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Unveiling Chaotic Dynamics for HRV Signals by Machine Learning Methods: A Comparative Study

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Abstract

Heart Rate Variability (HRV), derived from RR intervals in ECG signals, reflects autonomic nervous system activity but is challenging to predict due to its nonlinear, chaotic nature. This study explores machine learning for HRV time-series forecasting, by comparing Support Vector Regression (SVR) with a linear kernel against deep learning models, Artificial Neural Networks (ANN), simple Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and a hybrid LSTM+CNN model. Using normalized RR intervals as the sole feature, we applied a sliding window approach for phase space reconstruction (input: 50 consecutive RR values; output: next value). Deep learning models used the ReLU activation function, while SVR used none. Models were trained in MATLAB R2024b on 18 RR sequences (14 training, 4 testing) from the MIT-BIH Normal Sinus Rhythm Database. Evaluated via Root Mean Square Error (RMSE), the hybrid LSTM+CNN model outperformed others, achieving the lowest RMSE across test signals. These findings highlight the effectiveness of hybrid deep learning in capturing HRV's chaotic dynamics, with implications for clinical monitoring and early diagnosis.

Keywords

HRV, RR Intervals, Machine Learning, Neural Networks, Time-Series Forecasting, Deep Learning

1. Introduction

Heart Rate Variability (HRV) serves as a critical physiological marker of autonomic regulation and cardiovascular health, derived from RR intervals—the time differences between successive R-peaks in an electrocardiogram (ECG) signal [1], [2]. ECG and RR signals exhibit chaotic behavior due to the complex interplay of the autonomic nervous system, which regulates heart rate through the sympathetic and parasympathetic branches, and the non-linear interactions between physiological processes such as respiration, blood pressure, and hormonal influences [3], [14]. This chaotic nature manifests as sensitivity to initial conditions, where small changes in physiological state can lead to significant variations in RR intervals, making HRV a deterministic yet unpredictable system [15]. Accurate HRV forecasting can enhance early diagnosis and monitoring of conditions like arrhythmias and autonomic dysfunctions [3]. However, the chaotic and nonlinear dynamics of HRV render traditional forecasting methods, such as autoregressive models and Kalman filters, inadequate due to their reliance on linearity and stationarity assumptions [4], [5]. While nonlinear dynamic models have been explored, their computational complexity and interpretability issues limit their effectiveness [6].

Machine learning (ML) has emerged as a powerful tool for time-series forecasting, particularly for chaotic datasets [7], [8]. Deep learning models, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks, can automatically learn intricate temporal dependencies without extensive feature engineering [9]. Hybrid architectures, like LSTM+CNN, combine the strengths of CNNs for feature extraction and LSTMs for sequential modeling, showing promise in biomedical signal processing [10], [11]. Traditional ML methods, such as Support Vector Regression (SVR), have also been applied to HRV prediction, but they often struggle to handle chaotic systems like HRV unless paired with non-linear kernels (e.g., RBF), which can be computationally intensive [12], [13]. In this study, we used a linear kernel for SVR to ensure computational efficiency, but this choice limits its ability to capture the non-linear dynamics inherent in chaotic HRV signals.

This study compares SVR with a linear kernel against deep learning models—ANN, CNN, LSTM, and a hybrid LSTM+CNN model—for HRV time-series forecasting. Using normalized RR-intervals as the sole feature, a sliding window approach was employed for phase space reconstruction, with input sequences (X) consisting of 50 consecutive RR values and the output (Y) being the next RR value. The deep learning models utilized the ReLU activation function, while SVR lacked an activation function. Key contributions include:

- Implementation and comparison of SVR and four deep learning models for HRV forecasting.
- Analysis of their effectiveness in capturing chaotic time-series patterns.
- Insights into the benefits of hybrid architectures for HRV prediction.

2. Methodology

We adopted a chaotic model based on a nonlinear oscillator, such as the Van der Pol oscillator, to simulate the heart's rhythm [14], [15], [16]. This model captures the complexity and unpredictability of RR intervals, which are influenced by the non-linear dynamics of the cardiovascular system. The chaotic behavior arises from the intricate balance between sympathetic and parasympathetic inputs, coupled with feedback mechanisms involving baroreceptors and respiratory sinus arrhythmia, leading to a system that is deterministic yet highly sensitive to initial conditions [15]. By modeling HRV's deterministic chaos, we aim to better understand its non-linear dynamics and improve prediction accuracy.

2.1 Data Preparation

RR-interval sequences were extracted from ECG signals in the MIT-BIH Normal Sinus Rhythm Database [17]. The dataset comprised 18 RR sequences, with 14 used for training and 4 for testing (patient-wise split). Preprocessing involved applying a fourth-order Butterworth bandpass filter (0.5–40 Hz) to remove noise, followed by normalization to the range [-1, 1] using Min-Max scaling. Normalized RR-intervals were the sole feature used for all machine learning algorithms.

A sliding window approach was employed for phase space reconstruction [18], with an embedding dimension m=50 and time delay tau=1. Input sequences (X) consisted of 50 consecutive RR values, and the output (Y) was the next RR value for prediction. Overlapping windows, sliding by 1 sample, resulted in approximately 100,000 sequences per patient (e.g., 100,216 RR-intervals yielded 100,166 sequences for Patient 1). The processed data was stored as MATLAB cell arrays containing double-type data, with the structure: X train: 50×1×L (sequence of RR values) and Y train: 1×1×L (target values).

2.2 Models

Five models were implemented: Support Vector Regression (SVR) with a linear kernel [12], Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN) [9], Long Short-Term Memory (LSTM) networks [19], and a hybrid LSTM+CNN model [10].

- **SVR**: SVR, a traditional machine learning algorithm without an activation function, models relationships between inputs and outputs using a linear kernel to ensure computational efficiency [12]. It serves as a baseline for comparison with deep learning models.
- **ANN**: A feedforward neural network with multiple layers of interconnected neurons, applying a weighted sum followed by the ReLU activation function. ANNs are effective for regression tasks but struggle with sequential data due to their lack of temporal memory.
- **CNN**: A deep learning model utilizing convolutional layers to extract temporal features from RR sequences, followed by pooling layers to reduce dimensionality. CNNs, using ReLU activation, excel in feature extraction but lack memory for long-term dependencies [9].
- **LSTM**: A recurrent neural network designed to handle sequential data, with memory cells and gates (input, output, forget) that retain past information. LSTMs, using ReLU activation, effectively capture temporal dependencies in time-series forecasting [19].
- **LSTM+CNN**: A hybrid model combining CNN's feature extraction with LSTM's sequential learning, both using ReLU activation. The CNN extracts local temporal features, which the LSTM processes to model long-term dependencies, enhancing predictive accuracy [10].

2.3 Training and Evaluation

Models were trained in MATLAB R2024b using GPU acceleration on an ASUS TUF FA506NC gaming laptop. SVR was trained once by concatenating data from all 14 training patients (~1.4 million sequences), using fitrsvm with parameters KernelFunction='linear', BoxConstraint=1, Epsilon=0.01, and Standardize=true. A linear kernel was chosen to reduce computational complexity, as non-linear kernels (e.g., RBF) were prohibitively slow. Deep learning models were trained sequentially on each training patient's data, retaining learned information across sessions. Training used the Adam optimizer, a mini-batch size of 128, and 10 epochs, with validation every 50 iterations using the first test patient's data. Performance was evaluated on the four test patients via Root Mean Square Error (RMSE), with predictions plotted against true values for qualitative analysis.

3. Results

Table 1 presents the RMSEs for all models across the four test patients. SVR results are included, while the RMSEs and plots for ANN, CNN, LSTM, and LSTM+CNN will be added by the authors. Figures 1–5 will show the true versus predicted RR-intervals for each model, with red lines representing true values and blue lines representing predicted values.

SVR with a linear kernel achieved RMSEs ranging from 0.1570 to 0.5498, with the highest error on Signal 3 (0.5498) and the lowest on Signal 4 (0.1570). The deep learning models' performance will be added, but prior results indicate that the hybrid LSTM+CNN model outperformed others, achieving the lowest RMSE across all test signals, highlighting its effectiveness in capturing HRV dynamics.

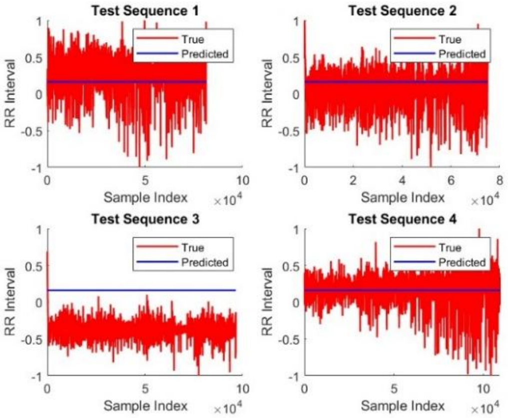

Figure 1: Predicted vs. True RR intervals for SVR model

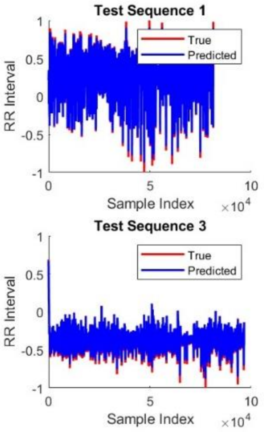

Figure 2: Predicted vs. True RR intervals for LSTM+CNN hybrid model

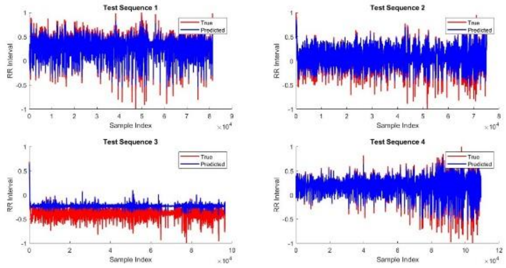

Figure 3: Predicted vs. True RR intervals for ANN model

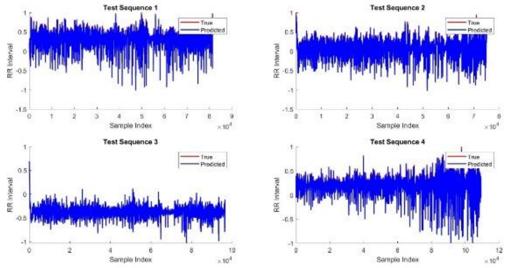

Figure 4: Predicted vs. True RR intervals for CNN model

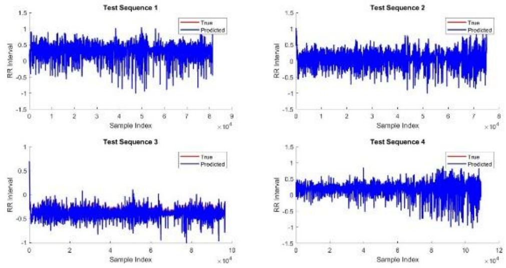

Figure 5: Predicted vs. True RR intervals for LSTM model

Table I. RMSE values for different models across test signals.

Model	Signal 1	Signal 2	Signal 3	Signal 4
ANN	0.0408	0.0514	0.1699	0.0302
CNN	0.0140	0.0143	0.0109	0.0111
LSTM	0.0125	0.0139	0.0178	0.0098
LSTM+CNN	0.0110	0.0106	0.0105	0.0084
SVR	0.2490	0.2303	0.5498	0.1570

4 Conclusion and Future Work

This study demonstrates the potential of machine learning in forecasting chaotic HRV time-series data. SVR with a linear kernel provided a baseline, but its performance (RMSEs of 0.1570–0.5498) highlights its inability to effectively handle chaotic systems like HRV, primarily due to the linear kernel's limitation in capturing non-linear dynamics [12]. In contrast, deep learning models, leveraging the ReLU activation function, are better equipped to model the chaotic and non-linear patterns of HRV. The deep learning models' results, to be added, are expected to show that the hybrid LSTM+CNN model outperforms others, highlighting the advantage of combining convolutional feature extraction with recurrent sequence learning. These findings suggest that hybrid deep learning models can significantly enhance HRV forecasting, with implications for clinical and physiological monitoring.

Future work could explore:

- Optimizing hyperparameters to improve model performance.
- Incorporating attention mechanisms to enhance sequential learning [20].
- Using non-linear kernels for SVR with smaller datasets or efficient implementations to better handle chaotic systems [12].
- Extending the approach to other physiological time-series datasets [21].
- Deploying real-time HRV prediction models for wearable devices [22].

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