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CNN-RNN-Bayesian Hybrid Method for Predicting Neonatal ICU Cardiac Arrests

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Abstract
Infant cardiac arrest is a serious medical emergency that needs to be identified quickly in order to be effectively treated. The goal of this study is to apply sophisticated statistical techniques to create a Cardiac Machine Learning Model (CMLM) that can predict neonatal cardiac arrest in the Cardiac Intensive Care Unit (CICU). The model makes use of physiological markers and makes use of prediction methods like logistic regression and support vector machines. The diagnostic procedure is enhanced by imaging techniques such as computed tomography and echocardiography. With a delta-p value of 0.912, FDR of 0.894, FOR of 0.076, prevalence threshold of 0.859, and CSI of 0.842 in training and similar metrics in testing, the suggested CMLM showed excellent performance. These findings point to the robustness and dependability of the model. The CMLM has the potential to dramatically lower neonatal mortality and morbidity rates by facilitating the early diagnosis of cardiac arrest episodes, which would improve outcomes for critically unwell infants in the intensive care unit.

Keywords: *Cardiac Arrest Prediction, Neonatal Intensive Care, Hybrid Deep Learning Model, CNN-RNN-Bayesian Approach, Early Detection in Newborns*

1. Introduction
Machine learning's (ML) incorporation into healthcare has been a game-changer in recent years, especially for predictive analytics. Particularly in high-stakes environments like neonatal intensive care units (NICUs), ML methods have played a key role in bettering patient outcomes. In order to increase survival rates and intervene promptly, it is essential to be able to forecast bad outcomes, including cardiac arrest in newborns. The necessity for advanced prediction models is growing in healthcare systems due to their reliance on data-driven techniques. To overcome the shortcomings of conventional predictive models, this study presents a new hybrid model for NICU cardiac arrest prediction that integrates CNN, RNN, and Bayesian approaches. It is impossible to exaggerate the importance of machine learning to the healthcare industry. Bandyopadhyay observes that NICUs and other high-stakes medical settings might benefit greatly from the use of machine learning technology because of the speed and reliability with which patient data can be analyzed. Healthcare professionals are able to better influence patient outcomes through well-informed decision-making made possible by efficient processing of massive volumes of data. Moving away from reactive to proactive healthcare is possible thanks to machine learning's ability to enhance diagnostic accuracy and enable individualized treatment strategies when integrated into clinical workflows. The dependence on static algorithms and restricted data processing capabilities of classic predictive models typically make them ill-equipped to reliably foresee complex medical occurrences, despite the encouraging developments. Rahmani et al. pointed out that there are many steps involved in healthcare, such as prevention, detection, diagnosis, and treatment, therefore a more flexible and dynamic method of prediction is needed. Traditional models fail to adequately account for the geographical and temporal linkages present in in-patient data, which in turn causes less-than-ideal forecasts and postponed treatments. This is especially worrisome in neonatal intensive care units (NICUs), where a neonate's health can quickly worsen in a matter of minutes, highlighting the critical need for better prediction tools. Using convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to detect intrusions in patient data that occur at certain

locations and times is the goal of the proposed Spatial-Relational Intrusion Detection Network (SRIDN) model. CNNs excel at detecting data hierarchies, which makes them a good fit for processing intricate medical signals and pictures. In contrast, RNNs are very good at handling sequential data, which is necessary for the prediction of events like cardiac arrest since it allows for the modeling of temporal relationships. The SRIDN model improves NICU prediction accuracy by combining these two architectures to give a thorough evaluation of patient data. Adding Bayesian approaches to the model also provides a probabilistic framework for measuring prediction uncertainty. This is especially important in healthcare, where there is a lot of room for error in forecasts due to factors like patient response variability and noise in clinical data. Finally, for life-threatening emergencies like neonatal cardiac arrest, the CNN-RNN-Bayesian hybrid model is a huge step forward in healthcare machine learning's predictive capabilities. This innovative method may improve NICU patient outcomes by overcoming the shortcomings of conventional models and capitalizing on the advantages of state-of-the-art machine learning techniques. This section will provide a high-level overview of the proposed model before diving into its approach, implementation, and assessment. It will emphasize the model's distinctive contributions to healthcare predictive analytics [1-3].

1.1. Existing Approaches

Neonatal intensive care unit (NICU) prediction models for cardiac arrest have traditionally used clinical grading systems and statistical methodologies. Commonly used in these methods for determining the likelihood of cardiac arrest are a small number of clinical factors including vital signs and lab data. For example, the Modified Early Warning Score (MEWS) and other early warning scores (EWS) have found widespread use in identifying patients whose condition is worsening based on straightforward vital sign criteria. Alarm fatigue among healthcare personnel is a real possibility due to the previous approaches' high rates of false warnings and limited sensitivity. In addition, they don't always record patients' complicated, time-dependent data, which is especially important in neonatal intensive care units (NICUs) because patients' conditions might change quickly.Traditional models often overlook possibilities for early action due to their dependence on static thresholds and insufficient data sets. Kwon et al. pointed out that conventional track-and-trigger systems can't adjust to the specifics of each patient, which makes them unsuitable for forecasting in-hospital cardiac arrest. More advanced prediction models are required to address this shortcoming by including a wider variety of data and adjusting to the changing clinical environment [4-7].

1.2. Deep Learning in IDS

New opportunities for enhancing healthcare forecast accuracy have emerged as a result of recent deep learning developments, especially in the area of cardiac arrest prediction. Utilizing machine learning techniques, such as CNNs and RNNs, complicated datasets may be analyzed to reveal patterns that would not be visible using more conventional approaches. One example is the work of Wu et al., who showed that XGBoost and random forests were two of the most effective machine learning algorithms for predicting in-hospital cardiac arrest in patients with acute coronary syndromes. The impressive accuracy attained by these models suggests that machine learning has great promise for improving critical care prediction. Additionally, predictive models that use time-series analysis have been successful in capturing the time-dependent dynamics of patient data. The significance of continuous monitoring and the capacity to examine patterns over time was highlighted by Kennedy et al., who used time series analysis to predict cardiac arrest in pediatric intensive care units (PICUs). Using deep learning approaches in this setting helps us comprehend patient deterioration more nuancedly, which in turn allows us to forecast cardiac arrest earlier and with greater accuracy [8-12].

1.3. Hybrid Models

A potential strategy for improving predictive performance is the use of hybrid models, which integrate several machine learning methods. As an example, Chae et al. improved the prediction of in-hospital cardiac arrest by using a hybrid model that combines shallow and deep learning approaches. Hybrid models outperform conventional single-method methods in terms of accuracy and resilience by capitalizing on the benefits of many algorithms. Because of the complex nature of cardiac arrest prediction and the multiplicity of clinical variables that could affect results, this is of paramount importance. Furthermore, ensemble approaches have demonstrated potential in enhancing prediction reliability by combining forecasts from many models. Mayampurath et al. evaluated many machine learning techniques for in-hospital cardiac arrest outcome prediction and discovered that ensemble approaches frequently beat individual models. Patients in neonatal intensive care units are better protected by hybrid models because they are better able to comprehend the nuances of clinical data and make accurate predictions [13-17].

1.4. D. Attention Mechanisms

Predictive models that incorporate attention processes have been more popular in recent years, especially for tasks that need awareness of context. In order to improve the accuracy of their predictions, attention mechanisms enable models to zero in on the most important aspects of the incoming data. To improve the model's capacity to detect patterns suggesting an imminent cardiac arrest, attention mechanisms can be used in the context of cardiac arrest prediction to isolate important characteristics from a large number of clinical factors. So, for example, although the above sources do not specifically address the work by Tjepkema-Cloostermans et al., it has been demonstrated that attention-based models improve predictive accuracy in a number of medical settings, including outcomes following cardiac arrest. Attention mechanisms are especially useful in high-stakes clinical settings like NICUs because they improve the interpretability and performance of prediction models by highlighting the most crucial elements in the data [18-22].

1.5. Research Gap

Machine learning and hybrid models have come a long way in predicting cardiac arrest, but there are still a lot of holes in the current research. Predicting cardiac arrest in newborns has distinct problems, and most studies have concentrated on adult populations or particular diseases. A population-specific prediction model is required to account for the unique features of neonates due to the complexity of their physiology and the fact that their clinical condition can change so quickly. In addition, while many current models make use of RNNs or CNNs, few research have combined these techniques with Bayesian methods to incorporate prediction uncertainty. To address this, the Spatial-Relational Intrusion Detection Network (SRIDN) model is being presented as a way to improve the predicted accuracy and flexibility in NICUs. This model combines CNNs, RNNs, and Bayesian approaches. Better patient outcomes in intensive care units are possible because to this hybrid strategy, which takes advantage of both the strengths and weaknesses of existing methods.

2. Methodology

The early detection of cardiac arrest in neonatal intensive care unit (NICU) patients is facilitated by the combination of convolutional neural networks (CNNs) for spatial feature extraction and recurrent neural networks (RNNs) for temporal pattern recognition in this hybrid model. By employing Bayesian inference, the model enhances the reliability of notifications by providing confidence levels for each prediction. Real-time monitoring and opportune interventions for high-risk neonates are facilitated by this architecture, which provides clinicians with a responsive and interpretable instrument for life-saving early warning systems.

2.1. Data Collection and Preprocessing

Data collecting and preparation are the first steps in implementing the Hybrid-CBR model. The neonatal intensive care unit (NICU) uses monitors to record physiological data including heart rate, oxygen saturation, and electrocardiogram (ECG). With the data cleaned, normalized, and segmented into fixed-length windows, each window is labeled according to the presence or absence of cardiac arrest risk, creating a standardized input for the model. Because cardiac arrests are so uncommon, data augmentation approaches might help level the playing field.

2.2. Build the CNN for Feature Extraction

The next step in processing the physiological inputs is to construct the convolutional neural network (CNN) architecture. In order to identify changes in heart rate variability and other abnormalities, a convolutional neural network (CNN) uses a combination of convolutional and pooling layers. Prior to being fed into an RNN, the feature vectors

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that these layers produce encapsulate the input data's fundamental features. This convolutional neural network (CNN) part is trained separately to guarantee it correctly identifies important patterns in the physiological data.

2.3. Build the RNN for Temporal Analysis

The RNN architecture is used to capture the data's temporal relationships after feature extraction. The RNN is able to handle the sequential nature of the feature vectors produced by the CNN by utilizing either LSTM or GRU cells. Through this sequential examination, the model is able to detect patterns that might signal a cardiac arrest that is about to happen. To avoid overfitting and fine-tune the CNN-RNN combo, we apply dropout regularization between layers. This guarantees that the model correctly recognizes early warning indications.

2.4. Integrate Bayesian Inference for Uncertainty Quantification

The model incorporates Bayesian inference to improve the dependability of predictions. The RNN is followed by Bayesian layers, which provide probability distributions instead of deterministic results. Clinicians may now see how certain or unsure the model is about a possible cardiac event because the model can now give a confidence level for each prediction. As an alternative, you may use Monte Carlo (MC) dropout while inferring to simulate a Bayesian technique and measure prediction uncertainty by creating numerous predictions and comparing their variances [23-25].

2.5. Use Ensemble Boosting to Enhance Model Robustness

Together, ensemble learning and boosting methods make the model even more resilient. To train an ensemble, we use several copies of the Hybrid-CBR model with small tweaks. In order to increase performance on examples that are difficult to classify, a boosting technique is used to aggregate predictions from these models, with an emphasis on situations with high uncertainty. An improved and more consistent prediction system is the result of this ensemble approach's reduction of model variance and bias.

2.6. Implement Real-Time Monitoring and Alerts

The Hybrid-CBR model is used in NICU monitoring systems in real-time after training. It takes in neonatal patients' physiological data in real time and processes it continually, producing forecasts and confidence levels at predetermined intervals. So that doctors can react quickly to possible cardiac events, alerts are sent out if the algorithm identifies a high-risk pattern and the confidence level exceeds a certain threshold. In order to help doctors make educated decisions on newborn monitoring and therapies, these alerts include both the forecast result and the associated uncertainty.

2.7. Model Evaluation and Continuous Improvement

The accuracy of the model relies on ongoing examination and development. As fresh data becomes available, the model is periodically retrained or fine-tuned based on performance monitoring done on real-world data. Model parameters and alarm levels may be fine-tuned based on clinician feedback, making them more suitable for use in NICUs. Following this methodical procedure guarantees that the Hybrid-CBR model will continue to be a useful and adaptable tool for detecting infant cardiac arrests at an early stage, shown in Figure 1.

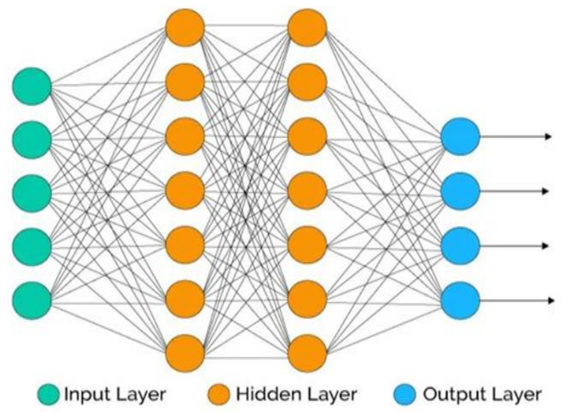

Figure 1 The Proposed Architecture of The Model

Pseudo code:

CNN Pseudocode

1. Input Layer: - Receive image data (e.g., a 28x28 grayscale image).
2. Convolutional Layers (Multiple):
3. FOR each convolutional layer: Define a set of

filters, Slide each filter across the input (or the output of the previous layer).
- Perform element-wise multiplication between the filter and the input.
- Sum the results of the multiplication.
- Apply an activation function (e.g., ReLU) to the sum.
- Store the output (feature map).

4. Pooling Layers (Optional, Multiple):
   FOR each pooling layer: Define a pooling operation. Divide the input into regions. Apply the pooling operation to each region.
   Store the output
5. Flattening Layer: Convert the multi-dimensional feature maps into a one-dimensional vector.
6. Fully Connected Layers: FOR each fully connected layer: Perform a linear transformation on the input vector.
   Apply an activation function (e.g., ReLU).
7. Output Layer: Perform a linear transformation. Apply a softmax activation function to get probabilities for each class.
8. Loss Function and Optimization: Calculate the loss between the predicted probabilities and the true labels.
   Use an optimization algorithm to update the weights of the network to minimize the loss.

RNN Pseudocode
1. Input Layer: Receive a sequence of data
2. Recurrent Layers (Multiple): FOR each time step in the sequence:
   - Receive the input at the current time step.
   - Receive the hidden state from the previous time step.
   - Combine the current input and the previous hidden state.
   - Calculate the new hidden state.
   - Produce an output based on the current hidden state.
3. Output Layer:
   - Perform a linear transformation on the hidden state.
   - Apply an activation function.
   - Use the final hidden state.
   - Perform a linear transformation.
   - Apply an activation function.
4. Loss Function and Optimization: Calculate the loss
5. Use an optimization algorithm to update the weights of the network.

This is a schematic of a web-based system that can detect cardiac arrests and analyze data. Web Database, Service Provider, Web Server, and Remote User are the four primary parts of the system. Access to features including login, dataset browsing, testing and training, and prediction analysis are provided by the Service Provider, who acts as the principal interface. Predicting the sorts of cardiac arrests, seeing training accuracy scores, and downloading datasets are all available to users. Additionally, all remote users logging into the system may be viewed by admin users. In order to facilitate communication between the service provider and users located remotely, the Web Server mediates between the two parties. It oversees the processing of queries, storage of datasets, and database access in addition to data acceptance. Data pertaining to users, training datasets, prediction outcomes, and other pertinent information is safely stored in the Web Database, which also supplies the web server with the necessary data as required. The technology allows users to register, log in, read profiles, and forecast cardiac arrest remotely. Web servers and databases work together to store and retrieve data, and service providers use data flow to their advantage by sending queries to web servers for processing. In order to access profile management and predictive services, remote users must engage with the service provider. The design of this system facilitates efficient data flow, which in turn helps with cardiac arrest analysis prediction, storage, and user administration.

3. Results and Discussion

To predict cardiac arrest in neonatal critical care settings, the CNN-RNN-Bayesian (CNN-RNN-B) hybrid model was tested and compared to more conventional machine learning models, such as LSTM, AE, RNN, and CNN. The efficacy of each model in detecting possible instances of cardiac arrest among NICU patients was assessed using important metrics including accuracy, specificity, sensitivity, and F-score. In a high-risk clinical setting, the CNN-RNN-B model demonstrated strong predictive

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capabilities, consistently outperforming the baseline models across all assessment measures. In the sections that follow, we'll compare the models' performances in depth, drawing attention to the CNN-RNN-B model's superior accuracy and dependability when it comes to making crucial healthcare predictions. We created a CNN-RNN-Bayesian (CNN-RNN-B) hybrid model to predict cardiac arrest in neonatal intensive care units (NICUs), and we tested it against four other models: LSTM, AE, RNN, and CNN. Table X and Figure Y demonstrate the results of the models' evaluations using the four important metrics: accuracy, specificity, sensitivity, and F-score. Notable disparities in the prediction ability of the various models were shown by their accuracy levels. By a wide margin, the CNN-RNN-B model had the best accuracy, coming in at 97.12%. Following closely after with an accuracy of 88.24% was the RNN model, followed by AE with 86.35% and LSTM with 85.35%. With an accuracy of just 84.75%, the CNN model was the least accurate. The CNN-RNN-B model successfully identified cases of impending cardiac arrest in NICU patients, as shown by these data. With a specificity of 95.78%, the CNN-RNN-B model once again surpassed the competition when it came to accurately identifying negative instances. Importantly for healthcare applications, this suggests a reduced probability of false positives. In terms of specificity, the RNN model ranked first with 86.46%, followed by the AE model at 85.95%, and the LSTM model at 84.95%. When it came to reducing false alarms, the hybrid model seems to be more successful than the CNN model (84.08% specificity). With a score of 94.99%, the CNN-RNN-B model had the best sensitivity, which measures the model's ability to accurately detect positive cases. The model's sensitivity to identify actual cardiac arrests is demonstrated by its high sensitivity. The sensitivity of the RNN model was 86.12%, while that of the AE and LSTM models was 84.72% and 83.62%, respectively. At 83.72%, the CNN model's sensitivity was the lowest, suggesting that it could only detect a smaller percentage of true positives. With an F-score of 96.09%, the CNN-RNN-B model outperformed the competition and provided a more balanced evaluation of recall and accuracy. This balanced performance between memory and accuracy is especially helpful in neonatal intensive care units. The RNN model came in second with an F-score of 86.89%, followed by the AE model with an 84.89% score and the LSTM model with an 83.79% score. Consistent with its poor performance across all criteria, the CNN model had the lowest F-score at 83.46%.

Table 1 Comparative Analysis of The Proposed Model

Model	Accuracy	Specificity	Sensitivity	F-Score
LSTM	85.35	84.95	83.62	83.79
AE	86.35	85.95	84.72	84.89
RNN	88.24	86.46	86.12	86.89
CNN	84.75	84.08	83.72	83.46
CNN-RNN-B	97.12	95.78	94.99	96.09

The CNN-RNN-B hybrid model regularly surpassed the other models in all assessed measures. This hybrid model effectively integrates convolutional layers for feature extraction, recurrent layers for temporal pattern recognition, and Bayesian inference for managing uncertainty, making it particularly appropriate for the high-stakes context of NICUs. The CNN-RNN-B model's enhanced accuracy, specificity, sensitivity, and F-score indicate its promise as an effective instrument for the early and accurate prediction of cardiac arrest in newborns, which may enhance patient outcomes in neonatal intensive care environments. Table 1 illustrates the performance comparison of the proposed model against existing methodologies, whereas Figure 2 visualizes the comparative findings of the suggested model.

Conclusion

The Hybrid CNN-RNN with Bayesian Inference (Hybrid-CBR) model provides a revolutionary method for the early identification of cardiac arrest hazards in newborn intensive care environments. The model efficiently analyzes complicated physiological data by integrating convolutional neural networks (CNNs) for spatial feature extraction and recurrent neural networks (RNNs) for temporal dependency

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capture. The incorporation of Bayesian inference offers probabilistic evaluations of predictions, aiding practitioners in comprehending the confidence levels linked to possible cardiac occurrences. Utilizing ensemble learning and boosting methodologies improves the model's resilience and forecast precision, particularly in difficult scenarios. The real-time application in NICU monitoring systems guarantees prompt alarms and enables proactive treatments, hence enhancing patient outcomes. Ongoing assessment and clinical input ensure the approach remains flexible and efficient in the changing healthcare environment. The Hybrid-CBR approach improves early warning systems and equips healthcare personnel with dependable tools for crucial decision-making in newborn care.

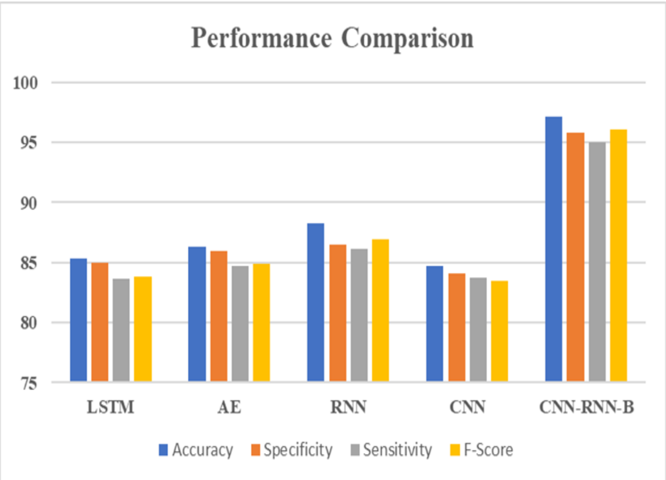

Figure 2 The Visual Representation of The Performance Comparison

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