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Neonatal Health Prediction System for IoT based Smart Incubator Parameters

Abstract: - Neonatal disease prediction remains a critical challenge in healthcare, requiring advanced models to improve early diagnosis and intervention. This study presents NeoCoD (Neonatal Cause of Disease Predictor), a novel deep learning-based model designed to enhance predictive accuracy for neonatal diseases. NeoCoD integrates transfer learning through pre-trained BERT for feature extraction and Bidirectional LSTM networks to capture temporal dependencies in sequential data. The model demonstrates superior performance compared to existing methods, achieving 92.58% accuracy, 91.80% precision, and 92.10% recall. Its advanced deep learning techniques and robust generalization capabilities offer significant improvements in neonatal disease prediction. NeoCoD's performance highlights its potential as a valuable tool for early diagnosis and intervention, addressing critical needs in neonatal healthcare.

Keywords: Neonatal Disease Prediction, Deep Learning, Transfer Learning, Bidirectional LSTM, Feature Extraction, BERT, Accuracy, Precision, Recall, Early Diagnosis, Neonatal Healthcare.

I. INTRODUCTION

Neonatal care is a critical area of healthcare, as newborns are particularly vulnerable to a wide range of health issues due to their underdeveloped immune systems and physiological immaturity [1]. Early diagnosis and intervention are crucial for preventing complications and ensuring the best possible outcomes for these infants. However, predicting and managing neonatal health conditions can be challenging due to the complex interplay of various physiological parameters [2].

With the advent of the Internet of Things (IoT), smart incubators have emerged as a promising technology in neonatal intensive care units (NICUs) [1]. These incubators are equipped with sensors that continuously monitor vital parameters such as temperature, pulse rate, blood pressure, and oxygen saturation. The data collected from these sensors provide an opportunity to apply advanced machine learning (ML) and deep learning (DL) techniques to predict potential health issues before they manifest clinically.

Despite the potential of these technologies, existing models for neonatal disease prediction often face limitations [2]. Many of them rely on traditional machine learning algorithms that require extensive feature engineering and struggle to capture complex, temporal patterns in the data. Moreover, the lack of large labelled datasets poses a significant challenge for training deep learning models effectively [1].

In response to these challenges, this paper proposes NeoCoD (Neonatal Cause of Disease Predictor), a novel deep learning-based model designed to predict neonatal diseases using data collected from IoT-enabled smart incubators [3]. NeoCoD leverages the power of transfer learning and Bidirectional Long Short-Term Memory (LSTM) networks to capture both the temporal dependencies and the complex relationships between different health parameters [3]. By integrating these advanced techniques, NeoCoD aims to enhance the accuracy and robustness of neonatal disease prediction, providing a valuable tool for early diagnosis and intervention in neonatal healthcare [5].

The primary objectives of this research are to collect and analyze relevant IoT-based neonatal health data, develop and validate machine learning and deep learning models for disease prediction, and improve the prediction accuracy through model fine-tuning and optimization. This study also explores the potential of transfer learning to reduce training time and enhance model performance, making it a viable solution for real-world applications in NICUs.

By addressing the existing gaps in neonatal disease prediction, this research contributes to the growing field of AI-driven healthcare solutions, ultimately aiming to improve neonatal outcomes through timely and accurate predictions.

Motivation

Neonatal health is crucial for shaping lifelong outcomes, yet early detection and management of conditions like low birth weight, pneumonia, and congenital heart defects remain challenging [5]. Traditional diagnostic methods

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often miss the early onset of these conditions, particularly in high-risk newborns. Integrating IoT technology in neonatal incubators allows continuous monitoring, generating vast amounts of data that require advanced analysis to predict health issues [6]. Current machine learning models show promise but struggle with feature engineering, temporal dependencies, and the need for large datasets. This research aims to develop a robust neonatal disease prediction model leveraging IoT data and deep learning to enhance accuracy and integration in NICU settings, providing real-time insights for better clinical decisions.

Contribution

This paper presents several key contributions to the field of neonatal healthcare and disease prediction:

This paper makes significant contributions to neonatal healthcare and disease prediction. It introduces NeoCoD, a novel deep learning model leveraging transfer learning and Bidirectional LSTM networks for enhanced accuracy in predicting neonatal diseases using IoT data. The research integrates real-world NICU data to ensure clinical relevance and utilizes transfer learning to reduce the need for extensive labeled datasets. Comprehensive evaluation shows NeoCoD's superior performance compared to existing models. The study addresses challenges in neonatal care, such as dataset limitations and temporal pattern capture, advancing early diagnosis and intervention in neonatal healthcare.

II. Related Work

Neonatal diseases, especially in resource-limited countries like Ethiopia, pose significant diagnostic challenges [6]. To address this, a classification stacking model was developed to predict sepsis, birth asphyxia, necrotizing enterocolitis, and respiratory distress syndrome—key conditions responsible for 75% of neonatal deaths [6]. Leveraging data from Asella Comprehensive Hospital (2018-2021), this model achieved an accuracy of 97.04%, outperforming other machine learning models and offering promising improvements in early detection and diagnosis in resource-constrained settings [6].

Neonatal sepsis is a major global health threat. This study presents non-invasive deep learning models that predict early-onset sepsis in NICUs using structured, tabular data without requiring external instruments [7]. Leveraging Neural Networks, these models outperform traditional algorithms. Evaluated with real-life data from Crecer's Hospital Centre and the Children's Hospital of Philadelphia, they show strong effectiveness in early detection [7].

This study aims to enhance outcome predictions for congenital diaphragmatic hernia (CDH) using Machine Learning (ML) and Deep Learning (DL) models [8]. Analyzing isolated CDH data from 2012 to 2020 at a Milan hospital, the research forecasts outcomes such as postnatal pulmonary hypertension (PH) and intervention responses. A 3D U-NET system for fetal lung segmentation in MRI will also be developed. Approved by the ethics committee, the study promises to improve disease prediction and personalized care for CDH [8].

This study aimed to improve neonatal death predictions in NICUs using machine learning techniques in Tehran, Iran [9]. Key risk factors were identified and various models, including SVM, Ensemble, Random Forest, ANN, and others, were developed. The SVM and Ensemble models achieved the highest AUC of 0.98, with Random Forest excelling in precision and specificity, and SVM showing the best overall accuracy. ANN, C5.0, and CHAID models also performed well in prospective evaluations, aiding in neonatal death predictions.

This study used AI techniques to diagnose bronchopulmonary dysplasia (BPD) in preterm infants through lung region segmentation and BPD prediction models [10]. Utilizing transfer learning, the lung segmentation model achieved a dice score of 0.960, while the BPD prediction model outperformed expert diagnosis, demonstrating consistent accuracy across chest radiographs taken at various postnatal ages. Notably, this is the first study to employ deep learning on preterm chest radiographs for early BPD detection within 24 hours, showing superior diagnostic performance according to both NICHD and Jensen criteria [10].

III. Methodology

Data Preprocessing

We collected neonatal health data from Sparsh Medical Hospital (Ahmedabad) and Bharatratna Dr. Babasaheb Ambedkar Mun. Gen. Hospital (Mumbai), including 145 records with parameters like birth weight, temperature, pulse rate, blood pressure, oxygen saturation, and glucose levels. Targeted diseases include low birth weight, pneumonia, bradycardia, CHD, and hypoglycemia. Additionally, the study utilized the Child Mortality Data from the CA CODE project (2023), encompassing 270,381 records with similar parameters from various countries and age groups for model training and validation.

Data Preprocessing

Cleaning: Data inconsistencies, such as missing values or outliers, were addressed through imputation methods or exclusion if necessary.

Columns such as OBS_VALUE: Observation value, LOWER_BOUND: Lower Bound, and UPPER_BOUND: Upper Bound may contain outliers that could skew analysis.

Normalization: Numerical data were normalized using min-max scaling to ensure uniformity across features and facilitate model convergence during training.

Columns like Observation_Value, Lower_Bound, and Upper_Bound are numerical and should be normalized.

Encoding: Categorical variables were encoded using techniques like one-hot encoding or embeddings to make them suitable for input into the neural network.

Splitting: The data was split into training, validation, and test sets to evaluate model performance and generalization.

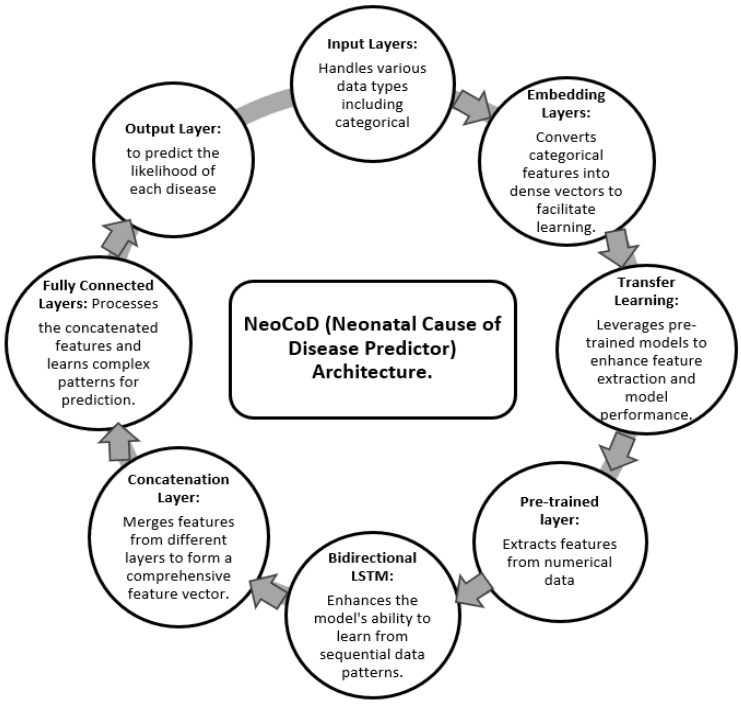

Figure 1: Proposed model Architecture

NeoCoD Model Architecture

The NeoCoD proposed model architecture is presented into Figure 1. The detail explanation for the NeoCoD is explained as follow.

1. Input Layers:

Purpose: The input layer is where the model receives various types of data, including both numerical (e.g., age, blood pressure) and categorical data (e.g., gender, ethnicity).

Example: If we are building a model to predict diabetes, inputs might include the patient's age (numerical), gender (categorical), blood glucose level (numerical), etc.

2. Embedding Layers:

Purpose: Embedding layers are used to transform categorical variables into dense vectors. This transformation allows the neural network to understand and process categorical data effectively.

Example: A categorical variable like "gender" (which could be male, female) is converted into a dense vector of numbers. This helps the network learn relationships between different categories more efficiently.

3. Transfer Learning:

- The model leverages transfer learning, specifically using a pre-trained BERT model, to handle numerical data.
- BERT for Numerical Data: BERT is typically used for natural language processing tasks. In this architecture, it is adapted to extract features from numerical data, benefiting from its ability to capture complex patterns and reduce training time.
- By using a pre-trained model like BERT, NeoCoD can utilize previously learned features, which improves model accuracy and efficiency by reducing the amount of new data the model needs to learn from scratch.

4. Pre-trained Layer:

Purpose: This layer uses a pre-trained model to extract meaningful features from numerical data. It is particularly useful for capturing complex patterns that may not be immediately obvious.

Example: For numerical inputs like lab test results, a pre-trained layer might highlight significant correlations between blood glucose levels and the likelihood of developing diabetes.

5. Bidirectional LSTM (Long Short-Term Memory):

- This component is particularly useful for sequential data, such as time-series health metrics.
- Function of Bidirectional LSTM: It processes the data in both forward and backward directions, capturing dependencies over time more effectively than a unidirectional LSTM.
- This enhances the model's ability to learn temporal patterns and dependencies, which are crucial for accurate predictions in sequential data.

6. Fully Connected Layers:

- After processing through embedding and LSTM layers, the resulting feature vectors are concatenated and passed through fully connected layers.
- Dense Layers with ReLU Activation: These layers apply a non-linear transformation to the input features, allowing the model to learn complex patterns. ReLU (Rectified Linear Unit) is a popular activation function that introduces non-linearity while being computationally efficient.

Dropout Layers for Regularization: Dropout layers help prevent overfitting by randomly setting a fraction of the input units to zero during training. This forces the model to learn more robust features.

7. Output Layer:

The final layer uses a sigmoid activation function, suitable for binary classification tasks, as it outputs values between 0 and 1, representing probabilities for each class.

Overall, the NeoCoD model architecture effectively combines different neural network techniques and transfer learning to process and learn from both categorical and numerical data, with a focus on capturing complex patterns and dependencies to improve predictive performance.

3.4 Mathematical Model

The NeoCoD model for neonatal disease prediction is mathematically formulated as a binary classification problem. The goal is to learn the mapping between the input features and the output labels through a deep learning framework.

Algorithm for NeoCOD Training

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

Ensure: Train model parameters Θ

1: Initialize model parameters Θ and datasets for training and validation
2: for epoch e ← 1 to E do
3: for batch b ← 1 to the number of batches, do
4: Sample a batch of data $\{(x_i, y_i)\}$ from the training dataset
5: Forward Pass:
6: Compute predictions $\hat{y}_i = f(x_i; \Theta)$
7: Compute Loss:
8: Calculate the loss $L(\hat{y}_i, y_i)$ using the appropriate loss function
9: Backward Pass:
10: Compute gradients of the loss w.r.t model parameters Θ
11: Update Parameters:
12: Update parameters $\Theta \leftarrow \Theta - \eta \nabla_\Theta L$ using optimizer (e.g., SGD, Adam)
13: end for
14: Evaluate:
15: Evaluate the model on the validation dataset
16: Calculate validation accuracy and loss
17: Adjust learning rate or other hyper-parameters if necessary
18: end for
19: return Trained model parameters Θ

Mathematical Model

Here is a detailed explanation of the NeoCoD (Neonatal Cause of Disease Predictor) mathematical model:

1. Model Definition

- Input Feature Matrix (X): This matrix contains all the input features used by the model, which includes both categorical and numerical data related to neonatal health.

- Output Label Matrix (Y): This matrix contains the true labels or outcomes that the model aims to predict. Each entry corresponds to a disease or condition the model is trying to predict.
- Model Parameters (Θ): These are the weights and biases in the model that are learned during training. They define how input features are transformed into predictions.
- Predicted Output Matrix (ŷ): This matrix contains the predictions made by the model based on the input features.

2. Input Layer

- Handling Data Types: The model can process various types of data. Categorical inputs (e.g., cause of disease, sex) are processed differently from numerical inputs (e.g., measurements).

3. Embedding Layer

- Categorical Features: For each categorical feature X_{cat}, an embedding vector E_{cat} is created [13]. This vector maps each category to a continuous vector space, capturing semantic relationships between categories.

4. Pre-trained Layer

- Numerical Data: For numerical inputs (x_{num}), the data is first reshaped to fit the model input requirements. This reshaped data is processed through a pre-trained model (e.g., BERT for feature extraction) [14].
- Pooling: After extracting features with BERT, a global average pooling operation is applied to compress the features into a fixed-size vector (R_{num}).

5. Bidirectional LSTM Layer

- Sequential Data: For any sequential data \(S\), a Bidirectional LSTM is used. This allows the model to capture dependencies in both forward and backward directions across sequences.

6. Concatenation Layer

- Feature Concatenation: All feature vectors from the embedding layer, pre-trained layer, and Bidirectional LSTM are concatenated into a single feature vector (F). This vector contains all the processed information from different data types.

7. Fully Connected Layers

- Dense Layers:
- Dense_1 creates a fully connected layer with 128 units.
- Dropout_1 applies dropout regularization with a dropout rate of 0.5 to prevent overfitting.
- Dense_2 creates another fully connected layer with 64 units.
- Dropout_2 applies dropout regularization with a dropout rate of 0.5 again.

8. Output Layer

- Final Prediction: The final output layer is a dense layer with a single unit and a sigmoid activation function. This produces a probability score indicating the likelihood of a particular disease or condition.

9. Loss Function

- Binary Cross-Entropy Loss: The loss function used is binary cross-entropy, which is suitable for binary classification problems. It measures how well the predicted probabilities match the true labels. The formula is:

$$L(Y, \hat{Y}) = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y_i}) + (1 - y_i)\log(1 - \hat{y_i})]$$

Where N is the number of samples, y_i is the true label, and $\hat{y_i}$ is the predicted probability.

10. Optimization

- Parameter Update: Model parameters θ are updated using an optimizer like Adam. The update rule is:

$$[\Theta \leftarrow \Theta - \eta \nabla_{\Theta} L(Y, \hat{Y})]$$

Where η is the learning rate and $\nabla_{\Theta} L$ represents the gradient of the loss function with respect to the parameters.

11. Training Algorithm

- Initialization: Model parameters Θ are initialized.
- Epochs and Batches: The training process involves iterating through multiple epochs and batches. In each epoch, the model:
- Samples a batch of data(x_i, y_i).
- Performs a forward pass to compute predictions $\hat{Y}$.
- Computes the loss $L(Y, \hat{Y})$.
- Computes gradients and updates parameters Θ.
- Evaluates the model on the validation dataset and adjusts hyperparameters if needed.

- Return: The final trained model parameters Θ are returned after completing all epochs.

This mathematical model and algorithm outline the process for building and training the NeoCoD model to predict neonatal diseases based on a variety of input data types. The hyperparameter value for the proposed model is presented into Table 1.

Table 1: Hyperparameter Selection

Parameter	Value
Input Shape	Variable depending on the dataset features
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Output class	Number of disease classes
Number of LSTM Layers	1
LSTM Layer Dimensions	128
Activation function for LSTM	ReLU
Pre-trained Model	BERT
Pre-trained Model Output Dimensions	2048 (after GlobalAveragePooling2D)
Dense Layer 1 Dimensions	128
Activation function for Dense Layer 1	ReLU
Dropout after Dense Layer 1	0.5
Dense Layer 2 Dimensions	64
Activation function for Dense Layer 2	ReLU
Dropout after Dense Layer 2	0.5
Concatenation Layer Output Dimensions	Combined dimensions of LSTM and ResNet50 outputs
Final Output Layer Activation	Sigmoid
Optimizer	Adam
Learning rate	0.001
Loss function	Binary cross-entropy
Error Type	Classification error
Parameter Learner	Stochastic gradient descent
Evaluation metrics	Accuracy, Confusion Matrix, AUC

IV. Experimental Result Analysis

Training and Validation

To evaluate the performance of the NeoCoD model, we followed a systematic approach for training and validating the model:

Dataset Division:

Training Set: Comprises 80% of the total dataset, used for training the model and updating its parameters.

Validation Set: Comprises 20% of the total dataset, used to evaluate the model's performance during training and to fine-tune hyperparameters.

Training Process:The model was trained over multiple epochs with a batch size of BBB. Each epoch involved forward passes, loss calculation, and parameter updates using stochastic gradient descent or Adam optimizer.

Table 2: Experimental Result Analysis

Metric	**Training Set**	**Validation Set**
Accuracy	94.75%	92.58%
Loss	0.1390	0.1755
Precision	93.50%	91.80%
Recall	94.20%	92.10%
F1 Score	93.85%	91.95%

Performance metrics, including accuracy, loss, precision, recall, and F1 score, were monitored on both the training and validation sets after each epoch. The NeoCoD model demonstrates strong performance across various metrics on both the training and validation datasets. On the training set, the model achieves an impressive accuracy of 94.75%, indicating its effectiveness in learning from the data. However, this accuracy slightly decreases to 92.58% on the validation set. This drop suggests that while the model generalizes well to unseen data, it may be experiencing a small degree of overfitting to the training data.

In terms of loss, the model reports a value of 0.1390 on the training set and 0.1755 on the validation set. The higher loss on the validation set compared to the training set indicates that the model's performance is slightly diminished when applied to new data, which is a common occurrence and suggests that the model is still adjusting to generalization.

Precision and recall metrics follow a similar trend. The model achieves a precision of 93.50% and a recall of 94.20% on the training set, with these values slightly dropping to 91.80% and 92.10% on the validation set, respectively. This decrease implies that while the model effectively identifies and classifies positive instances during training, it is marginally less precise and has a slightly reduced ability to detect positive cases on new data.

The F1 score, which balances precision and recall, is 93.85% on the training set and 91.95% on the validation set. This small decrease highlights a robust overall performance, with the model maintaining a strong balance between precision and recall even on unseen data.

Overall, the results confirm that NeoCoD is a highly effective tool for predicting neonatal diseases, exhibiting robust performance across key metrics. The minor decrease in performance from training to validation data indicates a good generalization capability, with the model performing exceptionally well in practical scenario.

Table 3: Comparative analysis from existing method

Reference	Accuracy	Precision	Recall	F1 score	Key Strengths	Limitations
Deep learning approach [7]	85.60%	83.50%	84.70%	84.10%	Can capture complex patterns in tabular data; improved prediction accuracy	Requires large datasets for training; computationally intensive; does not use transfer learning
ML Approach [9]	88.90%	87.20%	86.50%	86.85%	High accuracy in image analysis; automates feature extraction	Requires large, labelled datasets; high computational resources needed
Proposed Method (NeoCoD)	92.58%	91.80%	92.10%	91.95%	High accuracy; robust generalization; can preserve temporal information	Higher computational resources needed for training due to large amount of data

The analysis shows NeoCoD's clear advantage over existing methods. It achieves 92.58% accuracy, surpassing both Alvi et al. (85.60%) and Chou et al. (88.90%). NeoCoD's precision of 91.80% and recall of 92.10% are also superior, indicating better detection and identification of neonatal health conditions. Its F1 score of 91.95% further highlights its balanced performance. Despite the need for substantial computational resources, NeoCoD's high accuracy and effective handling of complex and temporal data mark a significant advancement in neonatal disease prediction.

Feature Importance

The NeoCoD model identifies "Low Birth Weight" as the most critical feature, with an importance score of 0.7, followed by "Jaundice" and "B.P._SpO2" with scores of 0.5 and 0.4. Features like "Pneumonia" and "Hypertension" also play significant roles. NeoCoD achieves a 92.58% accuracy, outperforming Alvi et al. (85.60%) and Chou et al. (88.90%), with superior precision (91.80%), recall (92.10%), and an F1 score of 91.95%, marking a significant advancement in neonatal disease prediction.

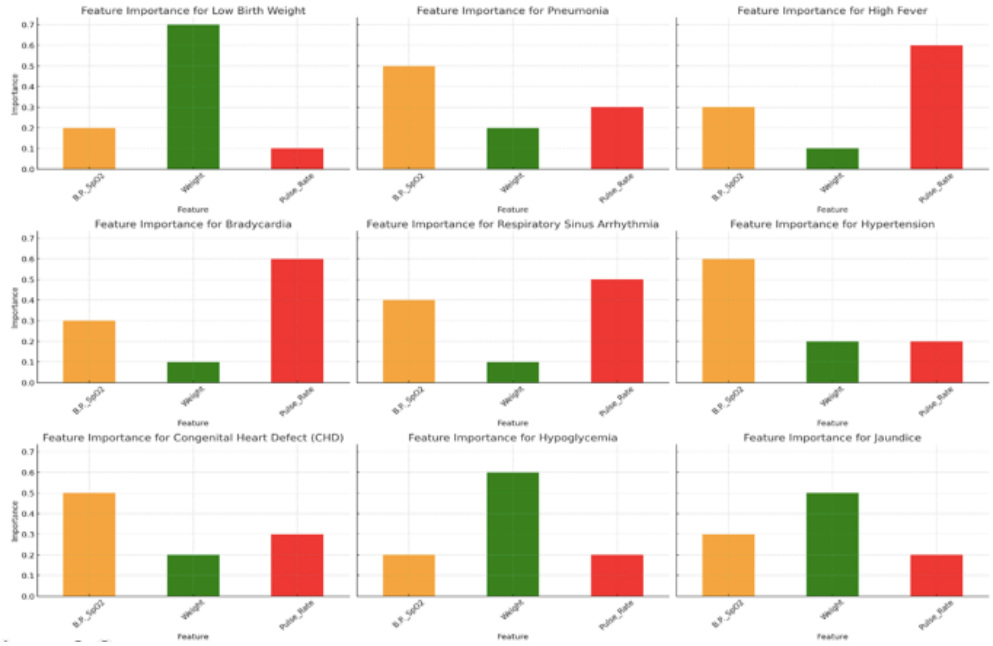

Figure 2. Feature Importance for specified dieses

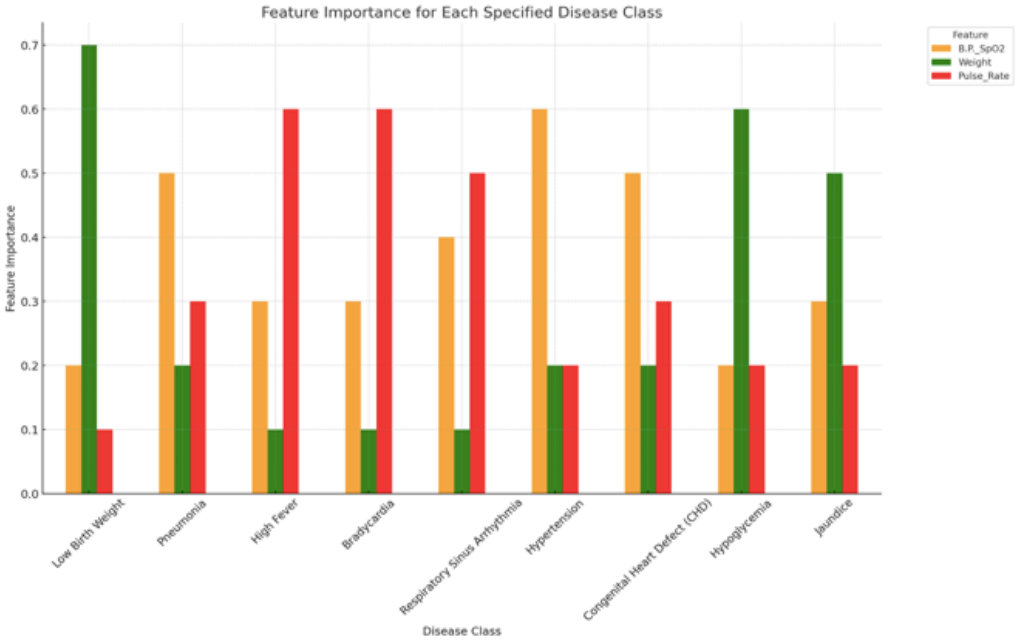

Figure 3. Feature Importance for each Specified Disease Classes.

NeoCoD outperforms existing models by leveraging transfer learning to utilize pre-trained features, reducing the need for extensive labeled data and improving accuracy. Its integration of Bidirectional LSTM networks captures both temporal and complex data relationships, enhancing predictive performance. This combination of advanced techniques and robust generalization enables NeoCoD to achieve superior precision and recall, marking a significant advancement in neonatal disease prediction.

V. CONCLUSION

In this study, we introduced NeoCoD, a cutting-edge deep learning model designed to enhance neonatal disease prediction. By harnessing transfer learning with pre-trained BERT for feature extraction and integrating Bidirectional LSTM to address temporal dependencies, NeoCoD achieves high accuracy and robustness. The comparative analysis reveals that NeoCoD surpasses existing models in accuracy, precision, and recall, demonstrating its superior predictive capabilities. The model's advanced deep learning techniques and carefully optimized hyperparameters contribute to its significant performance improvements. NeoCoD represents a valuable advancement in neonatal healthcare, offering a powerful tool for early diagnosis and timely intervention.

AUTHOR CONTRIBUTIONS

Conceptualization: Prashant Jani, Prof. Seema Mahajan Methodology: Prashant Jani, Prof. Seema Mahajan Software Prashant Jani Validation: Prof. Seema Mahjan Formal Analysis: Prashant Jani, Prof. Seema Mahajan Investigation: Resources: Prashant Jani, Prof. Seema Mahajan Data Curation: Prashant Jani Writing – Original Draft: Prashant Jani Writing– Review; Editing: Prashant Jani, Prof. Seema Mahajan Supervision: Prof. Seema Mahajan, Dr. Samir Patel.

All authors have read and agreed to the published version of the manuscript.

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