Prediction of Respiratory Tract Infections Using IoT and RNN Techniques

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ABSTRACT

This research examines the efficacy of an IoT-based system using Recurrent Neural Networks (RNNs) for the early identification and short-term prognosis of Respiratory Tract Infections (RTIs). The proposed system uses simulated real-time physiological data (respiratory rate, heart rate, temperature, oxygen saturation, and white blood cell count) from the MIMIC-III dataset to emulate IoT sensor outputs, achieving 92.1% classification accuracy. The findings highlight the efficacy of integrating continuous monitoring principles with advanced temporal modeling for proactive healthcare treatment. The novelty of this work lies in the use of LSTM-based RNNs with simulated multi-parameter IoT data for early RTI identification. This approach outperforms the traditional static models by effectively capturing the temporal dependencies in the physiological signals of Intensive Care Unit (ICU) patients.

Keywords-respiratory tract infections; pattern recognition; predictive analytics; health monitoring

I. INTRODUCTION

The potential for identifying the onset of Respiratory Tract Infections (RTIs) and cardiovascular illness using machine learning techniques is described in [1]. Lower RTIs are the main cause of mortality for children under the age of five globally. Authors in [2] aimed to optimize the healthcare resources for pediatric patients with these infections. To aid parents in detecting Acute Respiratory Infections (ARI) in toddlers, a system that utilizes Naive Bayes and Chi-Square methods was proposed. While Naive Bayes identifies patterns using probability, Chi-Square eliminates the non-significant features [3]. The COVID-19 pandemic significantly increased the telemedicine consultations [4]. To identify Pseudomonas aeruginosa in airborne samples, researchers have developed a paper biosensor that uses nanoparticles [5]. The annual mortality toll from ARI is 13 million, with 95% of these casualties occurring in underdeveloped nations. Approximately 34.8% of Indonesian children are affected by RTIs [6]. By integrating IoT, medical devices, and cloud computing, researchers are exploring the Internet of Medical Things (IoMT) to improve the healthcare services [7]. Deep learning approaches integrating IoT have been explored for infectious disease surveillance [8]. To provide patients with a rapid feedback on their health, this study investigates the potential of passive, safe, and nonintrusive smart monitoring technologies in healthcare [9]. TrackARTI, an intelligent tracking system for ARI, is used to remotely monitor patients in the 0-6 age range [10]. An urgent point-of-care decision is required in the treatment of RTI, a significant area involving the prescription of antibiotics. To investigate this idea at nine clinical locations in the UK, breath analysis [11] was used, employing commercially collected breath samples from over a thousand participants.

According to a Peruvian research on ARI, the situation was deteriorated in areas like Arequipa and Piura [12]. Separately, machine learning models have been applied in Taiwan to predict the outpatient visits for upper RTIs [13]. The fast and precise identification of URTIs is crucial in COVID-19 pandemic [14]. An efficient ensemble method integrated with an artificial neural network was deployed to detect the chronic lung disease, a condition that increases the susceptibility to RTIs [15]. CT lung peripheral TIB opacities are a prevalent pulmonary illness and were automatically identified in [16]. The proposed model integrates shape index, local gradient statistics, steerable wavelet features, and local scale information of pictures to detect the TIB patterns. A hybrid approach using RNN architectures was employed in [17]. It used the ResNet architecture and linear discriminant analysis along with RNN for the classification of X-ray images. In [18], it was found that the LRTIs were more common and that the diversity of the Lower Respiratory Tract Microbiome (LRTM) was decreased. Authors in [19] aimed to create a machine-learning approach for predicting sepsis-induced RTI. A respiratory specification was introduced by a bi-ResNet DL architecture in [20] that employs STFT and wavelet extraction. Algorithms for diagnostics in modern laboratories employ both traditional and molecular approaches [21-23].

The present research addresses the challenges of delayed identification of RTIs and the complexities in forecasting their course in critically ill patients in ICUs. Conventional diagnostic techniques are often slow, and the lack of accurate short-term predictions hinders the proactive interventions. Moreover, the extensive volumes of incessantly produced physiological data from contemporary medical equipment are inadequately leveraged for real-time predictive analytics, necessitating automated and prompt monitoring solutions. The present study addresses the issue of early diagnosis of respiratory infections in ICU patients by using advanced RNN algorithms, successfully managing both medical urgency and technological complexity. This research presents a novel architecture combining simulated IoT-based continuous physiological monitoring with RNN temporal learning to improve the RTI management. It enables an accurate early pattern identification and short-term symptom progression prediction. Utilizing the MIMIC-III dataset for training, the system presents opportunities for real-time clinical decision assistance, enhancing the use of deep learning in critical care to optimize patient outcomes and alleviate healthcare expenses related to RTIs.

II. PROPOSED METHOD

The proposed system is based on the ongoing collection of essential physiological characteristics, reflecting the high-frequency data streams anticipated from contemporary IoT medical devices. This research simulates real-time data features due to its reliance on the retrospective MIMIC-III database. The simulation focuses on key vital signs and a critical laboratory marker relevant to the RTI identification and progression. These characteristics, acting as substitutes for continuous IoT sensor data, are mathematically expressed as elements of a time-dependent vector X_t:

$$X_t = [RR_t, HR_t, T_t, SpO2_t, WBC_t] \quad (1)$$

where RR_t denotes the Respiratory Rate (breaths per min) at time t, HR_t denotes the Heart Rate (beats per min) at time t, T_t denotes the Body Temperature (^{o}C) at time t, $SpO2_t$ denotes the peripheral Oxygen Saturation (percentage) at time t, and WBC_t denotes the White Blood Cell count (thousands of cells per μL) at time t. The continuous monitoring of these metrics generates a multi-dimensional time-series dataset for each ICU patient, serving as the primary input for subsequent analysis.

Actual medical data often exhibit sporadic gaps or missing values. To resolve this issue, several imputation techniques may be used. A straightforward method involves using the most recent valid observation to impute the missing value (Last Observation Carried Forward (LOCF)) or the subsequent valid observation (Next Observation Carried Backward (NOCB)). Advanced techniques may include linear interpolation, mean or median imputation using adjacent data points, or predictive imputation employing machine learning algorithms. The selection of an imputation method is contingent upon the characteristics and prevalence of absent data. The selected physiological parameters have widely different numerical scales, which can hinder the RNN training. Z-score normalization is applied to feature x_t to standardize it to a mean of 0 and a standard deviation of 1, as shown in:

$$\hat{x}_t = \frac{x_t-\mu(x)}{\sigma(x)} \tag{2}$$

where $\mu(x)$ is the mean and $\sigma(x)$ is the standard deviation of the feature x across the dataset.

RNNs are designed to handle sequential data. The continuous time-series data for each ICU stay are divided into sequences of a predetermined length L (number of timesteps). The fixed-length input is essential for batch processing and the effective training of the RNN. For a specific patient i, the pre-processed time-series data may be shown as a collection of feature vectors:

$$X^{(i)} = \left(X_1^{(i)}, X_2^{(i)}, \dots X_L^{(i)}\right) \tag{3}$$

where each $X_1^{(i)}$ is the scaled and potentially imputed physiological feature vector at the j-th timestep of the sequence. The length L of these sequences is a hyperparameter that must be judiciously selected, often informed by the duration of relevant data and the intended temporal context for the RNN to assimilate. Overlapping sequences may be generated from extended ICU admissions to augment the training dataset and more effectively capture the temporal changes. Figure 1 presents a block diagram that offers a comprehensive overview of the data flow and the essential components of the proposed system.

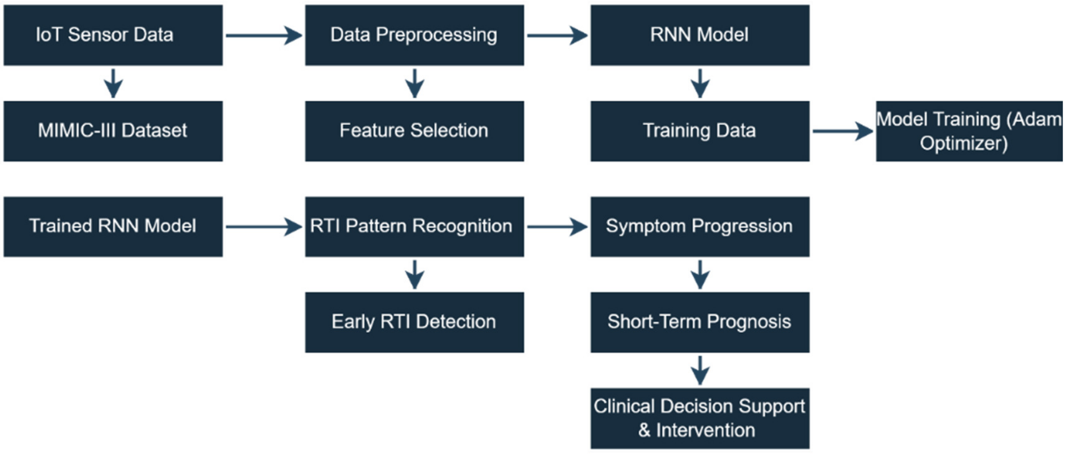

Fig. 1. Block diagram of proposed RTI detection and forecasting system.

The essence of the RTI detection component is an RNN model, which proficiently learns the temporal connections in sequential data. An essential RNN modifies its hidden state $h(t)$ at each time step t by considering the current input X_t and the information maintained from the preceding time step's hidden state h_{t-1}. This update is quantitatively delineated as:

$$h_{(t)} = f(W_x X_t + W_h h_{t-1} + b_h) \tag{4}$$

The final hidden state h_L predicts the probability of RTI using a sigmoid function:

$$\hat{y}_{class} = \sigma(W_o h_L + b_o) = \frac{1}{1+e^{-((W_o h_L + b_o)}} \tag{5}$$

where W_o is the output weight matrix, b_o is the output bias vector, and σ is the sigmoid function for binary classification. The proposed system not only allows instant RTI detection, but also tries to anticipate the short-term progression of the patient's physiological condition by projecting the values of the measured parameters up to 24 h ahead. This predictive capacity utilises the RNN's acquired temporal dynamics. Forecasting the future parameter values, $\hat{p}_{t+\tau}$ can be modeled as:

$$\hat{p}_{t+\tau} = W_{f,p} h_t + b_{f,p} \tag{6}$$

where $W_{f,p}$ and $b_{f,p}$ are learned weights and biases specific to parameter p and the forecast horizon τ. The primary loss function used for classification tasks, such as RTI detection, is the cross-entropy. It assesses the alignment between the model's predictions and the actual labels:

$$L(y_i, \hat{y}_i) = -\sum_{i=1}^{N}\left(y_i \log\left(\hat{y}_{class,i}\right) + (1-y_i)\log\left(1 - \hat{y}_{class,i}\right)\right) \tag{7}$$

For forecasting, a common loss is the Mean Squared Error:

$$L_{forecast} = \frac{1}{N\times k}\sum_{i=1}^{N}\sum_{j=1}^{k}\left(X_{t+j}^{(i)} - \hat{X}_{t+j}^{(i)}\right)^2 \tag{8}$$

where k is the forecast horizon (e.g., number of hours ahead). The model parameters are repeatedly updated using optimization algorithms, such as Adam, which modify the weights and biases according to the gradients of the loss function relative to these parameters. Equation (9) delineates the parameter update rule of the Adam optimizer, which was presumably used for training the RNN in the proposed system:

$$\theta_t = \theta_{t-1} - \propto \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \in} \tag{9}$$

where $\propto$ is the learning rate (a hyperparameter to be tuned), and $\in$ is a small constant added to prevent the division by zero.

Figure 2 depicts the architecture of the RNN, illustrating the progression of physiological time-series data through the model. The input sequence undergoes processing by one or more hidden layers to capture the temporal dependencies. The output layer thereafter diverges: one pathway for RTI categorisation and another for predicting future physiological values, facilitating an early identification and short-term prognosis.

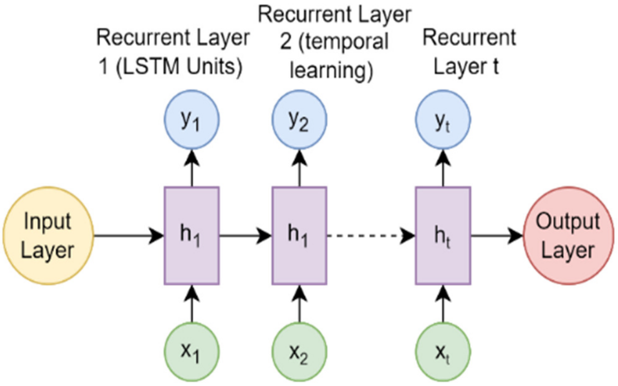

Fig. 2. RNN architecture for RTI forecasting.

RNNs are essential for proficiently handling the sequential physiological data, integrating temporal relationships throughout time. This capability enables an accurate early identification and forecasting of RTI by analyzing the dynamic progression of patient vital signs in ICU environments. The study selected LSTM networks because of its ability to identify long-term dependencies in sequential physiological data, which is critical for properly modeling the development of RTIs over time. Pretrained CNN models, such as VGG16 and ResNet are optimized for image data and are not appropriate for physiological time-series analysis. This work uses RNNs, which adeptly capture the temporal relationships, which are essential for forecasting RTI from sequential sensor data. Table I provides a detailed summary of the essential parameters that characterize the RNN model and the training procedure.

TABLE I. PARAMETER CONFIGURATION OF THE RNN

Parameter	Value	Parameter	Value
Model type	RNN	Optimizer	Adam
Input features	5	Learning rate	0.001
Sequence length	48–72 steps	Batch size	32
Hidden layers	2	Epochs	10
LSTM layers	64 units	Dropout	0.2
Activation	Tanh	Loss function	Binary CE

III. RESULTS AND DISCUSSION

The MIMIC-III (Medical Information Mart for Intensive Care III) database is a thorough and publicly accessible dataset created by the MIT Lab for Computational Physiology [24]. The dataset comprises de-identified electronic health records of more than 40,000 ICU patients who were hospitalized at the Beth Israel Deaconess Medical Centre from 2001 to 2012. The dataset also contains comprehensive clinical information. Essential factors that emulate the IoT sensor outputs were identified: respiratory rate, heart rate, body temperature, SpO_2 (oxygen saturation), and white blood cell count. Patients with diagnoses linked to RTI were identified using ICD-9 codes, including 486 (pneumonia) and 487 (influenza). The final dataset entailed 5,000 ICU admissions, each involving 48–72 h of time-series physiological data collected at hourly intervals. MIMIC-III provides retrospective hospital data, and the chosen physiological characteristics correspond well with the capabilities of IoT sensors often used in smart health monitoring, including wearable devices and bedside sensors. Figure 3 shows the time-series data from a single ICU stay in MIMIC-III database.

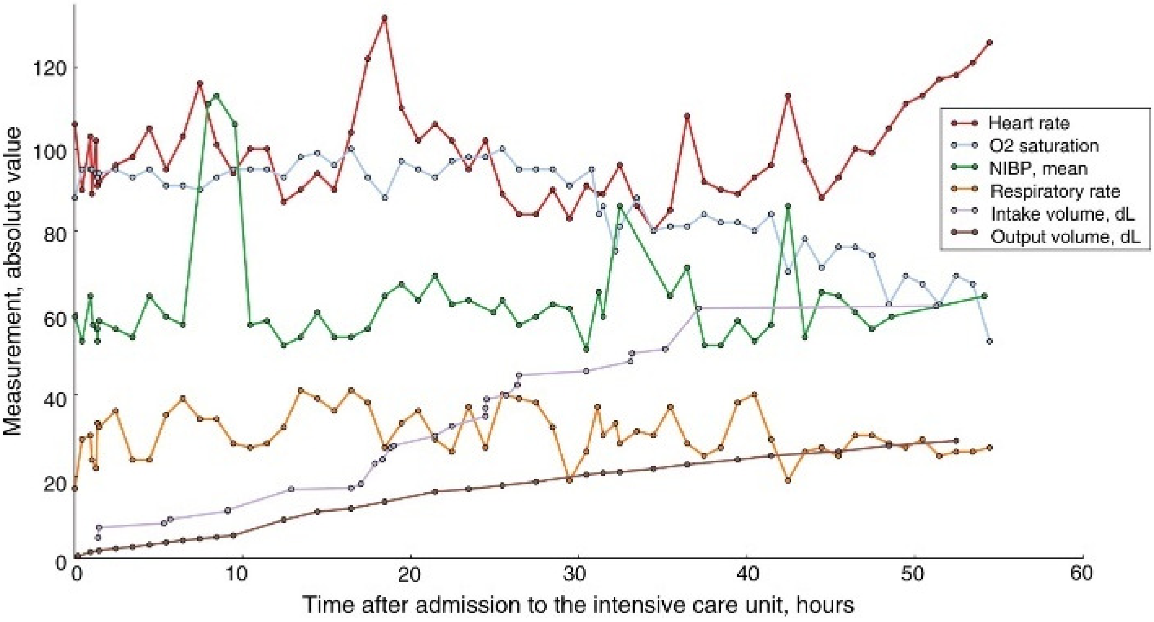

Fig. 3. Sample data from a single ICU stay.

The training set (70%) allows for model learning, whilst the validation set (15%) aids in hyperparameter optimization and mitigates overfitting. The unseen test set (15%) offers an impartial assessment of the model's generalization abilities for recognizing and predicting the RTI patterns. Stratification according to the RTI diagnosis is essential for a comprehensive assessment. The system emulates real-time collection of respiratory and cardiovascular data, enabling a seamless integration into IoT-enabled systems for remote surveillance. Regarding the samples, 3,500 of them were used for training, 750 for validation, and 750 for testing, with each including 48-72 h of hourly physiological time series data. The model achieves an inference time of around 20 ms, facilitating the quick identification of RTI in critical care settings. The findings suggest that combining IoT data with RNN models offers a scalable approach to managing RTIs in high-risk or resource-constrained settings. The MIMIC-III benchmark dataset was chosen for its richness, public availability, and inclusion of real ICU patient data. Hospital data collection was not pursued owing to ethical issues, patient privacy rules, and the time-consuming process of institutional permissions. The RNN captures a wider range of patient variances, possibly improving the accuracy and resilience in RTI prediction. Binary cross-entropy was chosen for the binary classification task (RTI versus no RTI). Figure 4 illustrates a comparison between the predicted and real SpO_2 levels over a 24-h duration using the RNN model. It demonstrates the model's capacity to accurately replicate the actual physiological trend, hence allowing effective short-term predictions for the proactive treatment of respiratory infections in ICU environments.

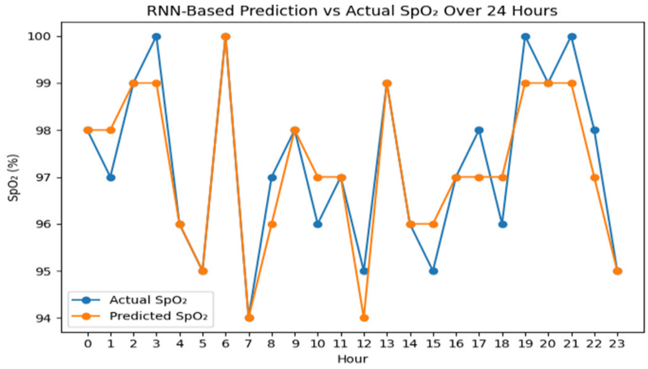

Fig. 4. RNN-based forecasting versus actual SpO_2 levels.

Figure 5 presents a confusion matrix, which serves as a performance assessment instrument for classification models. It displays the quantity of accurate and inaccurate predictions classified as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). It aids in evaluating the model accuracy, precision, recall, and overall classification efficacy.

Figure 6 exhibits the RNN model's accuracy in detecting RTIs over epochs. The training and validation accuracy curves provide a consistent improvement, indicating that the model is generalising well. A high accuracy approaching 92.1% indicates convergence and consistent classification efficacy.

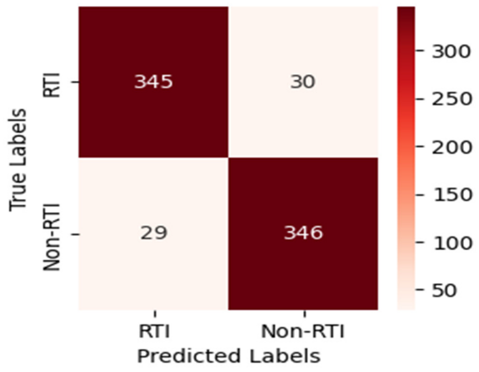

Fig. 5. Confusion matrix of RTI prediction model.

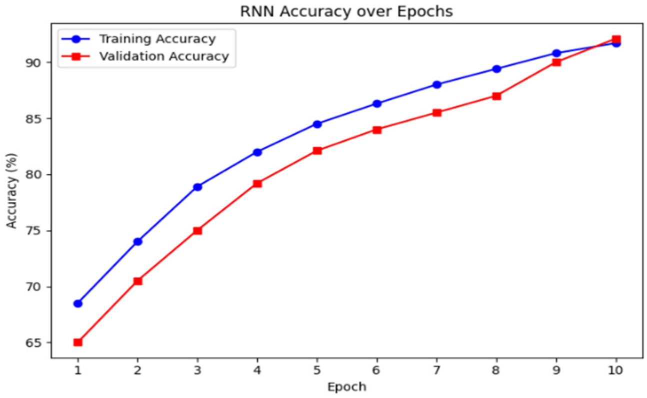

Fig. 6. Accuracy trends for RNN-based RTI prediction.

Figure 7 displays the loss graph, demonstrating the RNN model's reduction of classification errors during the training process. Both training and validation losses continuously decline throughout epochs, indicating successful learning. The steady flattening towards the conclusion exhibits convergence, with little overfitting, since the validation loss closely parallels the training loss curve.

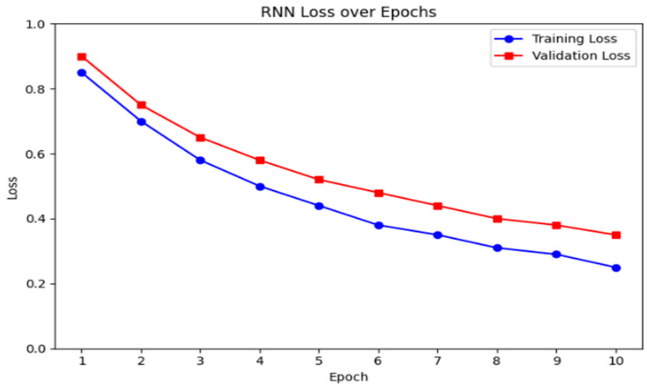

Fig. 7. Loss curve analysis for RTI forecasting.

Overfitting may be mitigated using approaches, such as early halting, dropout, L2 regularisation, cross-validation, model simplification, and augmenting the training data, hence guaranteeing that the model generalizes well to novel data. Figure 8 portrays the ROC curve, demonstrating the RNN model's proficiency in differentiating between RTI and non-RTI situations, exhibiting a high TP rate with low FP rates.

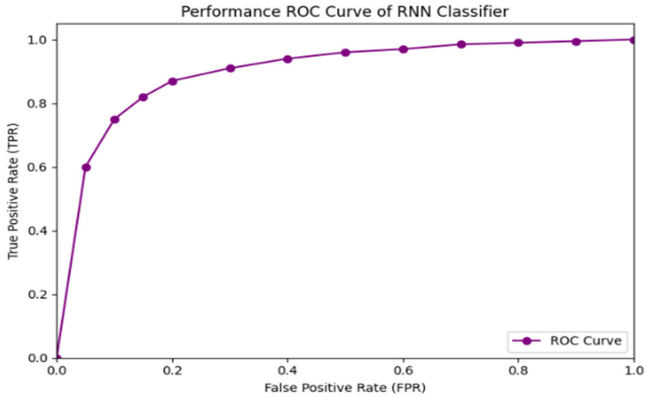

Fig. 8. RNN model ROC analysis.

Table II demonstrates the performance comparison with existing models for the RTI detection. The proposed RNN model has improved metric scores in accuracy, precision, recall, and F1 score, exhibiting enhanced pattern recognition and predictive capacity. The proposed RNN outperformed the others by accurately modeling time-series physiological data.

TABLE II. PERFORMANCE METRICS OF VARIOUS MACHINE LEARNING MODELS

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	70.4	70.6	69.9	70.24
Random Forest	72.7	73.0	72.0	72.48
Support Vector Machine	79.9	80.1	79.5	79.79
Gaussian Naive Bayes	86.5	86.6	86.4	86.52
RNN (proposed)	92.1	92.2	92.0	92.12

IV. CONCLUSION

This research proposes a Recurrent Neural Network (RNN)-based IoT system that accurately forecasts the Respiratory Tract Infections (RTIs) using physiological time-series data. The simulated real-time physiological data, along with the temporal learning skills of the RNN model, trained on the MIMIC-III dataset, achieved a classification accuracy of 92.1% in recognizing the RTI patterns. These results demonstrate the effectiveness of the IoT-based physiological monitoring and RNN-based temporal modeling for proactive RTI interventions. Future work can focus on real-time clinical validation, the integration with hospital monitoring systems and expansion to diverse patient groups.

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