Time Series Prediction Models in Healthcare: Systematic Literature Review

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Abstract: Technology has solved many of humanity's complex problems. Furthermore, healthcare providers and researchers are working together to achieve precision medicine, which is the goal of tailoring medical treatment to the individual characteristics of each patient. As a result, patients will receive better care. In this context, healthcare benefits from Time Series Prediction (TSP) models to improve service levels. TSP models have been successfully used to predict a variety of outcomes, such as patient readmission rates, disease progression, and treatment effectiveness. This study presents a systematic literature review (SLR) focusing on TSP models in healthcare. Based on a systematic search of IEEE, Science Direct, Springer, Hyper Articles en Ligne (HAL), and ACM, 50 articles published between 2018 and 2023 were identified. A review of predictive use cases in healthcare and the TSP models used for them has been conducted in this paper. We classified these models into four categories such as statistical models, Deep Learning (DL) models, Machine Learning (ML) models and Hybrid models.

1 INTRODUCTION

Time series prediction is a broad area of research with much potential application (Khabou et al., 2017), including physical, environmental science and healthcare. It can be defined as the process of predicting variables and future variables using temporal data. Time series data in healthcare have many sources. Electronic health records (EHRs) data is a type of Time Series (TS) data, that tracks patient health over time. Also, electrocardiogram (ECG) data is another type of TS used to record the electrical activity of the heart. Wearable devices can also provide TS data.

In healthcare, TSP models involve analyzing sequential data, such as medical records, patient vital signs, patient disease registries, and administrative clinical data to predict future trends and informed decisions. To the best of our knowledge, these models help in improving patient care and health management by the early decision about patient medical situations, and the prediction of resource hospitalization, such as the number of beds that will be needed (Prasad et al., 2022), the medication that will be used. In recent decades, TSP models have been extensively improved and expanded. In statistical models, An Autoregressive Integrated Moving Average (ARIMA) is a model that analyzes or predicts time series and represents the most used model in prediction. Machine learning and deep learning represent the recent widely utilized models for TSP. Our study aims to help readers to know the various TSP models in healthcare and the subjects that can be predicted by these models. Subject prediction means the predictive task of TSP. It can be any type of disease or quality of service. To achieve these objectives, we conducted a systematic review of the literature. This paper is organized as follows: section 2 represents the process of our SLR. Section 3 provides a discussion of SLR results. Section 4 represents the learned lesson from the SLR. We conclude with general highlights in section 5.

2 THE SLR PROCESS

The research methodology for this paper is an SLR, which consists of three steps: (i) Definition of Research Questions, (ii) Identification of search strategy and (iii) Selection of articles based on precise criteria.

2.1 Research Questions

The main goal of this systematic literature review is to extract and organize the findings from research on structured TSP models in healthcare, and to identify

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Table 1: Search results by Resource.

Resource	Number of papers
Springer	164
IEEE Xplore	34
ACM digital library	275
Science Direct	70
Hyper Articles en Ligne (HAL)	44
Total	587

related, future research opportunities subsequently. The key aspects that provide the focus for research study identification and data extraction are specified research question(s), as a result, we aimed to answer the following research questions.

1. RQ1: In which case are time series prediction models used in healthcare applications?
2. RQ2: What are the different models of Time Series Prediction in healthcare?

2.2 Search Strategy

We identified the initial studies in the database according to the following keywords Which are split into three groups.

- Group1: ("Time Series")
- Group2: ("Prediction Model","Prediction Models'',''Forecasting Model", ''Forecasting Models")
- Group3: ("Healthcare").

To get relevant results, the search method integrates the essential concepts in our search query. Both sets of keywords were combined with a Boolean search (AND, OR) in the article search process. The final search string in this study is ("Time Series") AND ("Prediction model " OR" forecasting model") OR ("Prediction models" OR "forecasting models ") AND (" healthcare'')

2.3 Selection Criteria

Following the acquisition of search results from different Databases, the articles were selected using a set of Inclusion and Exclusion Criteria. These criteria were applied to help in the identification of relevant primary studies. Also, the purpose of these criteria is to obtain results with more accuracy, objectivity, and significance for our study. The Inclusion Criteria are: (i) The predetermined keywords exist throughout the paper, or at a minimum in the title, keywords, or abstract section, (ii) The paper was published in a scientific peer-reviewed journal, (iii) Research studies that were published from January 2018 to March 2023 and (vi) Articles that are written in English language. The Exclusion Criteria are (i) Publications that are not related to the keywords of research questions, (ii) Review papers, book chapters, master and Ph.D. dissertations, (iii) Publications that are published before or on 31.12.2017 and (vi) Articles that are written in any language other than English.

2.4 Data Extraction

For this SLR we used five research databases: HAL, IEEE, ACM, Science Direct, and Springer. The search was conducted between 2018 and 2023. The execution of the defined research query has selected 587 articles from the different resources summarized in table 1. A total of 243 duplicate papers were removed, leaving 344, then we applied the filtering process to find 50 papers results for reading.

3 RESULTS AND DISCUSSION

TSP models are one of the important topics that many studies are investigating to provide robust and reliable healthcare solutions and help stakeholders in decision-making. This paper can be a good starting point for such researchers to understand these models and review existing work related to the proposed research questions. In this section, a discussion of the analyzed publications was presented to answer the proposed research questions

3.1 RQ1:In Which Case Are Time Series Prediction Models Used in Healthcare Applications?

Predicting is crucial in healthcare to identify possible health risks, prevent illnesses, and enhance patient outcomes. Various healthcare prediction approaches exist, depending on task specification and TSP models. Related works show that many approaches are about disease prediction and the quality of service to improve medical care. Table 2 answers our first research question by listing the studies included in the prediction task. Note that Coronavirus (COVID-19) pandemic prediction as confirmed cases, death cases, and recoveries cases (Masum et al., 2020), is the most studied prediction subject in recent years. Also, epileptic seizure represents the second intensive predictive task, it is a chronic brain disorder that causes recurrent seizures (Rasheed et al., 2020). In addition, infections can cause sepsis, the body's extreme response. Septic shock is the most severe form of sepsis and one of the leading causes of death in hospitals (Liu et al., 2014). The prediction of these tasks involved several models that we will discuss in the next part of our work.

3.2 RQ2:What Are the Different Time Series Prediction Models

This section answers our second research question as we will briefly discuss TSP models used in healthcare. After reviewing the included, we found that the asserted contributions of researchers within TSP models can be classified into statistical models, machine learning models, Deep learning models, and hybrid models.

3.2.1 Statistical Models

In this part, we present the statistical models namely ARIMA and SARIMA.

- ARIMA

Statistical models commonly used for time-series analysis include AutoRegressive Integrated Moving Average (ARIMA). ARIMA models are a popular method for analyzing and predicting TS data. Modeling TS data with seasonality, trends, and noise is possible with them. These models consist of three components: autoregression, integration, and moving average. Autoregression is used to model the correlation between observation and several lag observations. TS data persistence is modeled using this component. One of the most widely used time series models is ARIMA (Alqasemi et al., 2021). To predict the future trajectory of COVID-19 such as active, recovered, confirmed, and death cases(Kumar and Susan, 2020) analyzed temporal data on cumulative cases from the ten countries with the highest number of cases based on ARIMA and Prophet TSP models. They applied statistical measures to evaluate models. ARIMA performed better than Prophet on the scale Root Mean Square Error, Root Relative Squared Error, Mean Absolute Percentage Error, and Mean Absolute Percentage Error. However, they claim that the correlation of other variables, such as population density, weather, health system, and patient history, and the use of DL and artificial intelligence can also improve prediction levels. In the work of (Dash et al., 2021), ARIMA model was used for predicting the daily-confirmed cases for 90 days future values of six worst-hit countries of the world and six high-incidence states of India using time series data. (Kumar et al., 2021) have proposed a TSP model which is ARIMA for COVID-19 epidemic analysis and predict the number of confirmed cases in India between February 2020 and April 2020. ARIMA was applied to a wide range of time series data, including non-stationary and irregularly spaced data. Furthermore, they considered RMSE (Root Mean Square Error) as a performance metric for prediction error. ARIMA was suitable for time series analysis, and its superior performance compared to other models. This prediction model helps to assist public, private, and government agencies in designing and implementing decision-making policies. In Bangladesh (Akter et al., 2021) used a web-based electronic medical record system called "Lifeline of Medical Data" to compile medical data (health records and medication usage) to produce statistical graphs on medication usage and forecast outbreaks of deadly diseases such as dengue fever. This platform is based on the TSP model ARIMA to minimize the potential damage caused by the outbreak of recurrent diseases.

- SARIMA

Seasonal ARIMA (SARIMA) is an extension of the ARIMA model. It allows the modeling of time series with seasonal components SARIMA can help in identifying trends and patterns in data that can be used to make predictions about future values (Harper and Mustafee, 2019). It is an effective tool for forecasting and can be used to analyze seasonal fluctuations. It was implemented to predict the COVID-19 outbreak conditions represented by confirmed cases and deaths in Australia, Canada, Egypt, India, the United States, and the United Kingdom (Saad et al., 2022). SARIMA models were identified as the most suited for their data because of their residuals, trends, and seasonality characteristics. (Harper and Mustafee, 2019) have developed an application based on the SARIMA model to predict the number of patients who would arrive at the Emergency department shortly. The predictions from the SARIMA model were then used to initialize the real-time simulation model. The real-time simulation model was then used to simulate the flow of patients through the ED and to assess the impact of different strategies for managing patient flow.

3.2.2 Machine Learning Models

Machine learning has proven to be a powerful tool as TSP models in healthcare applications to reduce healthcare workers' cognitive load, by handling vast amounts of TS data using different models. After we review various studies, we note that Lasso Regression (LR), Decision Tree (DT), Support Vector Machine (SVM), and Gradient Boosting (GB) are the most common TSP models used in the healthcare field.

Table 2: List of Reviewed Studies Per Prediction Subject.

Subject	Reference
Covid-19	(Masum et al., 2020; Kumar and Susan, 2020; Kumar et al., 2022)
Septic Schok	(Hammoud et al., 2020; Hammoud et al., 2019; Kopanitsa et al., 2021)
Epileptic Seizure	(Bhowmick et al., 2018; Xu et al., 2023; Cheng et al., 2021)
Diabetes	(Song et al., 2019; De Falco et al., 2021)
Cervical Cancer	(Yan et al., 2021)
Asthma	(Do et al., 2019)
Mortality	(Darabi et al., 2018)
Cardiovascular disease	(Moshawrab et al., 2022; An et al., 2019; Perwej et al., 2018)
Coronary Heart disease	(Li et al., 2022)
Heart failure	(Balabaeva and Kovalchuk, 2019)
Alzheimer	(Alberdi et al., 2018; Mukherji et al., 2022)
Parkinson's disease	(Gottapu and Dagli, 2018)
Physician burnout	(Liu et al., 2022)
Strock disease	(Yu et al., 2022)
Accident risk	(Baek and Chung, 2021)
Lenght-of-stay	(Olivato et al., 2022)
Admission / Readmission	(Ali et al., 2022)
Predict pregnancy	(Liu et al., 2019)
Birthrates	(Alqasemi et al., 2021)
Dengue fever	(Akter et al., 2021)
Heart sound recovery	(Wang et al., 2020)
emergency call volume	(Sanabria et al., 2021)

- LR

(Hammoud et al., 2020) have proposed a real-time prediction system for septic shock in intensive care units that uses patient vital and laboratory TS data in combination with medical notes based on the Lasso Regression algorithm. Lasso Regression helps to select the most important features for predicting septic shock, which can improve the accuracy of the model and reduce overfitting. The authors also have introduced an extra hyper-parameter that allows the user to increase one performance metric (AUC or median detection time) at the expense of the other based on a user-defined utility, which provides more flexibility in model selection.

- DT

To optimize hospital services and resources, such as patient beds and medical equipment available, (Peixoto et al., 2022) have applied five ML models to predict Intensive Care Unit patient daily admissions to the hospital. The used models were Decision Trees, Random Forests, and Gradients. MAE, MSE, RMSE, and R2 were the evaluation metrics and showed that DT performs better than the other compared models. However, no model obtained sufficiently accurate results, so the exogenous variables used had a low predictive value.

- SVM

SVM performs well for TSP (Thissen et al., 2003) (Moshawrab et al., 2022) used four artificial intelligence models namely SVM, DNN, XGBoost, and a Neural Oblivious Decision to analyze the characteristics of heart rate variability and predict the occurrence of heart disease events based on a dataset of heart rate variability features extracted from ECGs. models were evaluated with the metrics of Accuracy, Precision, Recall, Specificity, Negative Predictive Value NPV, and F1 Score. The SVM model recorded accuracy, recall, and specificity results were 91.8%,96.66%, and 87.09% and it was able to predict cardiovascular disease 12 months before its onset with higher performance than the other models.

- GBT

(Darabi et al., 2018) have applied GBT and Deep neural networks for predicting 30-day mortality risk after admission to a single hospital's ICUs based on EHR data at the time of admission. They used medical embedding to train the models as it substantially helped with reducing the model dimensionality. The experimental result of the two models shows that GBT has better performance in prediction. GBT is a powerful model for training datasets that includes a limited number of records. GBT also can handle various types of data, including numerical and categorical features.

3.2.3 Deep Learning

DL models offer promising results for time series prediction, such as automatic learning of temporal dependencies and automatic handling of temporal structures such as trends and seasonality. Several different DL models are used for TS forecasting in healthcare. Recurrent neural networks (RNN) are well known to achieve strong results in many studies with time series and sequential data. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are a type of RNN that are specifically designed to handle long-range dependencies in TS data. Convolutional Neural Networks or CNNs, Multilayer Perceptrons (MLPs) are types of neural networks also used in TSP.

- GRU

The study of (Yan et al., 2021) used GRUs to build a clinical event prediction model for cervical cancer patients (Ma et al., 2018) have proposed a knowledge-based attention model called KAME for predicting patients' future diagnoses based on TS data from EHRs. KAME exploits medical knowledge in the whole prediction process and achieves significantly higher prediction accuracy compared to other models using three real-world medical datasets. Additionally, KAME learns interpretable representations of medical codes and interprets the importance of each piece of knowledge in the graph, making it more interpretable and robust. However, KAME may have limitations in terms of its generalizability to different datasets or its ability to handle noisy or incomplete data. Additionally, the effectiveness of KAME may depend on the quality and completeness of the medical knowledge graph used as input.

- LSTM

This is a type of RNN that is well-suited for predicting and extracting temporal features from long-time TS data. Using multimodal time series data, (Ali et al., 2022) have proposed a multitasking LSTM-based DL model that predicts patient LOS as a regression task and readmission within 30 days as a binary classification task. Bayesian optimizer was used to optimize the model against the real dataset of the patient's physical activity in the hospital with the new Bosch accelerometer sensor. The proposed LSTM model predicts the patient's readmission status with a high accuracy of 94.84% and predicts the patient's length of stay in the hospital with a minimum MSE of 0.025 and RMSE of 0.077, indicating that it is a promising, reliable, and efficient model. Based on historical data linking asthma severity levels and personalized trigger risk scores, in the work of (Do et al., 2019) LSTM was combined with Additive Interaction Analysis of Exposures and predicted respiratory and oxygen saturation risk scores. LSTM allows for more accurate and personalized predictions of asthma risk factors over time based on these risk scores. Additionally, doctors and patients can prevent asthma exacerbations by using personalized risk scores to predict the likelihood of an attack. In the work of (Hafiz et al., 2020) the LSTM model used is trained on past sales data of Analgesic medicine in different districts of Bangladesh, and it predicts the forecast value for the next few months. Overall, LSTM plays a crucial role in accurately predicting the demand for prescribed medicines in Bangladesh using an AI-based forecasting model. Based on the previous values of the signal, (Wang et al., 2020) have proposed a method for heart sound signal recovery that uses an LSTM prediction model based on the recurrent neuron network architecture. The complete heart sound signal is used to implement a prediction model to recover damaged or incomplete heart sound signals. (Masum et al., 2020) have contributed to the field of epidemiology and public health by providing insights into the spread of COVID-19 in Bangladesh and predicting the future trajectory of the pandemic as confirmed, death and recovery cases in the country using the LSTM model. The comparison of LSTM, RF, and SVM assumed that LSTM achieved the best result of prediction. So, LSTM is a perfect fit for real-time analysis.

- BiLSTM

SARSCoV2 spread was forecasted using BiLSTM (Makarovskikh and Abotaleb, 2022). BiLSTM model showed the power of decomposing daily SARSCoV2 data characterized by seasonality and trend. Researchers have utilized a combination of wavelet energy features and BiLSTM deep learning networks to enhance the extraction of more profound and meaningful features from EEG signals to predict epileptic seizures during sleep (Cheng et al., 2021).

- CNN

CNN is a typical network design for deep learning algorithms that are utilized for tasks including image recognition and pixel data processing (O'Shea and Nash, 2015). CNN was able to make accurate predictions of COVID-19 for a variety of indicators, including confirmed cases, hospitalization, hospitalization under artificial ventilation, and recoveries based on TS data (Saad et al., 2022). To address the critical objective of predicting the disease progression (Foo et al., 2022) have proposed a framework called DP-GAT. It is composed of three main modules: a region proposal module to extract fine-grained regions of interest (ROIs), a region features extraction module to obtain features for these ROIs, as well as a graph reasoning module for predicting disease progression. They employed a CNN that utilized a sequence of medical images as its input.

3.2.4 Hybrid Models

- CNN-LSTM

The approach of (Gottapu and Dagli, 2018) is the implementation of a hybrid deep learning model that combines LSTM and CNN to analyze and predict Parkinson's Disease. LSTM was used to identify which features should be extracted to predict the progression of the disease. CNN was used for the segmentation of the swallowtail, each voxel in the MRI must be accurately classified to determine the swallowtail's precise form.

- DRSN-GRU

(Xu et al., 2023) have proposed combining a Deep Residual Squeeze-and-Excitation Network (DRSN) and a GRU to make predictions about seizures based on a large dataset of EEG signals from epilepsy patients. Using a deep-learning neural network model, the epilepsy signal is analyzed through TS, and features are extracted by the hierarchical structure formed by GRU and DRSN. Also, DRSN reduces the difficulty of model training. The function of GRU is to learn long-term dependencies in data and predict epileptic seizures

- LSTM-MLP

The proposed approach of (Mukherji et al., 2022) involves predicting the likelihood of an individual developing Alzheimer's disease based on a hybrid model employing the LSTM model to forecast future test results and MLP to diagnose people (Liu et al., 2022) have implemented a framework, called HiPAL, that uses activity logs from EHRs to learn deep representations of physician workload and behavior. These representations are then used to predict burnout risk. It is based on LSTM that learns representations of physician workload and behavior and MLP estimates the burnout. The main benefit of this framework is that it can handle large EHR data.

- LSTM-GB

Using Knowledge Distillation based on LSTM and GB models (Ibrahim et al., 2020) implement a reliable system namely KD-OP to predict adversity indicated by death, ICU admission, and readmission. It is an ensemble of the dynamic learner and the static learner. The ensemble is trained using a technique of knowledge distillation, which allows the dynamic learner to transfer their knowledge to the static learner. The dynamic learner uses LSTM to learn from a patient's physiology time series. LSTM network can capture the temporal patterns in the data, which can help predict adverse outcomes. The static learner is a gradient-boosting model that uses static features to estimate the risk of adversity. The gradient boosting model can combine the static features in a way that is not possible with a single feature.

- EMD-LSTM

(Song et al., 2019) have proposed a hybrid EMD-LSTM model to predict patient blood glucose for 30 - 120 mins based on ECG. EMD decomposes TS of glucose measurements into empirical modes and a residual sequence, a different intrinsic mode function IMF and remove the noise by reasonably choosing IMF to Reconstruct the signal. LSTM trained each IMF to predict the patient blood glucose level. This model has higher accuracy than the LSTM model and can cope with the rapid change in trends in blood glucose levels.

4 LEARNED LESSONS

SLR process facilitates the research of the important and relevant studies that we need to answer our research questions. In addition, there are various types of TSP models used to predict healthcare outcomes. These include the length of stay, admission and readmission rates in hospitals, Parkinson's disease, cardiovascular disease, mortality rate, and risk of adverse events. Furthermore, TSP models improved healthcare services by early warning of many events and problems. Also, machine learning and deep learning TSP models are the most used in the healthcare field. Last but not least, the most commonly used Deep learning TSP model in healthcare is LSTM.In statistical models, ARIMA is prevalent in extant literature. Using CNN, diseases can be diagnosed and detected effectively, and the prediction results can be improved by combining them with RNN models.

5 CONCLUSION

This paper provides an overview of time series prediction models and the predictive cases in healthcare. For profound explanation, we categorize these models according to their types into statistical, machine learning, deep learning, or hybrid models. By answering the first research question, it has been shown that Comorbidities are the most considered research topic. Consequently, time series prediction models are crucial for monitoring the health of patients.

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