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Exploring Multimodal Machine Learning Approaches For Preterm Birth Forecasting With Neural Networks

Dr. R. Aruna[1], S. Sivaranjani[*1,2]

[1]Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, India.
Email ID: drraruna@veltech.edu.in
[*1]Vel Tech Rangarajan Dr.Sagunthala R&D Institute of Science and Technology, Chennai, India.
[2]Pachaiyappa's College for Men, Kanchipuram, India
Email ID: vtd1176@veltech.edu.in

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ABSTRACT
Premature delivery (PMD) refers to the occurrence of childbirth before 37 weeks of gestation. It is a significant worldwide health concern that can have adverse consequences on both infants and mothers. Models, including PMD-LSTM, PMD-GRU, PMD-Vanilla RNN, and PMD-ANN, are built and trained using the pre-processed PMD data. To forecast whether delivery would be preterm or non-preterm, a sigmoid activation function is employed in the output layer, together with binary cross-entropy loss, during the training process for binary classification. The performance of the model is evaluated using measures like loss, recall, accuracy, precision, and F1-score. The proposed models exhibit robust prediction abilities, with the LSTM achieving an accuracy of 0.6666, the GRU achieving an accuracy of 0.0166, the Vanilla RNN achieving a perfect accuracy of 1.0000, and the ANN achieving an accuracy of 0.9166. The metrics of precision, loss, recall, accuracy, and F1-score provide more understanding of the models' capacity to distinguish between preterm and non-preterm cases. This study contributes to the current research on employing neural network algorithms to detect preterm births at an early stage. This has the potential to result in timely interventions and improved outcomes for both moms and newborns. By comparing many architectures of Recurrent Neural Networks (RNNs), we can identify their respective strengths and weaknesses in addressing this critical healthcare problem.

Keywords: *Infants, medical treatment, gestation, newborns, healthcare.*

1. INTRODUCTION

Artificial Intelligence (AI) is significantly changing the healthcare sector by transforming how we handle diagnoses, treatment, and patient care. AI technology integrated into healthcare systems has the potential to significantly improve efficiency, accuracy, and overall healthcare results. Machine learning algorithms, a type of artificial intelligence, can process a comprehensive collection of medical data, encompassing patient information, diagnostic images and hereditary data, to help healthcare workers make better-informed decisions. AI-driven predictive analytics help in early illness identification, creating individualized treatment regimens, and optimizing resource allocation. Despite the presence of promising advancements, the process of incorporation of AI in healthcare must carefully address ethical, privacy, and regulatory obstacles to guarantee its appropriate and fair deployment in various healthcare settings. The expanding area of AI and healthcare is expected to bring forth a new age of precision medicine and patient-centred care through their synergy. Preterm birth, defined as the birth of a baby before 37 weeks of gestation, presents substantial obstacles and hazards for women. Expectant mothers who have premature delivery may encounter emotional, physical, and financial challenges. Being delivered prematurely can cause mom anguish, anxiety, and a feeling of powerlessness, especially when dealing with possible difficulties for the infant. Mothers may face health problems such postpartum depression, infections, or difficulties from medical procedures needed to help the premature baby. Preterm delivery can also interfere with the mother's bonding process and affect her capacity to participate in immediate and essential skin-to-skin contact with her infant. Mothers who give birth prematurely have a complicated set of obstacles due to the demands of caring for their preterm new-born, which typically involves lengthy hospital stays and specialized medical attention. It is essential to consider the many components of maternal well-being when implementing comprehensive healthcare strategies to assist moms during the preterm delivery process. Preterm delivery significantly affects new-borns, exposing them to several hurdles as they move from the safe environment of the womb to the outside world. Preterm new-borns frequently have acute health issues caused by immature organs and systems, necessitating specific medical procedures to manage respiratory distress, cardiovascular instability, and other problems linked to preterm delivery. Preterm new-borns may have prolonged developmental delays, cognitive impairments, and a higher likelihood of chronic health issues in addition to their initial health challenges. During the new-born period, preterm babies face a critical balance between life-saving medical treatments and the fragility of their underdeveloped systems. Advancements in new-born care and medical technology help preterm infants grow and overcome early challenges. Preterm new-borns frequently show impressive resilience as they develop, showcasing the exceptional ability to adapt and the strength commonly seen in those born prematurely. Preterm-born individuals often enjoy successful lives due to the collaborative efforts of medical experts, caretakers, and their resilience, showcasing the victory of life over challenges. The use of deep learning algorithms has advanced the prediction of preterm delivery, a significant issue in maternal and neonatal healthcare. Utilizing sophisticated neural network structures such as PDM-LSTM, PDM-GRU, PDM-Vannila RNN, and PMD-NN shows potential for improved accuracy and timely forecasting. Deep learning systems have the capability to effectively discover complex patterns in multimodal healthcare data by integrating different patient characteristics and medical markers. LSTM and GRU are optimized for sequential data and are adept at identifying temporal relationships, making them ideal for analysing time-series data commonly seen in healthcare records. Although less intricate, a Vannila RNN nevertheless offers useful insights into sequential patterns. ANN provides a flexible structure that can manage many sorts of data. The comparative analysis of these algorithms seeks to understand the complex relationship between neural network structures, data representation, and prediction precision. This research intends to improve preterm birth risk evaluations and improve treatment for mothers and new-borns. Artificial Intelligence (AI) is transforming healthcare by improving diagnostic precision, therapeutic effectiveness, and patient well-being. Machine learning algorithms, a subset of artificial intelligence, analyse extensive medical data to make well-informed decisions. Despite notable advancements, it is vital to address ethical issues and regulatory constraints. Mothers face substantial obstacles due to preterm birth, affecting their emotional, physical, and economic well-being. Mothers and premature babies face several challenges that require thorough healthcare approaches. Popular deep learning methodologies like LSTM, GRU, Vannila RNN, and NN Possess the capacity to predict preterm birth with enhanced precision. The objective of this research is to improve risk evaluations and improve the quality of treatment for moms and babies. Provide an in-depth introduction on preterm birth, then transition to conducting a more detailed research review on the topic.

2. LITERATURE SURVEY

Margie A. Ream1 & Lenora Lehwald (2018, June) discuss [1] new research on alterations in brain development due to preterm and how it affects neurodevelopmental problems. New Discoveries Recent discoveries have been facilitated by advanced imaging methods, long-term monitoring of patients born extremely preterm into adulthood, and enhanced knowledge of risk factors linked to neurologic disability. Sensory abnormalities are frequently linked to subsequent cognitive and social impairments and are hence ideal locations for therapeutic intervention. Preterm birth can impact many facets of neurological development. Further study is needed to clarify goals for therapies before and after birth to preserve the nervous system and enhance outcomes for premature babies. Although the survival rate of new-borns is rising, a considerable number of survivors face permanent neurodevelopmental challenges. Research is being conducted to research the reasons for altered brain development, and to improve methods to prevent and alleviate long-term handicaps. Ejay Nsugbe and colleagues (2022, November) provide [2] data on foetal heart rate (FHR) and maternal heart rate (MHR) for all subjects, together with EHG recordings to assess uterine contractions. Utilize deep wavelet scattering (DWS) for analysing physiological data and processing related signals. This study utilized an unsupervised decomposition and feature extraction technique that integrates deep learning convolutions and the classical wavelet transform to detect active preterm labour from physiological signals. The accuracy compared the efficacy of this technique with the metaheuristic linear series decomposition learner (LSDL). More AI techniques are evaluated using the collected physiological data to determine the optimal model architecture for this particular dataset. Additionally, develop a completely automated system for forecasting preterm deliveries using collected physiological data. Rawan AlSaad, et al., (2022, February) provide [3] a clinical prediction model called forecast PTB. This model utilises Clinical data extracted from EHR to forecast the likelihood of premature delivery reliably at several time points before delivery: 1, 3, 6, and 9 months. PredictPTB's architecture utilizes RNNs to analyse a patient's EHR visits over time. It incorporates a single code-level utilizing an attention mechanism to improve prediction performance accuracy and offers explanations at both code-level and visit-level for the predictions. The model also evaluates various combinations of prediction time points, data modalities, and data windows to assess performance. Using a substantial dataset of 222,436 deliveries and 27,100 distinct clinical concepts, our algorithm successfully forecasted premature birth. Hisham Allahem, et al., (2022) propose [04] employing neural network models to detect and forecast labour to reduce the negative impacts of preterm delivery on pregnant women and foetuses. The result of the investigation conveys that the deep learning method attained the highest accuracy rate of 0.98. It alerts the pregnant lady by tracking uterine EHG contractions. 7271 datasets of uterine EHG contractions were collected from the PhysioBank repository for assessment purposes framework's accuracy and dependability. Abin Abraham, et al., (2022, September) highlight [05] the ability to function by utilizing the data from EHRs for scalable and cost-effective risk modelling of various illnesses. However, EHR Functionality was not fully used in research. Machine learning was used on a dataset of 35,282 deliveries from electronic health records to forecast singleton preterm births with gestational ages. The model achieved an ROC-AUC of 0.75 and a PR-AUC of 0.40 at 28 weeks, surpassing other models trained on established risk factors which achieved an ROC-AUC of 0.65 and a PR-AUC of 0.25 same gestational age. The machine learning method may predict different forms of premature labour (spontaneous vs. indicated), mode of delivery, and recurring preterm birth. Additional research is required before using these models in clinical settings. Rakesh Raja and colleagues (2021, June) introduced [06] an AI approach called a risk prediction conceptual model (RPCM) designed to forecast PTB. This study introduces a feature selection approach that depends on the concept of entropy. A unique method is employed to identify the most significant maternal characteristics related to preterm birth in the obstetrical dataset, to achieve the maximum possible accuracy in predicting the classifier's performance. The e-paper primarily focuses on reviewing PTB cases, a topic often overlooked in many developing nations, including India. Obtain obstetrical data from the Community Health Centres in rural regions of Kamdara, Jharkhand. Employing three distinct models DT, SVM, and LR for PTB prediction. The model performance is evaluated based on accuracy, specificity, and sensitivity. The SVM model achieved an accuracy of 90.9%, surpassing the accuracy of other learning classifiers utilized in this investigation. The small dimensions of the risk variables for PTB and the dataset hamper the current research. Increasing the dataset size might enhance the quality of PTB prediction in future studies. In 2021, Tomasz Włodarczyk and colleagues explored [07] the application of multiple devices learning methodology for predicting premature birth. This survey benefits from the broad range of data types it examines. They can also create a potent and unbiased instrument for evaluating labour and implementing early intervention. Yan Li and colleagues (2022, September) introduced [08] a preterm birth prediction algorithm designed for easy and practical use in clinical settings. Such research information was received from the NVSS database for the years 2018 to 2019.LR analysis was used to identify variables linked to premature birth. Effect measurements were represented by the odds ratio (OR) and 95% confidence interval (CI). Model assessment criteria including ROC-AUC, accuracy, sensitivity, and specificity were used. Data from 3,006,989 pregnant women in 2019 and 3,039,922 pregnant women in 2018 were used to build the model and external validation, respectively. Out of 3,006,989 pregnant women, 324,700 (10.8%) experienced a premature delivery. The nomogram accurately predicts the probability of preterm delivery in pregnant women using easily accessible clinical indicators, offering a straightforward tool for preterm birth prediction. Kwang-Sig Lee and colleagues (2020, September) discuss [09] the current state and future potential of utilizing artificial intelligence to predict spontaneous premature labour and birth, often known as preterm birth. Multiple methodologies were used for different kinds of data. Enhancing data through a longitudinal design is anticipated to significantly enhance the efficiency of artificial intelligence. Extending these investigations to huge data would be an excellent subject for future study. Binary classifications (no, yes) are often used to classify preterm birth, however, they can be further refined. Elena Diaz and colleagues (2021, January) propose including [10] other parameters associated with maternal circadian disturbance to determine if their collective impact might enhance the prevention of premature delivery. The methods used to achieve this aim are grounded in the methodology of machine learning. Information collected from 380 births was categorized as either preterm or term. Variables connected to maternal behaviours, nocturnal exposure to light, or sleep length during gestation define each individual. Maternal factors relating to gestation and foetal features were also collected. An in-depth analysis utilizing machine learning reveals intriguing and less apparent connections between parameters associated with night-time light exposure and sleep patterns. The DT model shows that the amount of light entering through the window and the brightness level of the bedroom at night are crucial reasons for predicting premature birth. Ashwanthika. U, et al, (2020, September) propose [11] alerting pregnant women at the onset of labour contractions by utilizing uterine EMG or EHG. The setup comprises AgC12 electrodes positioned both above and below the navel. SVM and GB models produced better accuracy rates than KNN, NB, and DT. Deep learning models can be utilized in the future to enhance accuracy rates. Yi Sun and colleagues (2020, June) aim to investigate [12] the connections between the environment of living and preterm birth (PTB), pinpoint vulnerable periods, and investigate possible interplays between green spaces and air pollution. All births in California from 2001 to 2008 were acquired from their birth certificate. The NDVI was utilized to assess green space exposure. Gestational age was considered a time-to-event outcome. The research model was used to consider the connection between the environment of living and preterm birth (PTB), moderately preterm birth (MPTB - gestational age < 35 weeks), and very preterm birth (VPTB - gestational age < 30 weeks with multiple attributes. Additional interdisciplinary research is required to investigate this correlation in different environments and comprehensively analyse how the intricate interplay of a pregnant woman's bio-psychosocial and environmental factors impacts preterm birth. In December 2019, Muhammad Umar Khan and colleagues [13] introduced a Processing of signals method to forecast Preterm birth by analysing raw EHG signals with a very low period of 1 minute. Only four specific characteristics retrieved from segmented EHG data, including Shannon Energy, Log Energy, Median Frequency, and Lyapunov Exponent, are inputted into the SVM model. The algorithm attains a 95.5% accuracy rate to the Term-Preterm Database that is publically accessible. An accurate method will assist medical practitioners in making appropriate treatment selections. Therefore, women consistently experience minimal or no difficulties from premature labour. In the future, we will maintain our own EHG database including vast amounts of data to train classifiers more effectively. Zeynep Asli Oskovi Kaplan and A. Seval Ozgu-Erdinc (2018, October) discuss [14] the improvement of bedside tests for identifying indicators such as FFN, IGFBP-1, interleukin-6, and placental alpha-macroglobulin-1. The model advised to investigate the maternal history, health status, and sociodemographic variables. Additional ultrasound indicators including uterocervical tilt and placental strain ratio are being researched and also include cervical length measures. Studies on metabolomics, proteomics, and microRNA profiling have introduced a new dimension to this field. In the future, with precise identification of women truly at risk for preterm birth, the creation of more efficient preventative methods may become achievable. In their January 2023 study [15], In-Seok Song et al. utilize machine learning and large-scale population data to inspect the connections between preterm birth (PTB) and dental and gastrointestinal problems. The information was acquired from the Korea National Health Insurance claims, focusing on 124,606 primiparous women aged 25–40 who gave birth in 2017 in this research. The study incorporated 186 independent variables, encompassing demographic and socioeconomic factors, illness data, and prescription records. Random forest variable significance was utilized to discover key factors influencing PTB and to examine their relationships with dental and gastrointestinal conditions, medication history, and socioeconomic position. This study confirms the importance of closely monitoring obstetric and gastrointestinal risks for premature delivery, which has occurred previously ignored. Additional research is needed to understand how studying the physiological mechanisms related to GERD contributes to an increased risk of PTB. Several research carried out from 2018 to 2023 investigate premature delivery (PMD) by different AI methods. Researchers utilize multiple datasets, such as health information on population, EHR, physiological signals, and environmental variables. The studies highlight the significance of promptly identifying characteristics that increase the likelihood of preterm birth, including a wide range of characteristics such as demographic, socioeconomic, clinical, and physiological data. Different kinds of machine learning are used to create predictive tools. The models show high accuracy in predicting PT, providing doctors with convenient and useful tools for risk assessment. Studies also investigate how environmental elements like green spaces and mother circadian disruption affect preterm birth, highlighting the intricate relationships between biological, psychological, and environmental components that affect pregnancy outcomes. Researchers recognise the necessity for more prospective studies, validation, and investigation of varied datasets to improve the clinical effectiveness and applicability of prediction models for preterm delivery. Synthesis of prior research on preterm delivery, the research shifted towards innovative and novel research approaches.

3. METHODS AND MATERIALS

The PMD model's architecture, seen in Figure 1, emphasizes its intricate design tailored for accurate prediction of premature delivery. The model was trained using the PMD dataset, which provides detailed information on 58 women during their reproductive years. The PMD dataset was downloaded from the Kaggle repository (https://www.kaggle.com/datasets/ahmadalijamali/preterm-data-set). 80% of the training set comprised pregnancy records, establishing a robust foundation for learning. The PMD model was validated with a dataset including 1% pregnant women from an 80% training dataset. Model performance was assessed using 20% of test data. The architecture of the PMD model, as shown in Figure 2, highlights its complex design specifically crafted for precise preterm delivery prediction. The model was trained on the PMD dataset, which offers precise information about 58 women throughout their reproductive years. 80% of the training set consisted of pregnancy records, providing a strong basis for learning. The PMD model was validated using a dataset that consisted of 1% pregnant women from an 80% training sample. Model performance was evaluated using 20% of the test data. The PMD model is chosen by comparing it with other models such as PMD-LSTM, PMD-GRU, and PMD-Vanilla RNN. Using sigmoid activation functions during training enhances the model's ability to adjust to various input patterns and complexity. Multiple performance evaluation metrics, including model loss, precision, accuracy, recall, F-score, and AUC-ROC, were systematically utilized to test and validate the effectiveness of the models. The assessment framework offers a comprehensive understanding of the PMD model's abilities and sets a benchmark for its potential application in practical scenarios, aiding in the advancement of maternal healthcare.

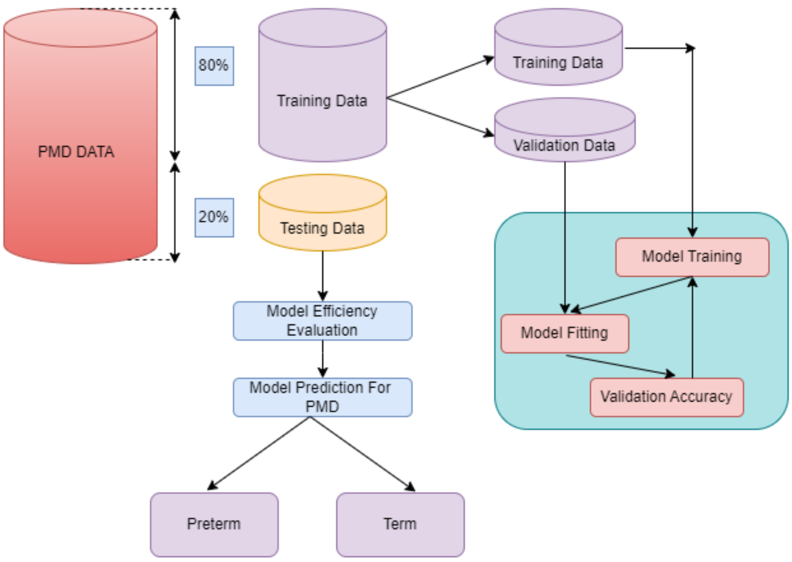

Figure 1. PMD model Architecture

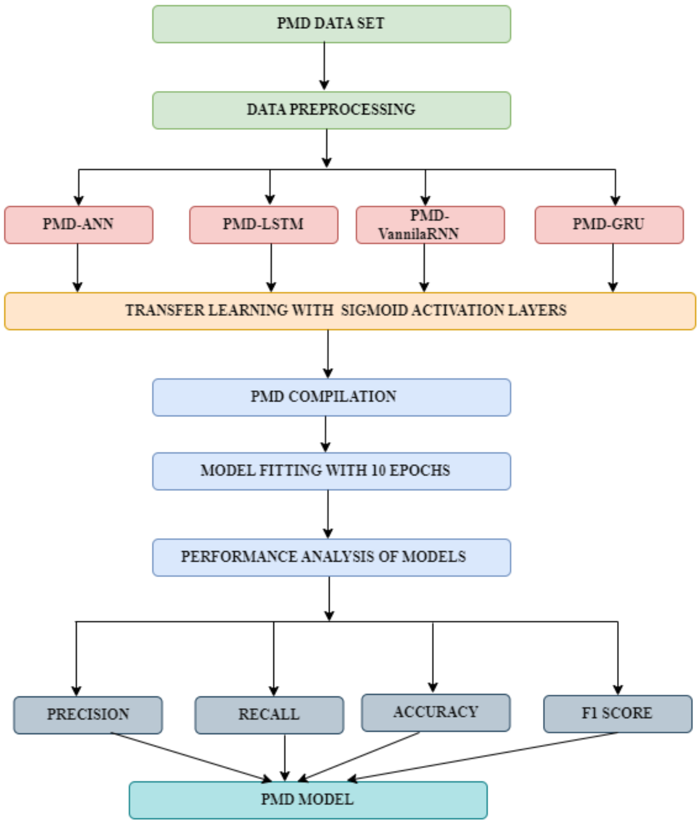

Figure 2. Process of PMD model

A complex PMD model was trained on 58 women's pregnancy data to predict premature delivery. The paper compares four model performances with metrics. The PMD model improved maternal healthcare using the sigmoid activation function. After developing the approach for creating the PMD model, the research process progresses to implementing the methodology.

4. IMPLEMENTATION SETUP AND RESULT ANALYSIS

PMD-LSTM, PMD-GRU, and PMD-Vanilla RNN are significant architectures in the field of predictive modeling for sequential data. Figure 3 illustrates the schematic depiction of these models, each consisting of 50 neurons and utilizing a sigmoid activation function. These designs have a recurring pattern, which enables them to efficiently record the relationship between events in a sequence. As a result, they are very skilled at tasks like predicting future values in a time series and interpreting spoken language. Using the Adam optimizer in conjunction with binary cross-entropy loss enables effective training and convergence towards optimum solutions. In the given situation, the models are specifically designed for a binary classification job. The outputs of the models indicate the probability of being preterm or term, which is crucial for medical prediction or risk assessment. By employing iterative learning, these models can identify complex patterns in input sequences that consist of five properties. This allows for precise predictions that are essential for making well-informed decisions in many fields.

A simple PMD -ANN equation (1) includes computing the weighted sum of inputs and applying an activation function. Suppose a feed-forward neural network has one hidden layer. Let X be the input vector, W the weight matrix, b the bias vector, f the activation function, h the hidden layer output, and y the final output:

$$h = \text{Sigmoid}\ (W_{input\_hidden}.\ X + b_{hidden}) \qquad (1)$$

$$y = \text{Sigmoid}\ (W_{hidden\_input.}\ h + b_{output}) \qquad (2)$$

PMD-LSTM model contains three gates: input, forget, and output equation (3-8). Gates control memory cell information flow in, out, and within. The input gate chooses the current input data to store in the memory cell. The forget gate chooses what prior state data to discard. Finally, the output gate regulates further network layer output. PMD-LSTMs capture sequential data dependencies by learning when to retain, discard, and output information, making them essential to PMD prediction.

$$\text{Input Gage } I_{t\,=}\ \text{Sigmoid}\ (W_{ii}\, X_t + b_{ii} + W_{hi} h_{t-1} + b_{hi} \qquad (3)$$

Forget Gate f_t= Sigmoid ($W_{if}X_t$ +b_{ig}+$W_{hg}h_{t-1}$+b_{hf} (4)

Cell State g_t= Sigmoid ($W_{ig}X_t$+ b_{ig}+$W_{hg}h_{t-1}$+b_{hg} (5)

Cell State Update (Continued)=$f_t \odot C_{t-1}+i_{tv}\odot g_t$ (6)

Output Gate O_t=$W_{io}X_t$+b_{io}+$W_{ho}h_{t-1}$+b_{ho} (7)

Hidden State update h_t=$O_t \odot$ Sigmoid (C_t) (8)

PMD-Vannila RNN handles sequential input by storing prior time step information in hidden states. The equation for a Vannila RNN at time step t comprises calculating the current hidden state (h_t) using input (x_t), prior hidden state (h_{t-1}), weight matrices (W_{ih} and W_{hh}), and a bias factor (b_h). Using the activation function sigmoid, the hidden state is calculated.

Hidden state update h_t= Sigmoid ($W_{hh}.h_{t-1}$+$W_{xh}.X_t$+b_h) (9)

The update gate in a PMD-GRU decides how much of the prior concealed state to keep and how much to add from the new candidate state. However, the reset gate determines which bits of the old concealed state to disregard while computing the new candidate state. The PMD-GRU update and reset techniques are mathematically designed to learn sequential PMD data dependencies efficiently.

Candidate hidden state update $\tilde{h}_t$ =Softmax($W_h x_t$+U_h)$r_t \odot h_{t-1}$+b_h (10)

Hidden state update h_t=(1-Z_t) $\odot h_{t-1}$+$Z_t \odot \tilde{h}_t$ (11)

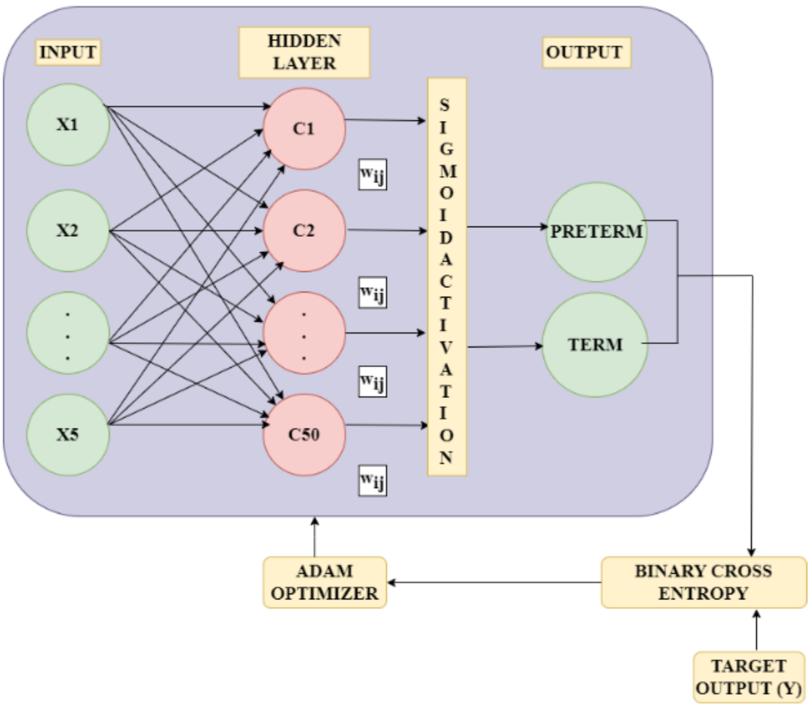

Figure 3. PMD prediction model

The provided content discusses the formulas for basic Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, and Simple Recurrent Neural Networks (RNNs). For ANNs, the focus is on the computation of hidden and output layers using weighted sums, biases, and activation functions. LSTMs are described as having memory cells with input, forget, and output gates, allowing effective learning of dependencies in sequential data. In contrast, Vannila RNNs maintain hidden states for sequential data processing. The content also introduces Gated Recurrent Units (GRUs), highlighting their simplified architecture with update and reset gates, making them computationally efficient for sequence modelling tasks.

5. PMD MODEL ANALYSIS

PMD-LSTM, PMD-GRU, and PMD-Vannila RNN models were trained on the PMD dataset. Activation mechanisms are critical to PMD model development. The sigmoid activation function controls network architecture learning using training datasets. Output layer activation functions determine model prediction. The activation state of a neuron is determined by an activation function at the end or centre of a neural network. Activation functions are complex nonlinear transformations of input signals. The signal is processed and sent to the next neuron layer. The sigmoid activation function reduced input values into the interval of 0 to 1. The mathematical equation (12) of sigmoid represents it as follows:

$$\textbf{Sigmoid } \boldsymbol{\sigma} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e^{x}}} \qquad \textbf{(12)}$$

Performance measures including step loss, accuracy, validation loss, and validation accuracy are assessed using the activation function and model assembly. The dysfunction calculates the model's output difference from the desired result. Losses throughout each cycle are called step loss. Binary categorical cross-entropy compares projected probability distributions to binary labels. In equation (13) y is the label (0 or 1) and $\hat{y}$ is the expected probability of class 1 sample membership.

$$\mathbf{L(y, \hat{y}) = -(y \log(\hat{y}) + (1-y)\log(1-\hat{y}))} \qquad \textbf{(13)}$$

The aggregate amount of Predictions in equation (14) for accuracy denotes the times the model's forecast matches the genuine class labels. Total predictions are the number of times the PMD model has predicted.

The tables illustrate the model's 10-epoch PMD model analysis of PMD data. Recall, also known as sensitivity or true positive rate, is another important metric used to evaluate the performance of a classification model.

$$\text{Recall} = \frac{\textbf{Total no.of correctly Predictions}}{\textbf{Total no.of correctly Predictions + Total no. of False negative}}$$

The F1-score is a metric that combines both precision and recall into a single value, providing a more balanced assessment of a classifier's performance. It is particularly useful when you want to consider both false positives and false negatives in the evaluation. The F1-score is calculated as the harmonic mean of precision and recall and is given by the equation. Ten complete epochs were used to compile the PMD model. As indicated in Tables 1-4, the PMD Model of PMD data was carried out by evaluating the performance indices for each epoch of 10.

$$\textbf{F1-Score} = \frac{\boldsymbol{2\ X\ Precision\ X\ Recall}}{\boldsymbol{Precision + Recall}}$$

Table 1. PMD-LSTM smodel.

Epochs	Step Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	0.7501	0.1463	0.7273	0.0000
2/10	0.7447	0.1707	0.7231	0.0000
3/10	0.7396	0.1463	0.7190	0.0000
4/10	0.7344	0.1463	0.7149	0.0000
5/10	0.7298	0.1463	0.7109	0.0000
6/10	0.7247	0.1463	0.7070	0.0000
7/10	0.7199	0.2195	0.7031	0.2000
8/10	0.7153	0.2195	0.6992	0.6000
9/10	0.7105	0.5366	0.6954	0.8000
10/10	0.7058	0.6829	0.6916	0.8000

Table 2. PMD-GRU model.

Epochs	Step Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	0.6362	0.8537	0.6262	1.0000
2/10	0.6290	0.8293	0.6193	1.0000

3/10	0.6222	0.8049	0.6126	1.0000
4/10	0.6154	0.8049	0.6060	0.8000
5/10	0.6090	0.8293	0.5996	0.8000
6/10	0.6025	0.8780	0.5935	0.8000
7/10	0.5962	0.9024	0.5875	0.8000
8/10	0.5901	0.9024	0.5817	0.8000
9/10	0.5841	0.9024	0.5759	0.8000
10/10	0.5784	0.9024	0.5702	0.8000

Table 3. PMD-Vannila Rnn model.

Epochs	Step Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	0.7035	0.3778	0.7411	0.0000
2/10	0.6872	0.4667	0.7182	0.0000
3/10	0.6712	0.5778	0.6958	0.0000
4/10	0.6553	0.7778	0.6736	1.0000
5/10	0.6399	0.8222	0.6519	1.0000
6/10	0.6244	0.8889	0.6304	1.0000
7/10	0.6098	0.9111	0.6092	1.0000
8/10	0.5951	0.9111	0.5887	1.0000
9/10	0.5811	0.9333	0.5687	1.0000
10/10	0.5668	0.9333	0.5493	1.0000

Table 4. PMD-NN model.

Epochs	Step Loss	Accuracy	Validation Loss	Validation Accuracy
1/10	0.6669	0.7778	0.6033	1.0000
2/10	0.6556	0.7778	0.5937	1.0000
3/10	0.6441	0.8000	0.5839	1.0000
4/10	0.6336	0.8000	0.5741	1.0000
5/10	0.6227	0.8000	0.5643	1.0000
6/10	0.6119	0.8000	0.5543	1.0000
7/10	0.6016	0.8000	0.5444	1.0000
8/10	0.5917	0.8000	0.5348	1.0000
9/10	0.5819	0.8000	0.5253	1.0000
10/10	0.5721	0.8000	0.5158	1.0000

The PMD dataset was trained using several RNN models, PMD-LSTM, PMD-GRU, and PMD-Vannila RNN, to extract key characteristics from the dataset. The designed base model was fitted to custom layers with activation layers Sigmoid, to assess the outcome of preterm labour identification in maternity women. The performance was analysed in the context of model loss, model accuracy, precision, recall, and F-score as illustrated in Tables 5 and Figures 4–6. It was noted that the efficiency of PMD-Vannila RNN was comparatively better, with greater accuracy and F-score values, followed by PMD-LSTM, PMD-GRU, and PMD-Vannila RNN models. Several measures were used to assess the model's efficacy, such as model evaluation loss, precision, recall, F-score, accuracy, and ROC-AUC score. Tables 5 show the result.

Table 5. PMD model with sigmoid activation

PMD Model	Precision	Recall	F1-Score	Accuracy
PMD-LSTM	1.0000	0.2000	0.3333	0.6666
PMD-GRU	0.0000	0.0000	0.0000	0.1666
PMD-Vanilla RNN	1.0000	1.0000	1.0000	1.0000
PMD-NN	1.0000	0.8000	0.8888	0.9166

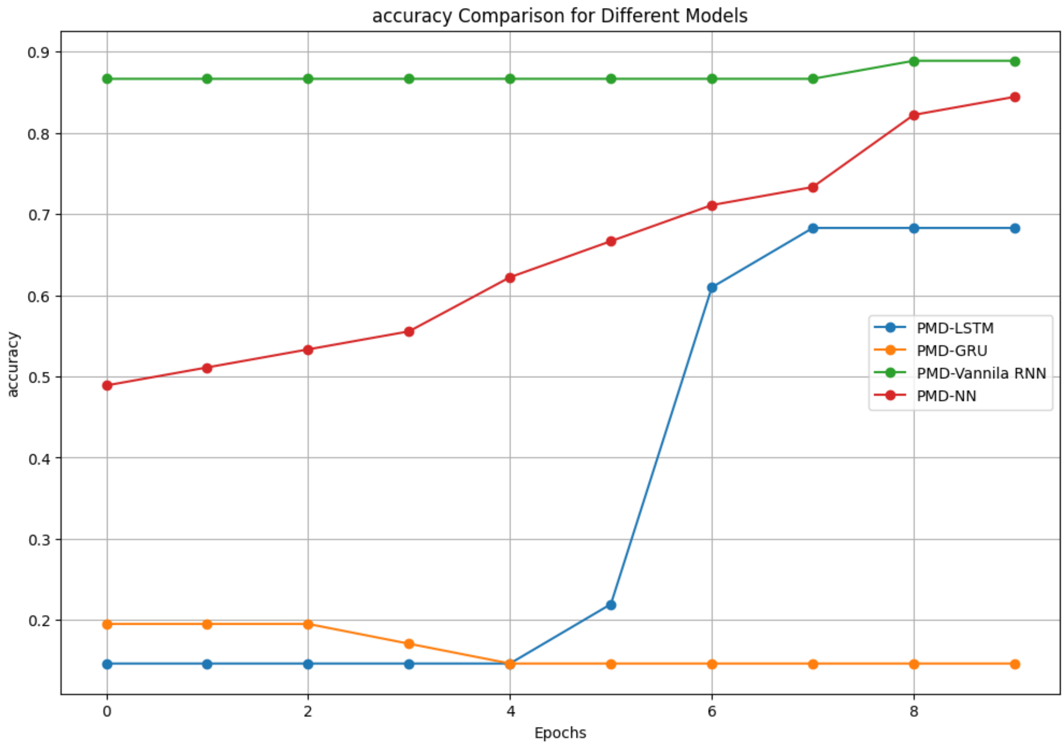

Figure 4. PMD prediction model Training accuracy

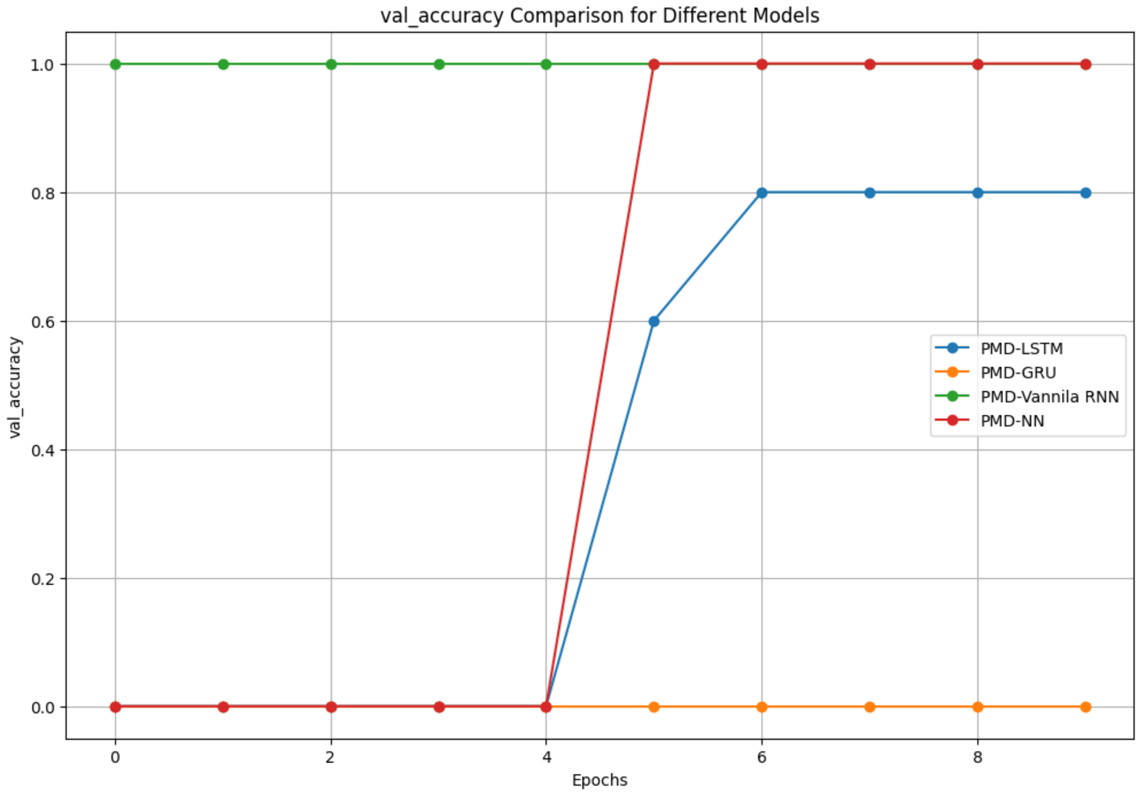

Figure 5. PMD prediction model validation accuracy

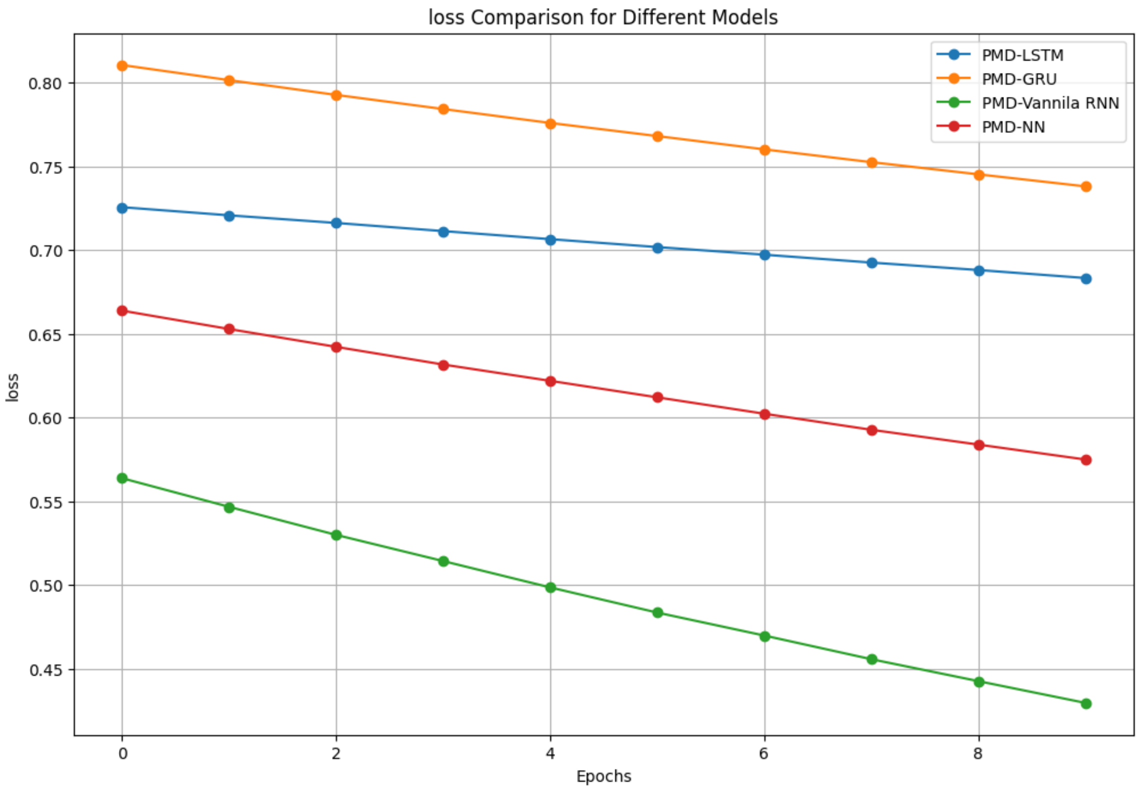

Figure 6. PMD prediction model Evaluation loss

6. CONCLUSION

Ultimately, neural network methods such as PMD-LSTM, PMD-GRU, PMD-Vannila RNN, and PMD-NN provide encouraging outcomes in forecasting premature births scheduled before 37 weeks of gestation. Based on pre-processed PMD data, the models exhibit robust prediction skills, with accuracies ranging from 0.0166 for PMD-GRU to 1.0000 for PMD-Vannila RNN. Through the utilization of a sigmoid activation function and binary cross-entropy loss, the models successfully differentiate between preterm cases and those that are non-preterm. To further evaluate the accuracy of classification, evaluation measures such as precision, recall, and F1-score are employed. The present study contributes to the advancement of neural networks in the early detection of premature deliveries, which has the potential to facilitate prompt treatments and enhance outcomes for both mothers and neonates. The comparative examination of recurrent neural network (RNN) architectures, such as PMD-LSTM, PMD-GRU, and PMD-Vannila RNN, and PMD-NN elucidates their merits and drawbacks in tackling the pressing healthcare concern of premature births. The performance of each architecture is impressive; yet, variations in accuracy highlight the need to choose the best appropriate model. Utilizing sophisticated machine learning methods to forecast premature delivery shows potential for enhancing maternal and neonatal healthcare results on a worldwide scale. Subsequent investigations should prioritize the examination of innovative computational methodologies and the incorporation of supplementary characteristics to augment the precision of predictions. Moreover, the incorporation of supplementary data sources, such as maternal health records and environmental variables, has the potential to yield useful insights conducive to enhancing prediction accuracy. Moreover, the advancement of comprehensible models and decision support systems can assist healthcare practitioners in making well-informed clinical judgments, thereby helping both moms and neonates.

7. FUTURE WORK

Future studies may improve and fine-tune the PMD hyperparameters, especially when combined with other optimizers. The model's durability and adaptability to different demographics and healthcare environments may also increase its utility and reliability. Real-time data streams and continuous monitoring might dynamically change the model and provide timely projections in future studies. Create interpretability tools and visualization methods to improve model decision-making comprehension and therapeutic trust. Additionally, transfer learning from related healthcare professions or multi-modal data sources may improve the model's adaptability and performance in various instances. Using new data to validate and update the model ensures its relevance and performance in changing healthcare situations. To resolve ethical issues, ensure responsible deployment, and successfully integrate the PMD model into clinical practice, healthcare practitioners, data scientists, and policymakers must collaborate.

DATA AVAILABILITY STATEMENT

Data sharing does not apply to this article because no datasets were generated or analyzed in this study.

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All authors have read and approved this paper.

ETHICS DECLARATIONS

ETHICS APPROVAL

This article does not contain any studies with human participants or animals performed by any of the authors

COMPETING INTERESTS

The authors declare no competing interests.

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