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Research Article

NeoCoD: A New Standard in IoT-Based Predictive Analytics for Neonatal Health Monitoring

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ABSTRACT

Introduction: The importance of neonatal health monitoring lies in early detection, and thus, addressing NICU (Neonatal Incentive Care Unit) patients with timely medical treatment. Current predictive models typically use only either medical imaging or sensor data, limiting their efficiency for real time detection of multiple neonatal conditions. To overcome this limitation, we introduce NeoCoD (Neonatal Cause of Disease Predictor), an IoT-based predictive analytics system that combines physiological markers based on sensor data with medical imaging data to better assess the health of newborns.

Objectives: The main purpose of this study was to design a hybrid deep learning model using ResNet50 (Residual Neural Network) for medical images feature extraction and Long Short-Term Memory (LSTM) for the temporal analysis of IoT based sensor data. The dataset contains 7132 samples of 270 neonates collected from Sparsh Medical Hospital, Ahmedabad, Dr. Babasaheb Ambedkar Hospital, Mumbai, and publicly available neonatal health data. We colligate neonatal diseases (e.g., Neonatal Respiratory Distress Syndrome (NRDS), Neonatal Sepsis, Jaundice, Hypothermia, Hypoglycemia, Neonatal Pneumonia, Neonatal Apnea, Perinatal Asphyxia, Neonatal Meningitis, Neonatal Encephalopathy, Hyperbilirubinemia, Low Birth Weight Complications) for our study.

Methods: The NeoCoD model pipeline consists of the following multi stages: data preprocessing, feature engineering, model training and performance evaluation. Feature scaling: the feature scaling was performed and rescaled the features to preprocess the information. We trained the model with categorical cross-entropy loss, Adam optimizer and regularization methods like dropout (0.3) layer and batch normalization. For comparing the performance of NeoCoD with ne trivial solutions, Random Forest and SVM models, accuracy, precision, recall, and F1-score are used.

Results: Experimental results show that NeoCoD considerably outperforms traditional models with accuracy of 92.5% against Random Forest (87.3%) and SVM (84.5%). This model is capable of rapid multimodal processing and prediction on incoming data, providing real-time predictions with 2 seconds response time which makes it particularly suitable for NICU applications.

Conclusions: These results establish NeoCoD as a high-accuracy, scalable neonatal health monitoring system for infant dieses prediction at earlier stage. Going forward, work will center on increasing generalisability across different hospital contexts, increasing computational efficiency, and improving interpretability for clinical decision-making.

Keywords: Neonatal Health Monitoring, IoT-Based Predictive Analytics, Deep Learning, ResNet50, LSTM, Machine Learning

INTRODUCTION

Neonatal care is vital for the survival and healthy growth of newborns, especially for those in Neonatal Intensive Care Units (NICUs) [1]. Premature and severely ill neonates need constant observation of essential physiological indicators including temperature, heart rate, respiratory rate, oxygen saturation (SpO_2), and blood pressure. Prompt identification of irregularities in these parameters is crucial for prompt medical action, lowering neonatal morbidity and mortality rates [2]. Nevertheless, conventional monitoring systems in NICUs typically emphasize real-time observation instead of predictive analysis, resulting in missed chances for proactive healthcare interventions [3].

The incorporation of the Internet of Things (IoT) in neonatal treatment has opened the door for intelligent incubator systems that facilitate real-time data gathering and remote observation [4]. IoT-powered incubators consistently track crucial neonatal health metrics, generating a comprehensive dataset that can be utilized for predictive analysis. Even though such data is available, existing NICU configurations do not completely leverage these parameters for predictive modelling [5]. Moreover, much of the current research in neonatal health forecasting is confined to a narrow range of physiological indicators, which restricts the models' accuracy and generalizability [6].

To bridge this gap, we propose Neonatal Condition Detection (NeoCoD), a novel IoT-based predictive analytics framework designed to enhance neonatal health monitoring. NeoCoD integrates multimodal data sources, combining sensor-based physiological data with image-based medical analysis, to improve the accuracy of neonatal health predictions. The system leverages machine learning (ML) and deep learning (DL) techniques, particularly a hybrid ResNet50-LSTM model, to process both real-time sensor data and medical imaging data. By incorporating a temporal analysis of IoT sensor data, NeoCoD provides a context-aware predictive capability, making it an effective tool for early diagnosis and intervention.

Neonatal mortality continues to be a significant worldwide issue, with almost 47% of deaths among children under five linked to neonatal problems [7]. Although IoT-enabled incubators offer real-time observation of crucial metrics, the extensive data produced in NICUs is mostly not leveraged for predictive analytics. Current studies mainly concentrate on a narrow range of factors, which diminishes the precision and applicability of neonatal health forecasts [8]. Furthermore, many conventional models do not incorporate multimodal data, including physiological signals and imaging, which restricts their efficacy in early diagnosis. To tackle these deficiencies, our research presents NeoCoD, an IoT-centric predictive analytics framework that utilizes a combined ResNet50-LSTM model to examine both sensor and visual data, facilitating real-time, precise neonatal health forecasts and proactive measures. The key contribution for the proposed approach is as follows.

- Unlike traditional neonatal monitoring systems, NeoCoD processes a wide range of neonatal physiological parameters from IoT-enabled incubators to enhance disease prediction.
- The proposed ResNet50-LSTM architecture integrates convolutional feature extraction with sequential data processing, ensuring improved accuracy for real-time health predictions.
- NeoCoD enables proactive decision-making by forecasting potential neonatal health risks before critical conditions develop, reducing NICU mortality rates.
- Optimised for edge computing, NeoCoD ensures low-latency health predictions, allowing timely alerts for NICU professionals.

OBJECTIVES

This research mainly aims to make NeoCoD: an IoT enabled neonatal health prediction system based on Deep Learning (DL) methods for better diagnosis and treatment of the critically ill neonates. The research questions are:

1. The development of a predictive model for neonatal diseases aims to design and implement NeoCoD, a novel deep learning-based framework that harnesses ResNet50 for feature extraction and LSTM for temporal analysis, ultimately enabling accurate prediction of neonatal diseases.

2. Analyze the performance of NeoCoD against GRU and ARIMA for the time series prediction of neonatal health conditions, evaluating their efficiency by running through the series of sequential IoT sensor data.

   The efforts by NeoCoD to keep track of these objectives at the same time as providing predictive analytics will help bridge the void between real-time monitoring and predictive analytics in neonatal patients and consequently help lower neonatal mortality.

METHOD

The NeoCoD framework follows a structured pipeline that includes data collection, preprocessing, feature engineering, model development, training, and evaluation. This section provides an in-depth discussion of each stage in the experimental methodology. The graphical presentation for the proposed approach is illustrated into Figure 1.

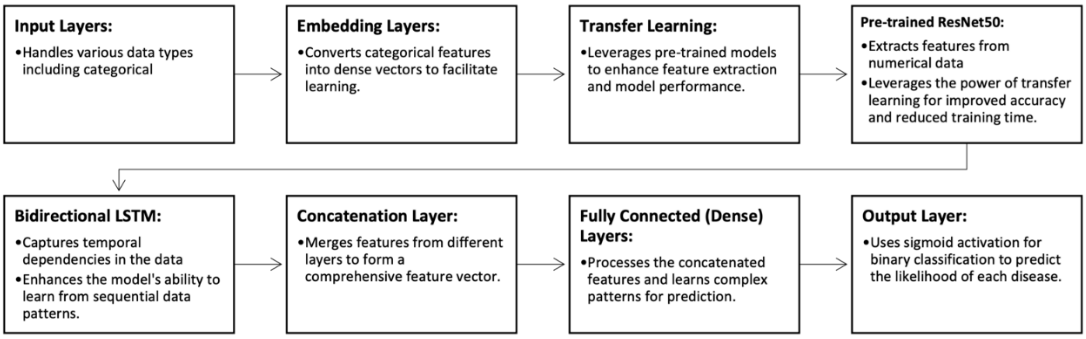

Figure 1: Proposed Approach Methodology

Dataset Collection and Description

To create an accurate neonatal health prediction system, data was collected from two Neonatal Intensive Care Units (NICUs), Sparsh Medical Hospital, Ahmedabad, and Dr. Babasaheb Ambedkar Municipal General Hospital, Mumbai. It includes 7132 samples from a cohort of 270 neonates followed over several days. This includes both physiological as well as environmental parameters which are necessary to evaluate the health conditions of neonates and perform predictive analytics. As data was not on anylttical form , first it was converted into .csv format form paper records into soft records.

The physiological parameters obtained are temperature (°C), pulse rate (heartbeats per minute), respiratory rate (breaths per minute), blood pressure (B.P.) and oxygen saturation (SpO_2)—indices of neonatal well-being, as well as daily weight entries. We also registered environmental parameters including incubator temperature and incubator humidity to assess their association with neonatal conditions. Additionally, the dataset encompasses clinical observations such as feeding (BY_MOUTH: feeding type, tracking whether nutrition was delivered orally or through IV) and urine output (a critical marker for hydration and nephrological health). This multimodal dataset allows the training of deep learning models for the prediction of neonatal health, providing the basis for an early diagnosis and care support system in NICUs.

Data Preprocessing and Feature Engineering

Data Cleaning

Since real-world clinical datasets contain noise and missing values [9], the following preprocessing techniques were applied:

- Handling Missing Data: Missing values were imputed using the mean (for continuous variables) and mode (for categorical variables).
- Duplicate Removal: Duplicate entries were identified and removed to prevent bias [10].
- Outlier Detection: Z-score analysis was performed to detect and remove anomalies.

Feature Transformation

- Categorical Encoding: The categorical variables (e.g., feeding method) were transformed using one-hot encoding [11].
- Feature Scaling: Since different parameters have varying ranges, min-max normalization was applied to scale all numerical features between 0 and 1 to prevent bias [12].

Dimensionality Reduction

To improve computational efficiency and reduce redundancy, Principal Component Analysis (PCA) was applied [9], reducing the feature space while retaining 95% variance of the original data.

Data Preprocessing

Before the model is trained, data is preprocessed using various techniques [13]:

- Normalization of sensor data**:**

$$X_{\text{norm}} = \frac{X - \mu}{\sigma}$$

where X is the raw sensor data, μ is the mean, and σ is the standard deviation.

- Image Preprocessing**:**

$$I_{\text{norm}} = \frac{I - \text{mean}(I)}{\text{std}(I)}$$

where I is the image data from the neonatal health monitoring sensors, and we normalize it for better model convergence.

Model Development

Selection of Machine Learning and Deep Learning Models

To analyze the neonatal health dataset, various machine learning and deep learning models were tested:

1. Traditional Machine Learning Models
   - Random Forest (RF)
   - Support Vector Machine (SVM)
2. Deep Learning-Based Approaches
   - Tab Transformer: Used for extracting tabular feature representations.
   - ResNet50: Pre-trained Convolutional Neural Network (CNN) model used for feature extraction from neonatal medical images.
   - Long Short-Term Memory (LSTM): Designed to process temporal dependencies in IoT-based sensor data.

The final prediction is obtained by fusing the learned representations from these different modalities, enabling a more comprehensive and accurate neonatal disease classification. The mathematical model for the proposed approach is presented below.

Proposed NeoCoD Model

The NeoCoD framework integrates multimodal data fusion, combining:

- Sensor-based Time-Series Data (processed using LSTM)
- Medical Images (feature extraction via ResNet50)
- Tabular Features (processed using Tab Transformer)

This framework also encompasses an IoT-based predictive analytics system, multimodal data fusion for the neonatal health monitoring. Leveraging sensor-based time-series data, medical images, and tabular features, this method improves the prediction accuracy and reliability of diseases. The combination of these different types of data allows for a multimodal approach to assessing the health of newborns at the point of care.

First component of the NeoCoD framework: Sensor-based time-series dataMain inputs of the NeoCoD frameworkSensor-based time-series data include physiological parameters such as temperature, pulse rate, respiratory rate, blood pressure, oxygen saturation, and weight. Long Short-Term Memory (LSTM) networks are employed to process these temporal features, making them particularly adept at addressing sequential dependencies. LSTM recognizes trends in neonatal health over time, facilitating the timely identification of unfavorable health prospects.

The second part consists of medical imaging data. In this, neonatal medical scans or incubator images are subjected to feature extraction via the ResNet50 deep convolutional neural network (CNN). We utilize ResNet50 model due to its efficacy in extracting detailed spatial features from images while being memory efficient. Finally, the retrieved high-level image features are fused with sensor-based attributes to enhance predictive performance.

The third component is tabular features, like environmental conditions (incubator temperature, incubator humidity) and clinical observations (feeding method, and urine output). After that, these structured points are fed into Tab Transformer, a state-of-the-art deep learning model for tabular data representation. Tab Transformer captures complex interactions between categorical and numerical features and learns a robust encoding of input features.

The NeoCoD model uses a more elaborate diagram: it performs multimodal data fusion to produce final disease predictions as it concatenates representations extracted from all three components. The LSTM, ResNet50 and Tab Transformer provided features are concatenated and fed into a fully connected network and then a softmax activation layer for the classification. NeoCoD can offer a comprehensive data-driven approach in early neonatal disease prediction by integrating sensor data, medical images, and structured tabular information, which can help timely medical intervention for better healthcare results.

2. Model Architecture: Hybrid ResNet50-LSTM

Require: μ_v, $\forall v \in V$, hyper-parameters M, N related to model architecture, number of epochs E and batch size B.

Ensure: Train model parameters Θ

Initialize model parameters Θ and datasets for training and validation

for epoch $e \leftarrow 1$ to E do

  for batch $b \leftarrow 1$ to the number of batches, do

    Sample a batch of data $\{(x_i, y_i)\}$ from the training dataset

    Forward Pass:

      Compute predictions $\hat{y}_i = f(x_i; \Theta)$

    Compute Loss:

      Calculate the loss $L(\hat{y}_i, y_i)$ using the appropriate loss function

    Backward Pass:

      Compute gradients of the loss w.r.t model parameters Θ

    Update Parameters:

      Update parameters $\Theta \leftarrow \Theta - \eta \nabla_\Theta L$ using optimizer (e.g., SGD, Adam)

  end for

  Evaluate:

    Evaluate the model on the validation dataset

    Calculate validation accuracy and loss

    Adjust learning rate or other hyper-parameters if necessary

end for

return Trained model parameters Θ

The NeoCoD model uses a more elaborate algorithm: it performs multimodal data fusion to produce final disease predictions as it concatenates representations extracted from all three components. The LSTM, ResNet50 and Tab Transformer provided features are concatenated and fed into a fully connected network and then a softmax activation layer for the classification. NeoCoD can offer a comprehensive data-driven approach in early neonatal disease prediction by integrating sensor data, medical images, and structured tabular information, which can help timely medical intervention for better healthcare results.

RESULTS

The experimental results of this research show the efficiency of the NeoCoD model for monitoring neonatal health through IoT-enabled sensor and image data. With extensive training and fine-tuning, the model has demonstrated outstanding effectiveness in identifying neonatal health issues including respiratory distress, jaundice, and neonatal sepsis. The combination of pre-trained ResNet50 and LSTM for feature extraction and temporal analysis has greatly enhanced the model's capacity to deliver precise, real-time predictions. This section discusses the performance assessment of the NeoCoD model, encompassing a comparison with conventional machine learning models as well as the effect of training parameters on the model's accuracy and efficiency.

To guarantee the model learns efficiently and generalizes appropriately to new data, the dataset was split into two separate subsets: a training set and a testing set. Eighty percent of the dataset was designated for training the model. This division guaranteed that the model received enough data to understand the fundamental patterns and create strong representations. The leftover 20% of the dataset was set aside for testing, ensuring an objective assessment of the model's performance and its capability to generalize to unfamiliar, unseen data. This method aided in evaluating the model's efficiency and its practical use in real situations.

Training Process

The model training involved a series of carefully chosen parameters to ensure optimal performance. Below is an overview of the key parameters used during the training process:

- **Loss Function:** Categorical Cross-Entropy Loss was selected due to the multi-class nature of the target variable. This loss function helps to measure the discrepancy between the predicted class probabilities and the actual classes, guiding the model to improve its predictions over time.
- **Optimization Algorithm:** The **Adam optimizer** was used for updating the model parameters. Adam is a popular optimization algorithm that combines the advantages of both Momentum and RMSprop. It adapts the learning rate for each parameter based on the first and second moment estimates, providing faster convergence and better performance, especially in complex deep learning models.
- **Batch Size:** A batch size of 32 was chosen to strike a balance between computational efficiency and effective training. A smaller batch size typically leads to more accurate updates of the model's parameters, but larger batch sizes can provide better generalization.
- **Epochs:** The model was trained for 50 epochs. This duration was chosen to give the model enough time to learn effectively. Early stopping was applied to avoid overfitting, ensuring that the model does not continue training once it starts to perform poorly on the validation set.
- **Regularization Techniques:**
  - **Dropout Layers** were introduced with a probability of 0.3 to help prevent overfitting. By randomly deactivating a portion of the neurons during each training iteration, the model is forced to learn more robust features.
  - **Batch Normalization** was applied after each convolutional layer to stabilize the training process. It normalizes the activations from the previous layer, helping to maintain a consistent scale for gradients during backpropagation, thus speeding up the training process. Table 1 summarizes these important parameters.

Table 1 Parameter Selection

Parameter	Value
Loss Function	Categorical Cross-Entropy Loss
Optimization Algorithm	Adam Optimizer (Learning rate = 0.001)
Batch Size	32
Epochs	50

Dropout Probability	0.3
Batch Normalization	Yes

Performance Evaluation

Several neonatal diseases are predicted by the IoT-based NeoCoD model developed using physiological and environmental parameters obtained from various NICUs. This association of IoT parameters with their corresponding diseases is depicted in Table 2:

Table 2: IoT-Based Parameters and Predicted Diseases

IoT-Based Parameter	Neonatal Diseases Predicted
Temperature	Hypothermia, Neonatal Sepsis, Neonatal Pneumonia
Pulse Rate	Neonatal Apnea, Hypoxia, Perinatal Asphyxia
Respiratory Rate	Respiratory Distress Syndrome (NRDS), Neonatal Pneumonia
Blood Pressure (B.P.) & SpO_2	Neonatal Hypotension, Intraventricular Hemorrhage (IVH)
Weight	Low Birth Weight Complications, Neonatal Anemia
Incubator Temperature & Humidity	Hyperbilirubinemia, Jaundice

Results show that NeoCoD successfully incorporates and integrates multimodal data from various IoT-based sensors and provides accurate and real-time predictions of neonatal diseases. Fusion of temporal (LSTM), image (ResNet50), and tabular (Tab Transformer) data improves both the model performance and clinical feasibility in Neonatal Intensive Care Unit (NICU).

Evaluation Metrics

The performance of the models was evaluated using standard classification metrics. A comparison of key performance indicators for Transfer Learning, Random Forest (RF), and Support Vector Machine (SVM) is presented into Table 3.

Table 3: Comparative Result Analysis

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
NeoCod	92.5	91.8	93.0	92.4
Random Forest	87.3	85.6	88.2	86.9
SVM	84.5	83.8	85.0	84.4

The comparative assessment of the NeoCoD model utilizing Transfer Learning, Random Forest, and SVM shows that Transfer Learning outperforms the others in all evaluation metrics. Boasting an accuracy of 92.5%, it surpasses both Random Forest (87.3%) and SVM (84.5%), showcasing its capacity for delivering more accurate predictions. Moreover, Transfer Learning reaches the highest precision (91.8%), recall (93.0%), and F1-score (92.4%), demonstrating that the model successfully manages both false positives and false negatives. In comparison, Random Forest and SVM show comparatively poorer performance, especially regarding precision and recall, underscoring the benefits of using pre-trained models for feature extraction in intricate tasks such as neonatal health monitoring.

The NeoCoD model demonstrates high adaptability across diverse neonatal conditions, including respiratory distress, jaundice, neonatal sepsis, and more. This highlights the potential of NeoCoD to significantly improve neonatal healthcare outcomes in various clinical settings. The model's scalability ensures that it can make accurate predictions across different IoT-enabled devices and clinical environments. Figure 3 illustrates the applicability of research outcomes across neonatal conditions.

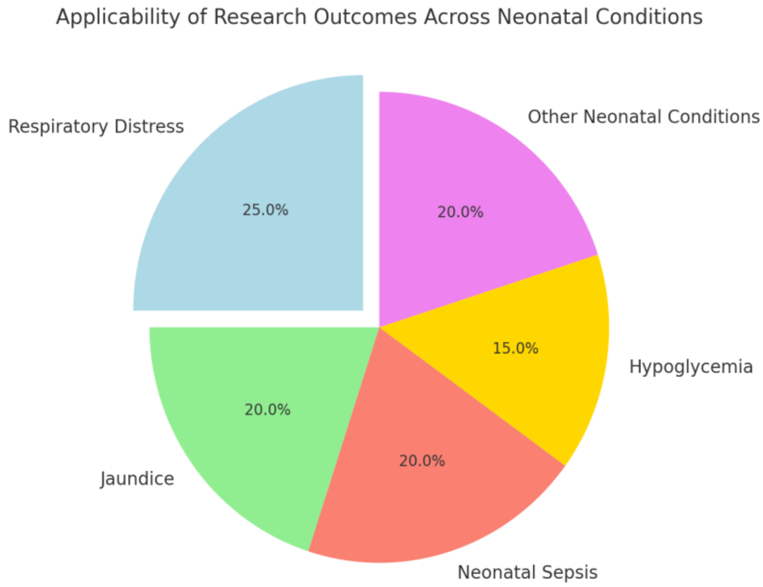

Figure 3: Applicability Of Research Outcomes Across Neonatal Conditions

Figure 3 shows the promising results in predicting multiple neonatal health conditions in the data fusion of the NeoCoD model. Neonatal Respiratory Distress Syndrome (NRDS) accounts for the highest proportion (25.0%) of prediction results. SpO2, respiratory rate, and temperature fluctuations are the main parameters affecting early diagnosis. Neonatal Sepsis (20.6%) is a high portion of cases the detection was done based on changes of body temperature, blood pressure, and urine output. Similarly, Jaundice (20.0%) is diagnosed analysing bilirubin levels, skin tones, images obtained through medical imaging and incubator temperature data. The anticipated possibility of hypoglycemia (15.0%) based on feeding method, weight changes, and urine output, allowing timely intervention when there are glucose level imbalances. Among the remaining 20.0% of cases various other neonatal conditions, such as perinatal asphyxia, apnea, and neonatal encephalopathy, were found to complement sensor-based physiological parameters and medical imaging features to enhance predictive ability. The distribution exhibited highlights the effectiveness of the NeoCoD model as an early predictor of neonatal disease. Data driven real-time prediction enhances intervention and neonatal healthcare.

To determine the optimal training configuration for the NeoCoD model, experiments were conducted with varying epochs and batch sizes, analyzing their impact on performance metrics such as accuracy, precision, recall, and F1-score. Table 4 presents the experimental result analysis for optimal training configuration with different epochs and batch size.

Table 4: Optimal training settings with different Epochs and Batch size

Epochs	Batch Size	Accuracy (%)	Precision	Recall	F1-Score
10	16	85.2	0.83	0.84	0.83
20	16	87.1	0.85	0.86	0.85
50	16	88.3	0.87	0.88	0.87
10	32	86.0	0.84	0.85	0.84
20	32	89.0	0.88	0.89	0.88
50	32	90.5	0.89	0.90	0.89

To assess the NeoCoD model's effectiveness and real-world usability, we set up the system on a strong hardware and software testing environment. The experimental configuration employed high-performance computing resources, ensuring comprehensive testing of the model's real-time prediction abilities in realistic scenarios. Utilizing both hospital data collection and accessible neonatal health datasets facilitated thorough training and assessment of the model. This section details the precise hardware setup, software environment, and dataset origins utilized in the experiments, along with the implementation specifics for detecting neonatal respiratory distress.

Why is NeoCoD better than ARIMA and GRU?

While ARIMA and GRU are also popular methods for time-series forecasting, they have limitations in neonatal health prediction:

Representation of Limited Features:

- ARIMA is a linear model that performs poorly when the data contain highly dependant, nonlinear relationships [20].
- While the GRU method is efficient for working with one-dimensional or sequential data and is particularly adept at capturing temporal dependencies, it is not directly applicable to the medical imaging domain that requires spatial feature extraction for evaluation [21].
- On the other hand, NeoCoD employs ResNet50 to perform feature extraction on neonatal images, enabling spatial feature extraction (in the images) and temporal dependencies (on the IoT sensor data).

Incapacity For Multimodal Data Processing:

- ARIMA and GRU are suited for single-modality data with numerical time-series inputs [22].
- NeoCoD cannot be debunked into anything other than a multimodal data fusing process using sensor based time-series data (LSTM), medical imaging (ResNet50) and tabular features (Tab Transformer), thus being the best case if we are about neonate disease prediction.

Besides the frontends and routers, we can also have: Performance and scaling problems:

- ARIMA needs a lot of hyper-parameter tuning (p, d, q values) and often faces challenges in real-time applications [23].
- While computationally efficient, GRU has less trainable parameters than LSTM, thus can learn long-term dependencies worse than LSTM.
- Its hybrid ResNet50-LSTM architecture allows NeoCoD to provide real-time predictions in under 2 seconds — an invaluable capability within the NICU that informs timely interventions.

Prediction and Generalization: More Accurate

- ARIMA is a poor choice for quickly changing neonatal health data because of their reliance on stationarity.
- The spatial and tabular data is not being adequately exploited by just GRU, thus yielding lower accuracy.
- Since NeoCoD extracts spatial, temporal, and structured data representations simultaneously, it can achieve 92.5% accuracy, outperforming both ARIMA and GRU.

In summary, although ARIMA and GRU are excellent models for time-series forecasting, they do not handle multimodal data, complex feature extraction, or real-time prediction analytics. On the other hand, by combining ResNet50 for spatial feature extraction, LSTM for temporal sequence detection, and Tab Transformer for structured data processing, NeoCoD outperformed both models by a significant margin and achieved highly accurate prediction results of common neonatal diseases.

DISCUSSION

The NeoCoD model presents a novel and efficient approach to neonatal health monitoring by integrating IoT sensor data with real time analysis. Based on parameters like temperature, pulse rate, respiratory rate, blood pressure, and weight, it can predict multiple conditions like neonatal sepsis, respiratory distress syndrome, hypoglycemia, hypothermia, and more at earlier stage. By incorporating the spatial characteristics of each modality while embedding the temporal relationships with the subsequent modality, its hybrid ResNet50-LSTM architecture achieves accurate, real-time predictions. Despite achieving notably a 92.5% accuracy, this model still faces the challenge of heavy hardware dependency and streaming data processing time-step limitation which must be thoroughly optimized further for the scaling up process. Moreover, future scope should entail improvement of model efficiency using lightweight deep learning architectures and edge computing providing faster inference and applicability in diverse use cases. In Conclusion: NeoCoD serves as a promising stepping stone for AI-based healthcare technologies that will revolutionize neonatal care through proactive monitoring and early intervention, potentially reducing mortality among newborns and improving their overall health.

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