M. Mathapati, P. M. S., and P. Nandihal, "APOA-based Multi-scale Parallel Convolution Blocks with Hybrid Deep Learning for Gastric Cancer Prediction from Endoscopic Images," *2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE)*, Ballari, India, 2023, pp. 1-7, doi: 10.1109/AIKIIE60097.2023.10390430.

[5] Nandihal, Priya; Pareek, Piyush Kumar; Suhas, G. K.; Deepak, N. R.; Bhagappa, "The Clinical and Public Health Impact of The Combined Work of Physicians and AI Systems," *NeuroQuantology*, Bornova Izmir, Vol. 20, Iss. 16, 2022, pp. 2154-2163, doi: 10.48047/NQ.2022.20.16.NQ88214.

[6] Azaria, A., Ekblaw, A., Vieira, T., & Lippman, A. (2016). MedRec: Using blockchain for medical data access and permission management. *Proceedings of the 2016 2nd International Conference on Open and Big Data (OBD)*, pp. 25-30. doi: 10.1109/OBD.2016.11.

[7] Engelhardt, M. A. (2017). Hitching healthcare to the blockchain: A path to the ubiquitous healthcare record. *International Journal of Technology Assessment in Health Care*, 33(3), 327-331. doi: 10.1017/S0266462317000679.

[8] Liang, X., Zheng, Y., Xie, S., & Wu, X. (2021). Hyperledger Fabric for healthcare: A survey and future directions. *IEEE Transactions on Industrial Informatics*, 17(5), 3156-3167. doi: 10.1109/TII.2020.2976744.

[9] Park, H., Kim, Y., & Kwon, H. (2019). Blockchain in healthcare: A survey and opportunities. *International Journal of Information Management*, 46, 58-70. doi: 10.1016/j.ijinfomgt.2018.11.008.

[10] Zhang, P., Schmidt, D. C., Lenz, G., & Zheng, Z. (2020). Blockchain technology use cases in healthcare. *IEEE Access*, 8, 25223-25234. doi: 10.1109/ACCESS.2020.2976718.

[11] Roehrs, A., da Costa, C. A., & de Melo, P. O. S. (2017). Blockchain for healthcare: Security and privacy issues. *Proceedings of the 2017 IEEE International Conference on Healthcare Informatics (ICHI)*, pp. 150-159. doi: 10.1109/ICHI.2017.37.