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REAL-TIME MATERNAL AND FETAL CONDITION PREDICTION USING IOT AND OPTIMIZED CONVOLUTIONAL NETWORK

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ABSTRACT

The convergence of Internet of Things (IoT) technologies and Artificial Intelligence (AI) is reshaping modern healthcare by enabling continuous, intelligent, and automated diagnostic systems. In this study, an advanced monitoring framework is introduced to support maternal and fetal health, particularly in high-risk pregnancies. The system combines IoT-enabled sensors with deep learning techniques to ensure real-time data collection and analysis.

Various physiological parameters of the mother, such as body temperature, blood pressure, oxygen saturation, and heart rate, along with fetal heart rate, are continuously captured through interconnected sensors. These sensors are integrated using MICOT hardware (NodeMCU with MCP3008) and transmit the collected data to a cloud-based platform for storage, monitoring, and predictive analysis.

To enhance the accuracy of identifying potential complications, the study proposes an optimized one-dimensional Convolutional Neural Network (1D-CNN) model. This model is specifically designed to classify and predict critical maternal and fetal conditions more effectively than traditional approaches.

A dataset comprising approximately 9,000 records was used to validate the system. The proposed model's performance was compared against several established machine learning algorithms, including K-Nearest Neighbors (KNN), Random Forest (RF), Support Vector Machines (SVM), standard Convolutional Neural Networks (CNN), and Extreme Learning Machines (ELM). Evaluation metrics such as accuracy, precision, recall, sensitivity, and F1-score were used to assess performance.

The results demonstrate that the proposed model consistently achieves superior outcomes across all evaluation parameters. These findings suggest that the developed IoT and AI-based system offers a reliable, efficient, and scalable solution for real-time maternal and fetal health monitoring.

Keywords: Health Monitoring, Women Healthcare, Fatal Health

1. INTRODUCTION

Maternity care plays a crucial role in safeguarding the health and overall well-being of both mothers and their unborn children. The condition of a mother during pregnancy has a direct and lasting influence on the baby's health, not only at birth but also later in life. In addition, complications such as high blood pressure and gestational diabetes during pregnancy can increase the mother's risk of developing health issues in the future[1].

Ensuring proper maternal care is therefore essential, not only to avoid immediate pregnancy-related complications but also to support the long-term health of the population. Globally, a significant proportion of deaths among children under the age of five occur during the

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neonatal period. The leading causes include complications from premature birth, issues during labor and delivery, and infections such as sepsis and meningitis.

In countries like Pakistan, neonatal mortality remains a serious concern, with reported rates among the highest worldwide[2]. This highlights the urgent need for improved prenatal care and monitoring systems. Regular antenatal visits are vital for early detection of potential complications, helping to reduce the risks of injury, severe health issues, or even loss of life[3-5].

In recent years, Artificial Intelligence (AI) has emerged as a powerful tool in healthcare. By analyzing multiple physiological parameters using advanced mathematical models, AI can assist in early diagnosis and decision-making, ultimately improving maternal and fetal outcomes[6].

Advanced computational models have increasingly been applied to improve the accuracy and reliability of medical diagnostics. They have shown strong performance in analyzing radiological data such as CT scans and MRI images, as well as in predicting outcomes like cancer recurrence, mortality rates, and cardiovascular risk.

In parallel, researchers from both clinical and engineering domains have been working toward automating the interpretation of Cardiotocography (CTG) data. This effort aims to reduce variability and subjectivity in clinical assessments, leading to more consistent and dependable results.

Traditionally, pregnancy monitoring has relied on key clinical indicators such as blood pressure, blood glucose levels, urine analysis, uterine growth, and maternal weight gain. While these parameters remain essential, comprehensive maternity care also involves guidance on lifestyle factors like physical activity, rest, and self-care practices. Unfortunately, these aspects are not consistently tracked or evaluated in a structured manner.

This gap highlights the need for continuous and systematic monitoring of pregnant women's health. Ongoing assessment can help identify potential complications at an early stage, enabling timely intervention and ultimately improving both maternal and fetal health outcomes[7-10].

Continuous tracking of multiple health parameters enables the collection of detailed and precise data, which can significantly enhance our understanding of pregnancy and its progression. Recent advancements in Information and Communication Technology (ICT) have played a key role in improving the quality and accessibility of healthcare services[11].

One such advancement is the Internet of Things (IoT), an emerging ICT paradigm that integrates sensing devices, communication networks, and computing systems. This interconnected framework allows real-time data collection and remote access, making it possible to monitor health conditions anytime and from virtually any location[12].

The evolution of IoT technologies has been further strengthened by the incorporation of Artificial Intelligence (AI), enabling the development of smarter and more efficient diagnostic systems. A variety of machine learning techniques—such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN)—have been explored for use in IoT-based maternal and fetal health monitoring.

Despite these advancements, existing systems still face challenges related to high costs, operational complexity, and the risk of inaccurate predictions. To address these limitations, this study introduces a new framework. This approach integrates IoT devices for real-time clinical data collection with an optimized CNN-based prediction model. The system is designed to automatically detect potential health risks affecting both the mother and the fetus.

The key contribution of the proposed framework lies in its ability to provide a unified and intelligent solution that enhances prediction accuracy while aiming to reduce complexity and improve overall system efficiency.

a. Integration of multiple IoT-based medical sensors with Artificial Intelligence to enable continuous monitoring of both maternal and fetal health.

b. Development of a cloud-supported, optimized deep learning model capable of analyzing diverse physiological parameters and accurately classifying or predicting the health condition of the mother and fetus.

c. Implementation of a real-time data analytics system combined with a cloud-enabled alert mechanism to provide timely notifications during critical situations.

2. LITERATURE REVIEW

In a study by Zhao et al. [13], fetal heart rate classification was investigated using several supervised machine learning approaches, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and Extreme Learning Machines (ELM). These models were developed to analyze and categorize fetal heart rate patterns based on features extracted from routinely monitored maternal health parameters. The researchers utilized the publicly available "Sis Porto" dataset for both training and testing the models. Their results showed that the ANN model achieved the highest accuracy in classifying fetal heart rate signals, particularly when evaluated using synthetically generated data.

F. Sarhaddi et al. [14] proposed an automated approach for detecting prenatal hypoxia by analyzing fetal heart rate (FHR) signals during labor. Their method follows a three-stage process in which fetal signals are first segmented into time-series frames and then analyzed using normalized compression distance as a classification measure. The system continuously monitors fetal heart activity and compares it with standard heart rate patterns to identify signs of hypoxia. To perform classification, two machine learning models—K-Nearest Neighbors (KNN) and Support Vector Machines (SVM)—were implemented as fetal movement detectors, achieving an accuracy of around 88% on a dataset of approximately 1,000 subjects. However, the approach has limitations, including reduced effectiveness when applied to larger datasets and increased processing time, which leads to delays in prediction.

M. Ahmed et al. [15] proposed an unsupervised learning approach for Electronic Fetal Monitoring (EFM) aimed at identifying fetal hypoxia through the analysis of fetal heart rate (FHR) signals. In their method, one-dimensional preprocessed FHR signals were converted into two-dimensional representations using recurrence plots, allowing the model to capture complex nonlinear patterns effectively. Various recurrence plot parameters were adjusted to enhance the quality and diversity of the generated image dataset, which was subsequently used to train a Convolutional Neural Network (CNN). Although the approach demonstrated promising capabilities, it is limited by its high computational demands and longer training time when compared to other existing classification techniques.

A. Baccouche et al. [16] developed an IoT-based system to monitor maternal health, tracking factors like stress, sleep, and activity using energy-efficient wearable devices.

A. Matonia et al. [17] proposed a real-time maternal and fetal monitoring approach using supervised learning models trained on a newly created dataset transmitted via IoT.

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Their dataset included features such as maternal age, heart rate, and fetal heartbeat but requires further validation with unsupervised methods.

Z. Hoodbhoy et al. [18] introduced a deep learning model combining BiLSTM and BiGRU for detecting heart abnormalities as a binary classification problem.

X. P. Burgos-Artizzu et al. [19] applied PCA and ICA techniques to extract key features from maternal heart rate data to analyze fetal position and labor conditions.

R. Beri et al. [20], conducted a study focusing on evaluating the performance of various AI-based methods in analyzing cardiotocography (CTG) data to identify high-risk fetal conditions. The dataset, consisting of records from 2,126 pregnant women, was sourced from the University of California Irvine Machine Learning Repository. In this work, ten different machine learning classification models were trained using the CTG data. The models were assessed based on key performance metrics such as sensitivity, precision, F1-score for each category, and overall accuracy, with the aim of classifying fetal states as normal, suspicious, or pathological.

B. Priyanka et al. [21] examined the readiness of modern deep learning classification methods for practical use in maternal–fetal clinical environments. Their study utilized a large dataset of routine ultrasound images collected from two different clinics using multiple operators and machines, with all images carefully annotated by an expert clinician. The dataset was categorized into six groups, including key fetal anatomical views such as the abdomen, brain, femur, thorax, the maternal cervix, and a miscellaneous category for less common cases. In another study, Ali Akbar Movassagh et al. [22] focused on enhancing the accuracy of a perceptron neural network by incorporating meta-heuristic optimization techniques, which reduced prediction error but increased training time. Omar A. Alzubi et al. [23] introduced a secure framework combining blockchain and artificial intelligence for reliable medical data transmission in IoT systems, using signcryption to ensure data security and privacy, though at the cost of higher computational complexity. Similarly, Jafar A. Alzubi et al. proposed a blockchain-based approach utilizing Lamport Merkle Digital Signatures to secure medical IoT devices, successfully reducing computational overhead but facing challenges with delay. In a related work, they also developed a privacy-preserving medical data transmission and classification model using deep learning and multi-key homomorphic encryption optimized through sailfish optimization, achieving improved accuracy and efficiency, albeit with increased computational demands.

3. PROPOSED ARCHITECTURE

The proposed framework, illustrated in Fig. 1, describes the overall flow of data through the system. Initially, IoT-based sensor nodes collect physiological information from both the mother and the fetus. This data is then transmitted to a cloud platform, where it is stored and prepared for further processing. After preprocessing, the refined data is fed into an optimized one-dimensional Convolutional Neural Network (1D-CNN), which analyzes the inputs to identify and classify potential emergency conditions. Based on the classification results, the system triggers alerts when necessary. Finally, a detailed medical report is generated and shared with healthcare professionals to support timely decision-making and appropriate intervention.

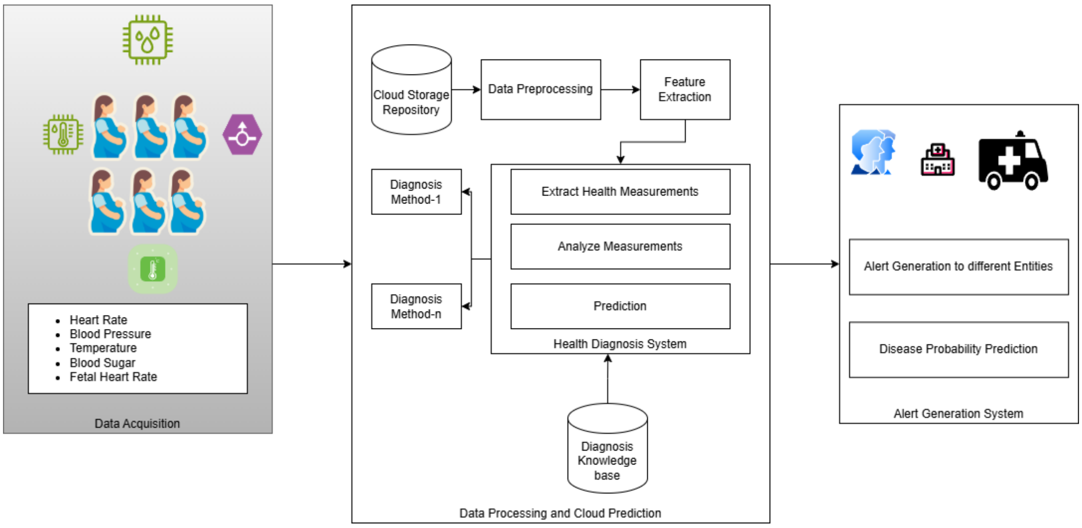

Figure 1: Proposed Architecture

3.1 Data Acquisition Layer

This layer consists of a network of clinical sensors connected to battery-powered MICOT boards, which combine NodeMCU and MCP3008 modules for efficient data acquisition. The system includes sensors such as accelerometers, respiration monitors, temperature sensors, maternal and fetal heart rate sensors, and pulse oximeters. These devices continuously capture key maternal parameters—such as heart rate, body temperature, blood pressure, blood glucose levels, and oxygen saturation—along with fetal heart rate. The collected data is then transmitted to the cloud through ESP8266-based Wi-Fi modules for further processing and analysis.

Fetal heart rate (FHR) is the primary indicator used to assess fetal well-being. It is measured using a Doppler ultrasound sensor, which captures data at a sampling rate of 4 Hz. This sensor is connected to MICOT boards for continuous monitoring, and the collected data is transmitted to the cloud for storage and further analysis

3.2 Data Processing and Cloud Prediction

The second component of the proposed system focuses on data analysis, specifically for extracting features related to both maternal and fetal health. Signal processing techniques are applied to ensure the quality and reliability of fetal heart rate (FHR) data as well as maternal parameters. Since accurate interpretation requires a sufficient observation window, the system initially analyzes the first 15 minutes of collected data and then updates the results at regular intervals of two minutes on the cloud platform. Based on medical expert guidelines, the processed data is categorized into eight distinct classes to support diagnostic prediction for maternal and fetal conditions. The proposed system adopts a hybrid approach by combining Convolutional Neural Networks with optimization techniques to enhance prediction performance. In this framework, the model's hyperparameters are fine-tuned using the Whale Optimization Algorithm (WOA), which helps improve efficiency and accuracy. This integrated model, referred to as Hybrid WOCN (Whale Optimized Convolutional Network), is specifically designed to minimize overfitting and improve the model's ability to generalize across different data samples.

4. RESULTS AND DISCUSSION

This section outlines the details of the dataset used to evaluate the proposed framework. It presents the experimental findings and analyzes the system's performance across different

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evaluation parameters. Finally, the results of the proposed prediction model are discussed and compared with those of existing classification approaches to highlight its effectiveness.

The study involved monitoring 101 patients using the smart monitoring system over an average duration of 10 hours. Data collection was conducted over a period of 30 days, with an extended sampling window of 150 days used for testing purposes. Among the participants, 54 were in the antepartum stage and 57 were in the intrapartum stage. All data was gathered at Sri Venkateshwara Hospital, Puducherry, Government of India, resulting in a dataset of approximately 9,000 records for evaluating the proposed system. The IoT sensor operations were programmed using Embedded C, while the learning algorithms were developed in Python.

The proposed architecture incorporates four convolutional layers to improve classification performance and reduce errors. The hyperparameters of these layers are fine-tuned using the Whale Optimization Algorithm to enhance model efficiency. To address class imbalance, randomized data sampling was applied during training. The system's performance was assessed using standard evaluation metrics, including accuracy, sensitivity, specificity, recall, and F1-score, with their corresponding mathematical formulations provided for analysis.

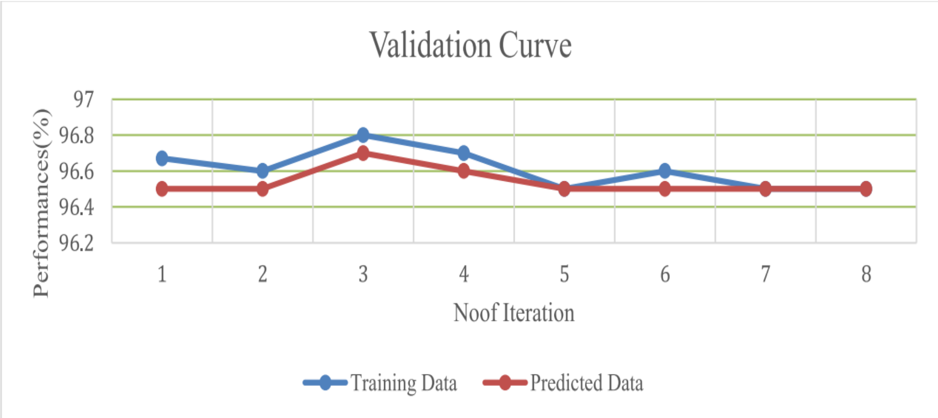

Figure 6: Validation performance for the proposed architecture in predicting the average values

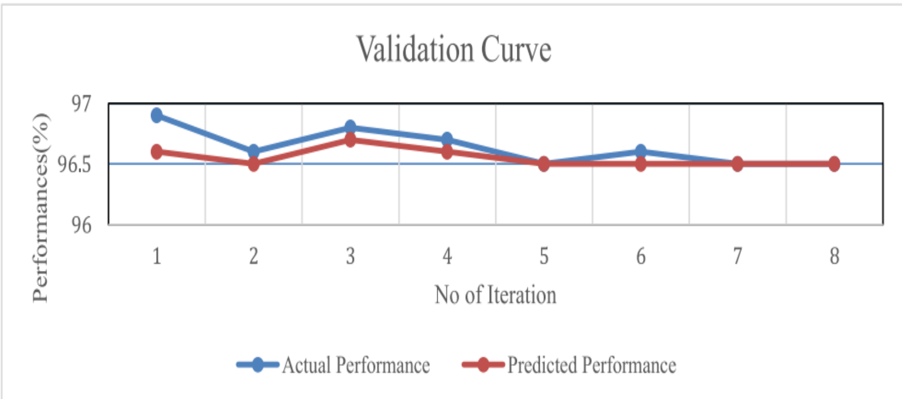

Figure 7: Validation performance for the proposed architecture in predicting the abnormal value

Figures 6 and 7 present the validation curves, which demonstrate the model's capability to deliver consistent and accurate predictions for both normal and abnormal cases.

The effectiveness of the proposed approach was evaluated by comparing it with several existing machine learning models, including Convolutional Neural Networks (CNN), Extreme Learning Machines (ELM), Support Vector Machines (SVM), Random Forest, K-Nearest Neighbors (KNN), and Naïve Bayes. The performance of these models in predicting maternal and fetal conditions.

Across all evaluation scenarios, the proposed method consistently achieved the highest results, with an accuracy of 96.5%, precision of 96%, recall of 96%, F1-score of 96.5%, and specificity of 96.2% in classifying normal and abnormal conditions. Although the one-dimensional CNN (1D-CNN) also demonstrated strong performance, it remained slightly below the proposed model. In contrast, Naïve Bayes and KNN showed comparatively lower effectiveness in prediction tasks. Overall, the findings confirm that the proposed algorithm outperforms other existing models in accurately identifying different maternal and fetal health conditions.

CONCLUSION

This study introduces a hybrid framework for continuous risk monitoring of maternal and fetal health by integrating IoT-based sensors with cloud-driven artificial intelligence techniques. To improve prediction accuracy, a novel Whale Optimization-based one-dimensional Convolutional Neural Network (WOA-1D CNN) is proposed. Approximately 9,000 real-time data samples were collected, and extensive experiments were conducted using multiple classification models. The results demonstrate that the proposed approach delivers strong performance in identifying various maternal and fetal health conditions, making it a reliable solution for cloud-based diagnostic systems. Clinical experts have also found the system practical and effective for real-time monitoring and decision support.

For future work, wider deployment of the system in real healthcare environments could provide deeper insights and validation. Additionally, aspects such as data security, privacy protection, and system robustness need further attention. Exploring alternative AI techniques for the classification module may also help enhance overall system performance.

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