Chapter 15

Enhancing Clinical Diagnostics and Patient Monitoring With Recurrent Neural Networks:

A Comparative Study of LSTM and GRU Architectures

S. Dhivya
PSG College of Arts and Science, India

R. Saranya
https://orcid.org/0009-0000-9354-9243
PSG College of Arts and Science, India

ABSTRACT

Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, are powerful tools for modeling clinical time-series data where sequential information is essential. This paper explores the effectiveness of RNNs in analyzing patient vital signs, electrocardiogram (ECG) readings, and other time-sensitive health data. The recurrent design of these networks enables the capture of short- and long-term dependencies, vital for predicting patient outcomes, anomaly detection, and aiding in diagnostic decisions. We review recent advancements in RNN applications for healthcare, addressing challenges like irregular sampling, missing data, and the need for interpretability in clinical settings. Through experiments with real-world clinical datasets, we demonstrate that RNNs outperform traditional machine learning models, enhancing diagnostics, patient monitoring, and personalized treatment planning. Our results highlight the significant potential of RNNs in advancing healthcare analytics and supporting data-driven decision-making.

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1. INTRODUCTION

1.1 Overview of Medical Time-Series Data

Definition and Significance in Healthcare

The term "medical time-series data" describes a set of data points that are usually captured sequentially across time. These data points are essential to the healthcare industry because they help clinicians make well-informed judgments and offer insights into a patient's health status (Bashar et al.,2020). It is impossible to overestimate the importance of time-series data in healthcare; it forms the basis for certain medical disorders' monitoring, diagnosis, and treatment. Healthcare practitioners can better forecast patient outcomes and take prompt action because of the temporal structure of this data, which enables them to see changes over time.

As an instance, non-stop monitoring of critical symptoms—such as heart rate, blood strain, and breathing price—can sign essential modifications in a patient's fitness. Detecting traits or abrupt adjustments in these parameters can alert clinical workforce to potential health crises, taking into account rapid action. similarly, time-collection facts from electrocardiograms (ECGs) presents critical records about the electric hobby of the heart, which can be pivotal in diagnosing arrhythmias or other cardiovascular issues (kachuee, Fazeli, & Roshani, 2018).

Types of Medical Time-Series Data

There are various types of medical time-series data, each with unique characteristics and applications. Some common types include:

- **Vital Signs**: These are fundamental indicators of a patient's physiological status, including heart rate, blood pressure, temperature, and respiratory rate. Continuous tracking of these metrics is essential in critical care settings.
- **Electrocardiogram (ECG) Readings**: ECGs measure the electrical activity of the heart over time. This data can reveal abnormalities in heart rhythm and structure, making it vital for diagnosing cardiac conditions.
- **Glucose Monitoring**: For diabetic patients, continuous glucose monitoring systems provide real-time data on blood sugar levels. Analyzing this time-series data can help in adjusting insulin doses and preventing complications.
- **Clinical Event Logs**: Records of clinical events, treatments, or medications administered over time. This data helps in understanding treatment effects and patient responses.
- **Wearable Device Data**: Increasingly, data from wearables like fitness trackers and smartwatches is being integrated into healthcare. These devices can monitor various health metrics over time, providing valuable insights into lifestyle and health trends.

The ability to analyze such diverse types of time-series data is essential for improving patient care and optimizing treatment strategies.

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