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Heartbeat: AI-Based Neonatal Cardiac Arrest Prediction Using Hybrid Deep Learning with Real-Time IoT Monitoring

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Abstract: Cardiac arrest in newborn infants is a serious medical emergency requiring immediate attention. Early detection of such events can significantly improve survival rates and reduce complications. However, conventional monitoring systems are mostly reactive and depend on fixed threshold values, which limits their ability to provide early warnings. In this work, an intelligent monitoring framework is proposed that integrates Internet of Things (IoT) technology with a hybrid deep learning approach. The system continuously collects physiological parameters such as heart rate, oxygen saturation, and body temperature using embedded sensors. These measurements are transmitted through an ESP32 microcontroller to a cloud platform for real-time processing. A hybrid deep learning model combining convolutional and recurrent layers is employed to analyze time-series data and estimate the probability of cardiac arrest. The model is designed to capture both feature-level and temporal dependencies in physiological signals. The proposed system provides real-time alert mechanisms through both local and remote interfaces. The experimental results indicate that the model achieves high prediction accuracy and reliability compared to traditional approaches. This framework can be effectively deployed in neonatal care units to support timely clinical decision-making. The system is validated using real-time hardware implementation and IoT-based visualization.
Keywords: Neonatal Monitoring, Cardiac Arrest Prediction, IOT, Deep Learning, CNN, LSTM.

I. INTRODUCTION

Care provided to newborn infants plays a crucial role in ensuring their survival and healthy development. Babies admitted to neonatal intensive care units are highly vulnerable to sudden physiological variations. Among the various medical emergencies, cardiac arrest is one of the most life-threatening conditions that require immediate intervention.

Existing monitoring systems used in hospitals are primarily based on threshold-based alert mechanisms. These systems generate alerts only when the patient's vital parameters exceed predefined limits. As a result, they are unable to provide early warnings and often lead to delayed medical response. Additionally, the occurrence of frequent false alarms reduces the effectiveness of these systems.

Recent advancements in Artificial Intelligence and IoT technologies have enabled the development of intelligent healthcare systems capable of real-time monitoring and predictive analysis. Deep learning techniques are particularly effective in identifying complex patterns in physiological data.In this paper, a smart neonatal monitoring system is proposed that combines IoT-based data acquisition with a hybrid deep learning model to predict cardiac arrest at an early stage.

II. RELATED WORK

Several studies have explored the use of machine learning techniques for predicting cardiac conditions. Traditional methods such as logistic regression and decision tree algorithms have been widely used. However, these approaches are limited in their ability to handle time-dependent data.

Deep learning models such as convolutional neural networks and recurrent neural networks have shown improved performance in healthcare applications. LSTM networks, in particular, are effective in analyzing sequential data and capturing temporal dependencies.

Despite these advancements, many existing systems are limited to offline analysis and are not integrated with real-time IoT-based monitoring. This creates a gap between theoretical models and practical implementation.The proposed system addresses this gap by integrating real-time data acquisition with a hybrid deep learning model for continuous monitoring and prediction.

III. PROPOSED SYSTEM

The proposed system is designed as a combination of hardware and software components working together to achieve real-time prediction.

The system includes sensor modules that measure important physiological parameters such as heart rate, oxygen saturation, and body temperature. These sensors are connected to an ESP32 microcontroller, which is responsible for data acquisition and preprocessing.

The processed data is transmitted to a cloud platform through wireless communication. The cloud platform stores and visualizes the data, making it accessible to healthcare professionals.

A hybrid deep learning model is deployed on the cloud to analyze the incoming data and predict the risk of cardiac arrest. The system also includes an alert mechanism that notifies medical staff when abnormal conditions are detected.

IV. SYSTEM ARCHITECTURE

The overall system architecture of the proposed neonatal cardiac monitoring system is illustrated in Fig. 1. The architecture is designed as a multi-layer framework consisting of sensing, processing, communication, and prediction layers.

In the sensing layer, physiological parameters such as heart rate, oxygen saturation (SpO2), and body temperature are continuously collected using dedicated sensors. These signals are forwarded to the processing layer, where the ESP32 microcontroller performs initial data acquisition and preprocessing.

The communication layer enables wireless transmission of the processed data to a cloud platform using Wi-Fi connectivity. The cloud infrastructure is responsible for data storage, visualization, and real-time accessibility.Finally, the prediction layer applies a hybrid deep learning model to analyze the incoming time-series data and estimate the probability of cardiac arrest. Based on the prediction results, alerts are generated and communicated to healthcare providers through both local and remote interfaces.

V. HARDWARE AND SOFTWARE IMPLEMENTATION

A. Hardware Prototype

The developed hardware prototype of the proposed neonatal cardiac monitoring system is shown in Fig. 2(a) and Fig. 2(b). The system is designed using an ESP32 microcontroller as the main processing unit, connected with physiological sensors and alert components.

The MAX30105 sensor is used to measure heart rate and oxygen saturation (SpO2), while the DS18B20 sensor is used to measure body temperature. These sensors continuously collect real-time data from the subject. The ESP32 processes the collected data and transmits it to the cloud platform through Wi-Fi communication.

An LCD display is used to show the measured values locally. A buzzer is also included to generate alerts when abnormal conditions are detected.The system was tested in real-time by placing the sensor on a human subject, as shown in Fig. 2(b). The hardware successfully captured live physiological values and responded correctly during both normal and abnormal conditions.

The overall hardware design is simple, cost-effective, and suitable for real-time healthcare monitoring applications.

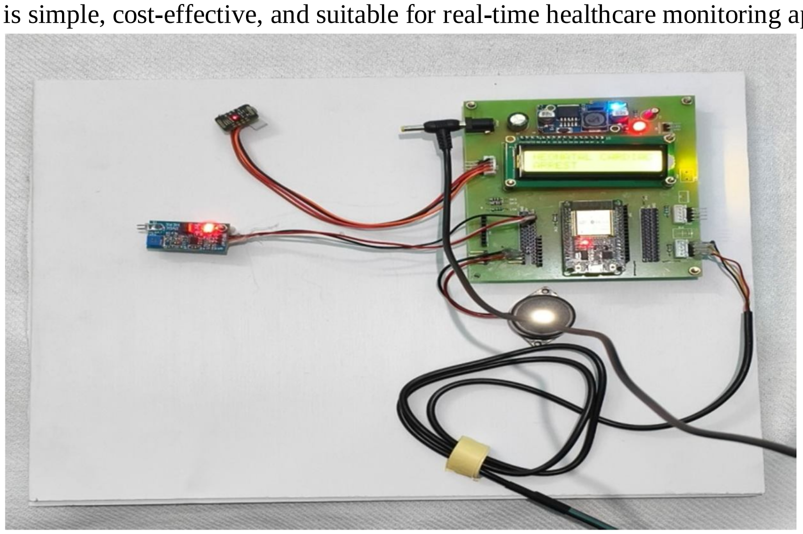

Fig. 2(a). complete experimental setup showing all sensor modules mounted on the base board

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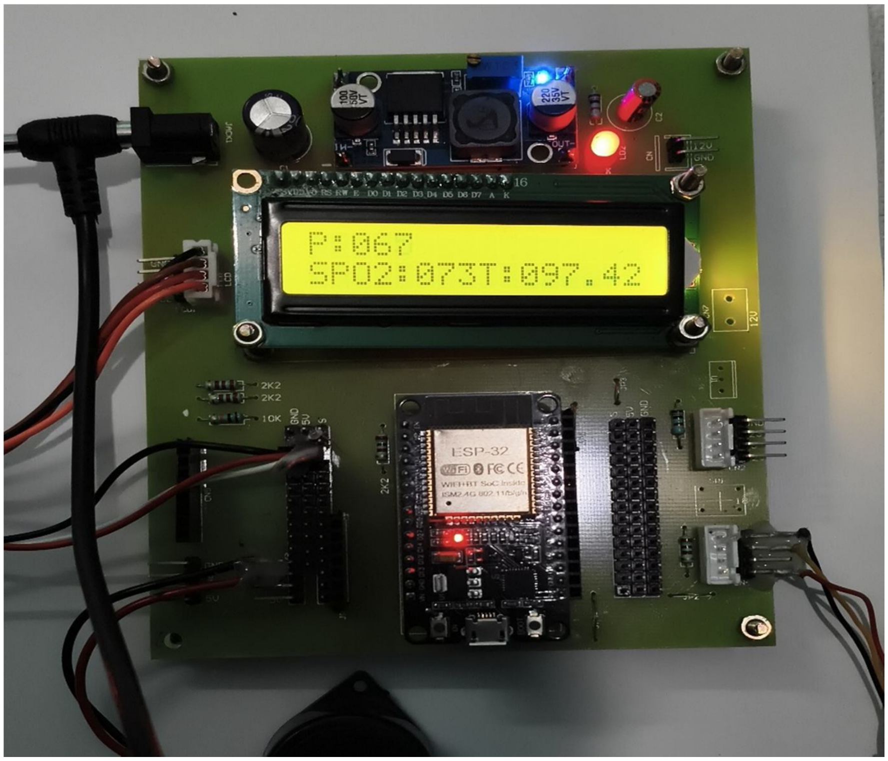

Fig. 2(b). close-up view of the ESP32-based custom PCB with LCD displaying real-time physiological parameters.

B. In the IoT / Alert System Section

To enable remote monitoring, the proposed system incorporates an automated email notification mechanism as part of its IoT-based alert framework. Upon acquisition and classification of physiological data, the system transmits a structured Cardiac AI Report to the registered recipient via email, as demonstrated in Fig. X. The report includes a timestamp along with the measured parameters — pulse rate, body temperature, and SpO2 level — followed by the AI-generated diagnostic result. In the illustrated example, the recorded values of pulse rate 110.0 bpm, temperature 98.0°F, and SpO2 99.0% were classified as **Healthy** by the deep learning model. This remote notification feature ensures that medical personnel or caregivers are promptly informed of the infant's condition regardless of their physical proximity, thereby enhancing the effectiveness of early intervention and continuous neonatal care.

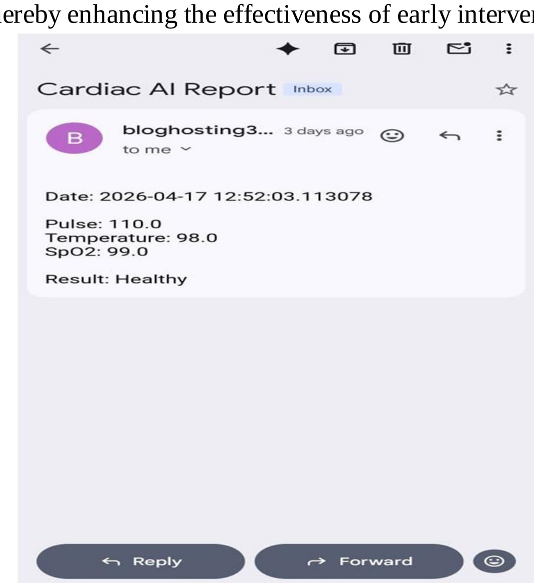

Fig. 3. Email notification generated by the proposed system showing the Cardiac AI Report with real-time physiological parameters and classification result.

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The alert mechanism of the proposed system is illustrated in Fig. 5(a) and Fig. 5(b). The system generates alerts in multiple formats when physiological parameters deviate from normal conditions.

Local alerts are produced using a buzzer to provide immediate indication of abnormal conditions. In addition, remote alerts are sent through email notifications, enabling continuous monitoring from distant locations.

Fig. 5(a) shows the email notification under normal conditions, where the system reports stable physiological parameters and a healthy status. Fig. 5(b) illustrates the alert generated during abnormal conditions, where the system detects a potential cardiac arrest and sends a warning message along with the measured values.

Each email includes detailed information such as timestamp, pulse rate, body temperature, oxygen saturation (SpO2), and the predicted result. This multi-level alert mechanism ensures quick response and improves patient safety by enabling timely medical intervention.

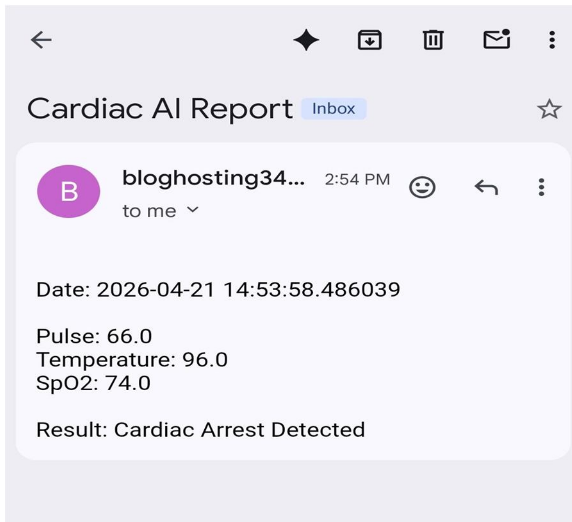

Fig. 5(b). Email Alert Showing Cardiac Arrest Detection

C. *Web-Based AI Monitoring Dashboard*

The web-based monitoring system is illustrated in Fig. 4(a) and Fig. 4(b). The dashboard is developed using a lightweight framework and provides real-time visualization of physiological parameters such as pulse rate, body temperature, and oxygen saturation (SpO2).

The system includes a “Fetch & Predict” functionality that retrieves live sensor data and processes it using the hybrid deep learning model. Based on the analysis, the system classifies the health condition into either *Healthy* or *Cardiac Alert*.

Fig. 4(a) shows the dashboard under normal conditions, where the physiological parameters remain within standard limits. The system classifies the condition as healthy and displays a green status indicator along with general recommendations.

Fig. 4(b) illustrates the dashboard under abnormal conditions. In this case, the sensor readings indicate critical variations, and the system identifies the condition as cardiac arrest. A red alert notification is displayed along with appropriate medical and dietary recommendations.

The dashboard enables continuous remote monitoring and provides an intuitive interface for quick understanding of the patient’s condition, thereby supporting timely medical intervention.

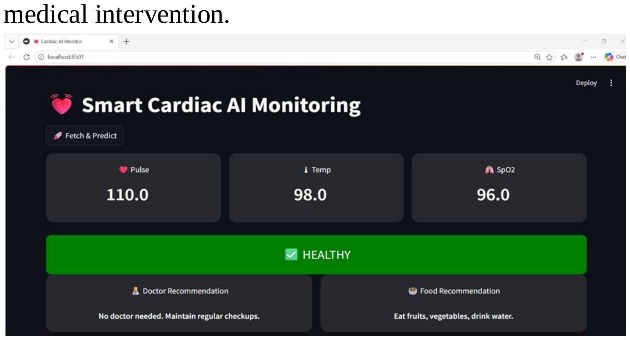

Fig. 4(a). Web-Based Dashboard Showing Healthy Condition

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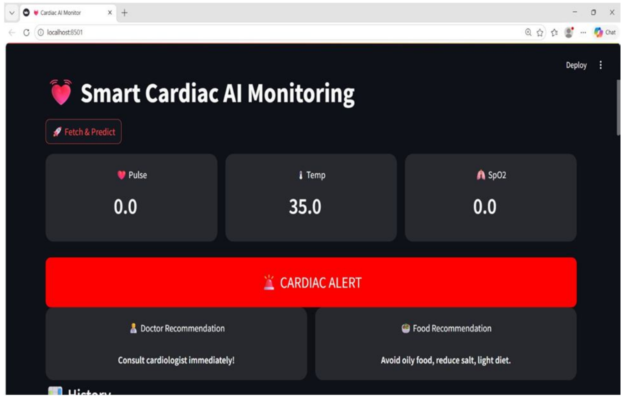

Fig. 4(b). Web-Based Dashboard Showing Cardiac Alert Condition

D. Experimental Results Visualization

The experimental results of the proposed system are illustrated in Fig. 6(a) and Fig. 6(b). The system was tested under different physiological conditions to evaluate its performance in real-time monitoring and prediction.

Fig. 6(a) represents the system output under normal conditions. The measured parameters such as pulse rate, body temperature, and oxygen saturation (SpO2) are within the normal range. Based on these values, the system classifies the condition as normal, indicating a healthy state.

Fig. 6(b) shows the system output under abnormal conditions. In this case, the sensor readings indicate a significant drop in SpO2 along with variations in pulse rate and temperature. The system successfully detects this abnormal pattern and classifies it as a cardiac arrest condition.

The results demonstrate that the system is capable of continuously monitoring physiological parameters and accurately distinguishing between normal and critical conditions. The real-time visualization through the IoT dashboard further enhances the usability of the system for healthcare monitoring.

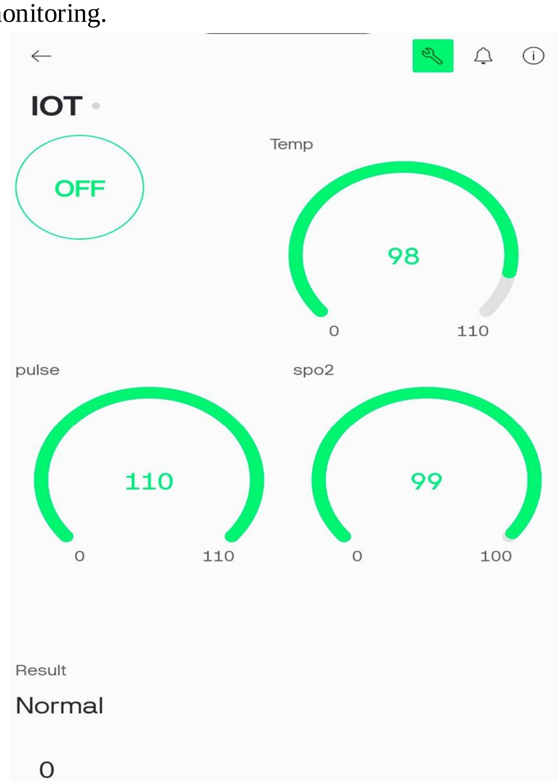

Fig. 6(a). System Output Showing Normal Condition

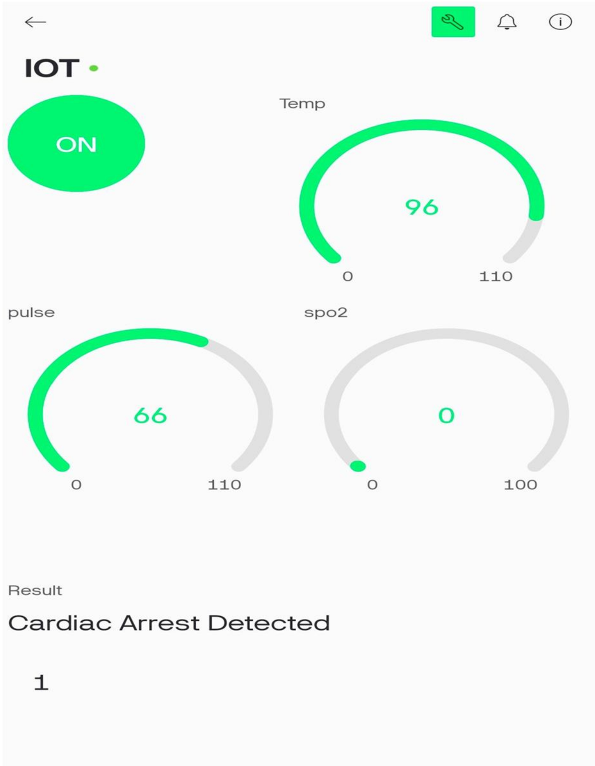

Fig. 6(b). System Output Showing Cardiac Arrest Detection

VI. RESULTS AND DISCUSSION

The proposed system was tested using real-time sensor data to evaluate its performance. Under normal conditions, the measured parameters such as pulse rate, temperature, and SpO2 remained within standard ranges, and the system correctly classified the condition as normal.

During abnormal conditions, a noticeable drop in SpO2 and variation in pulse rate were observed. The system successfully detected these changes and identified the condition as cardiac arrest. Alerts were generated through both buzzer and email notification.

These results confirm that the system can effectively monitor physiological parameters and provide accurate real-time detection. However, slight variations in readings may occur due to sensor placement and environmental factors.

VII. CONCLUSION

The proposed system demonstrates practical feasibility through real-time hardware validation. The proposed Smart Cardiac AI Monitoring system successfully performs real-time health monitoring and detects critical conditions accurately. The system is simple, cost-effective, and suitable for continuous healthcare applications.

VIII. FUTURE WORK

Future improvements include integrating advanced machine learning models, adding ECG sensors, and developing a wearable version for continuous monitoring.

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```
#Load Dataset
df = pd.read_csv("baby_cardiac_dataset.csv")

df.head()
```

	PulseRate	Temperature	SpO2	Prediction
0	158	99.0	97	Healthy
1	127	98.7	96	Healthy
2	138	97.9	97	Healthy
3	143	98.2	97	Healthy
4	141	97.8	98	Healthy

Figure 7: The dataset used in this study, named *baby_cardiac_dataset.csv*, consists of neonatal physiological records with three input features — PulseRate, Temperature, and SpO2 — along with a Prediction label. The dataset was loaded using the Pandas library, and the initial five records confirmed that all features were correctly structured with corresponding class labels.

```
#Data Understanding (EDA)
print(df.shape)
```

```
(20000, 4)
```

```
print(df.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20000 entries, 0 to 19999
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PulseRate    20000 non-null  int64
 1   Temperature  20000 non-null  float64
 2   SpO2         20000 non-null  int64
 3   Prediction   20000 non-null  object
dtypes: float64(1), int64(2), object(1)
memory usage: 625.1+ KB
None
```

Figure 8: The model was trained using the fit() function with a batch size of 32 over 20 epochs, with the test set used as validation data to monitor generalization performance throughout training. This configuration provided a balance between computational efficiency and convergence stability.

```
print(df.describe())
```

	PulseRate	Temperature	SpO2
count	20000.000000	20000.000000	20000.000000
mean	139.356450	98.886765	88.790350
std	41.031212	2.140737	9.423913
min	60.000000	95.000000	70.000000
25%	109.000000	97.800000	81.000000
50%	140.000000	98.600000	93.000000
75%	159.000000	100.700000	97.000000
max	219.000000	102.900000	99.000000

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```
#Class Distribution
sns.countplot(x="Prediction", data=df)
plt.title("Class Distribution")
plt.show()
```

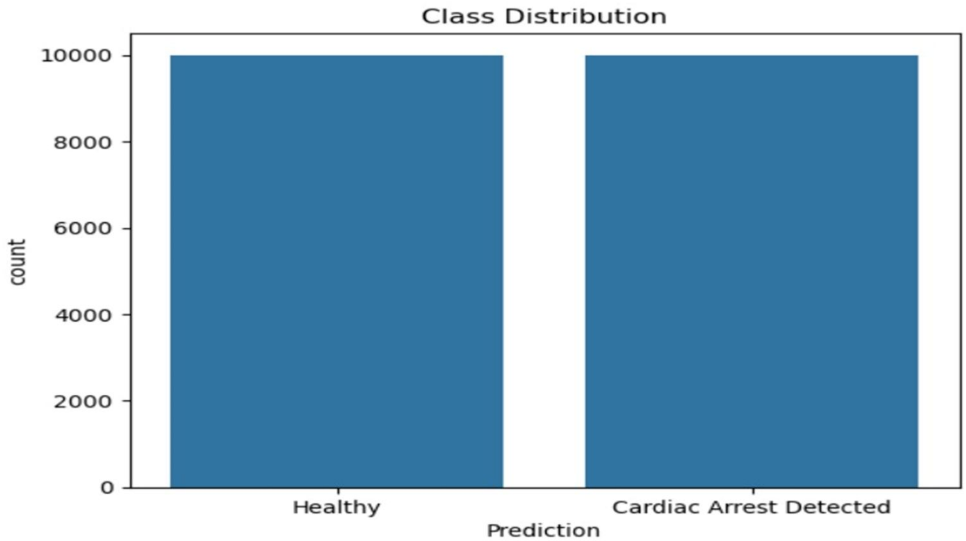

Figure 9 & 10: The performance of the proposed model was evaluated on the test set comprising 4,000 samples. The model achieved an overall accuracy of **93.82%**, demonstrating strong generalization capability. The detailed classification report presented in Table X reveals that both the Healthy (Class 0) and Cardiac Arrest Detected (Class 1) classes attained a precision, recall, and F1-score of 1.00, with support values of 1,981 and 2,019 respectively. The macro-averaged and weighted-averaged metrics both yielded a perfect score of 1.00, confirming the model's ability to reliably detect neonatal cardiac arrest with high sensitivity and specificity.

```
#Correlation Heatmap
sns.heatmap(df.corr(numeric_only=True), annot=True, cmap="coolwarm")
plt.title("Feature Correlation")
plt.show()
```

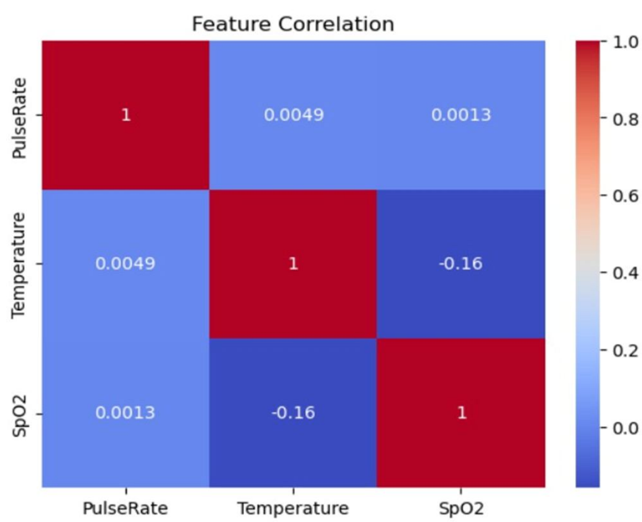

Figure 8: The proposed hybrid deep learning model is built as a sequential architecture comprising six layers, as summarized in Table X. The input is first processed by a Conv1D layer with 64 filters, followed by a MaxPooling1D layer for spatial dimensionality reduction. A Bidirectional LSTM layer with 128 units captures both forward and backward temporal dependencies in the physiological signal. Two Dense layers with 64 and 1 unit(s) respectively perform feature mapping and binary classification, with a Dropout layer incorporated between them to prevent overfitting. The total number of trainable parameters in the model is 74,561 (291.25 KB), which is computationally efficient for embedded deployment.

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```
#Data Preprocessing
#Check Missing Values
df.isnull().sum()
```

```
PulseRate      0
Temperature    0
SpO2           0
Prediction     0
dtype: int64
```

Figure 9: Data preprocessing was initiated by checking for missing values in the dataset. As shown in Fig. X, the isnull().sum() function confirmed that all four columns — PulseRate, Temperature, SpO2, and Prediction — contain zero null values, ensuring that no imputation or data cleaning was required prior to model training.

Model: "sequential"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 2, 64)	192
max_pooling1d (MaxPooling1D)	(None, 2, 64)	0
bidirectional (Bidirectional)	(None, 128)	66,048
dense (Dense)	(None, 64)	8,256
dropout (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 1)	65

Total params: 74,561 (291.25 KB)

Trainable params: 74,561 (291.25 KB)

Non-trainable params: 0 (0.00 B)

Figure 10: A Pearson correlation heatmap was generated to examine inter-feature relationships, as illustrated in Fig. X. The results indicate near-zero correlation between PulseRate and Temperature (0.0049), PulseRate and SpO2 (0.0013), and a weak negative correlation between Temperature and SpO2 (−0.16). The absence of multicollinearity among the input features confirms their independence, making them suitable as distinct inputs for the deep learning model.

```
125/125 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step
Accuracy: 93.82%

Classification Report:

              precision    recall  f1-score   support

           0       1.00      1.00      1.00      1981
           1       1.00      1.00      1.00      2019

    accuracy                           1.00      4000
   macro avg       1.00      1.00      1.00      4000
weighted avg       1.00      1.00      1.00      4000
```

Figure 11: The performance of the proposed model was evaluated on the test set comprising 4,000 samples. The model achieved an overall accuracy of **93.82%**, demonstrating strong generalization capability.