

A Comprehensive Study on Time Series Analysis in Healthcare

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Abstract—There has been a lot of interest in time series forecasting in recent years. Deep neural networks have shown their effectiveness and accuracy in various industries. It is currently one of the most extensively used machine-learning algorithms for dealing with massive volumes of data due to the reasons stated above. Statistical modeling includes forecasting, which is used for decision-making in various fields. Time-varying variables may be forecasted based on their past values, which is the goal of forecasting. Developing models and techniques for trustworthy forecasting is an important part of the forecasting process. As part of this study, a systematic mapping investigation and a literature review are used. Time-series researchers have relied on ARIMA approaches for decades, notably the autoregressive integrated moving average model. But the need for stationary makes this method somewhat rigid. Forecasting methods have improved and expanded with the introduction of computers, ranging from stochastic models to soft computers. Conventional approaches may not be as accurate as soft computing. In addition, the volume of data that can be analyzed and the efficiency of the process are two of the many benefits of using soft computing.

Index Terms— ARIMA, Deep Learning, Healthcare, Survey, Time Series.

I. INTRODUCTION

According to Time Series Data, a process is observed at predefined intervals and a predetermined sample rate. Developing rules from data and generating predictions about future values based on current observations are at the heart of time series analysis. There has been an increase in the use of time-series observation data across various industries and fields. Furthermore, the amount of time series data being produced is rising. One of the most prominent academic fields is forecasting time series data. Meteorological and weather forecasting, industrial production forecasting, and stock trend forecasting have benefited from its implementation. It might assist decision-makers in avoiding danger and making better choices. Traditional time series forecasting methods based on chance and statistics have succeeded in various fields, including meteorology, economics, and more.

Time series forecasting algorithms face substantial issues with the influx of large, non-linear time series data that follow various distribution patterns due to the introduction of data science in health care. Outstanding results have been achieved by using deep and machine learning to very sophisticated algorithms for forecasting time-series data. This article aims to categorize the many approaches for predicting time series that are currently available.

II. BACKGROUND STUDY

A. A survey on Health care Time series analysis using ARIMA MODEL

In our research study, Abdul Jalil Niaza et al. [2] looked at the current and projected prevalence of COVID-19 in Afghanistan. From 22 March to 24 June 2020, to gather COVID-19 pandemic data from Afghan patients using the time-series model (ARIMA). Three ARIMA models were created and chosen: ARIMA (0,2,2) for recovered cases and (ARIMA 0/2) for death cases with the lowest AIC values.

Pratyaksa, Hans; et al. [44] Using daily data from Prof. Soeparwi Veterinary Hospital, an ARIMA model was used to forecast the quantity of povidone-iodine antiseptic treatment that was used. R software was used to create an ARIMA forecasting model. Results show that ARIMA(1,0,1) works well with the historical data. $AR(1) = -0.6463$, $MA(1) = 0.9436$, and intercept/constant = 14.6796 were the model coefficients. The chosen model's MAE value was found to be 24.769. By developing better resource management policies and forecasting future medicine demand, stakeholders and pharmacy departments may benefit from medication consumption prediction.

B. A survey on Health care Time-series Analysis of Deep learning

Divya Gupta et al. [13] As shown in this study, cutting-edge medical technologies such as artificial intelligence (AI), distributed ledger technology (DLT), and robots — all of which are part of the current ubiquitous healthcare paradigm — may help enhance diagnostic procedures as well as patient care. The sheer volume of data makes it difficult for medical personnel to make timely decisions and implement new technologies, even while certain devices may aid in illness prevention, fitness promotion, and remote assistance in emergencies. A CNN model was trained using the original IoMT-based WESAD mental health dataset. Scalability difficulties have been addressed by restricting intra-cluster similarity computations by time and reducing processing costs in the k-medoid model. These researchers used the k-medoid approach to summarize the WESAD dataset. Data clustering reduced the execution time by half.

Fabien Viton et al. [15] An increasing number of researchers are looking at how to explain DL models, particularly in the healthcare industry. The work may be made easier by using visual-based solutions. This paper's CNN models for multivariate TS issues were explained using heat maps. A visual representation of the relevance of each TS variable over time was presented in addition to the forecasts. The research focused on predicting in-hospital mortality as a practical healthcare application. Using heat maps allows you to see which factors have the most impact and when it is most important to use them throughout your ICU stay. The model predictions are seen to be better supported by this visual explanation. Our next step is to study the heat map output with healthcare professionals interacting with patients in the intensive care unit (ICU).

Kristoffer Wickstrom et al. [30] Deep ensemble strategies for explainable CNNs are presented here. The suggested strategy was tested using both synthetic and real-world data. According to the findings, clinical time series may benefit from using deep ensembles to identify key traits, and modeling the uncertainty in relevance scores can help to give more accessible and reliable explanations for the results. New thresholding methods have been presented and tested. In this work, a single thresholding approach was explored; however, utilizing other thresholding strategies is an exciting area for future research. Using the results of this study, it is feasible to construct more reliable and precise decision-support systems than those based on deep learning.

C. Multivariate Time-series Analysis in Healthcare

Kale, David C et al. [28] An rising need for fast and reliable time series comparisons, especially in healthcare, is shown in this study. According to experts, no one-time series similarity metric performs consistently well across all datasets and situations. Most of these approaches also have problems with large time-series datasets. Hashing a time series with kernelized hashing is flexible and consistent regardless of the format or distance measure. With KLSH and arbitrary time series similarity measures, an efficient and reliable framework is provided for searching for time series that are similar to each other.

Ordonez, P et al. [40] Each interactive and animated, multivariate time-series visualization customized to an individual patient and tailored to the physicians' baseline and thresholds was provided in this research. Visualizations were created to help physicians rapidly and efficiently identify important changes in a patient's state of health. In our study, visualizations are as accurate as or less than conventional techniques for detecting PDA. Hence these authors did not reject the null hypothesis. As a result, this is acceptable given its innovative interface despite a lower overall level of trust in the visualization. However, the research found that around two-thirds of the providers preferred to employ the conventional way following training and before usage.

Yanke Hu et al. [63] Although RNNs' slow processing speed is typically neglected, new research has shown that RNN-based strategies may be useful in numerous time series applications. By converting vital signs into a (0, 1) vector and treating the problem as a computer vision problem, this article proposes a novel method for the multivariate time series classification challenge in healthcare.

Zina M et al. [65] A Voronoi diagram-based approach for detecting outliers in time series data has been described. The technique has several major benefits. Outliers are dealt with by considering the multivariate nature of the data in the first place. Because the authors may choose whether or not to use a parametric model, it is versatile in extracting relevant characteristics for separating outliers from non-outliers (such as a regression model, as in this paper). Finally, Voronoi diagrams reveal the underlying geometric connection of the data points. According to Experimental Data, our MVOD technique can accurately, sensitively, and robustly identify outliers in a multivariate time series.

D. Multi-Dimensional Time Series Analysis

Dai, Xiangfeng et al. [12]. Researchers in this research provide three different ways of altering hypothesizing the HASF approach for finding patterns in fragmented time series. This technique has proven to be resilient because of the HASF's capacity (a) to retain the underlying trend, (b) to cope with the nonstationary and heteroscedasticity of data, and (c) to represent the relevance of data samples that remain after deleting nearby data.

Dugast, Mael, et al. [14] An early decision-making aid for Emergency Department administrators is crucial for financial and public health reasons. When respiratory-like infections spread, these authors know that ED admissions increase. Sometimes, the clinical signs of these disorders may be recognized. In particular, RSV is linked to bronchiolitis symptoms in children by doctors. It is thus possible to address the RSV pandemic by analyzing the temporal series of bronchiolitis admissions to pediatric emergency rooms. There is a need for a new and unique method for recognizing early on the start of epidemic-related aberrant arrival in emergency departments (EDs) and calculating the maximum number of arrivals, which indicates how soon the epidemic will fade away. Detrended Fluctuation Analysis was utilized to get the admissions time series variability, and the authors applied the persistent homology technique (DFA). To get the best DFA parameter value, solve a multi-objective optimization problem.

TABLE I: COMPARATIVE ANALYSIS OF VARIOUS MACHINE LEARNING TECHNIQUES IN HEALTH CARE

Author Name	Techniques Used	Merits	Demerits
Abbasi et al. (2011)	FRN	Efficiently enable the inclusion of extended sets of heterogeneous Ingram features	Irrespective of the feature subset sizes.
Chen & Tseng (2011)	Product reviews	An effective information quality framework	Classification problem
Jiang et al. (2011)	Twitter sentiment classification	Incorporating target-dependent features and good performance	Targetindependent features
Xu et al. (2011)	Mining reviews from travel blogs	Using three supervised machine learning algorithms	Slightly improve accuracy
Sobkowicz et al. (2012)	Opinion formation framework	Content analysis of social media and socio physical system modeling.	Accuracy
Liu et al. (2012)	Word based Translation Model (WTM)	To extract opinion targets and to generate a global measure	The problem of error propagation in traditional

			bootstrap based methods
Kamal et al. (2012)	A rule-based system and opinion mining system	To identify candidate feature-opinion pairs from review documents and product features	Opinions that are related either directly or indirectly
Lin et al. (2012)	JST, Reverse-JST and LDA	Detects sentiment and topic simultaneously from text	Weakly supervised nature of JST and no labeled documents.
Moraes et al. (2013)	Document-level sentiment analysis, SVM and ANN	Achieved better levels of classification accuracy	Unbalanced data contexts
Bagheri et al. (2013)	A novel unsupervised and domain-independent model	To learn multiword aspects, bootstrapping iterative algorithm and pruning methods	Accuracy
Kalaivani&Shunmuganathan (2013)	The performance for sentiment classification	Good accuracy	Compare various sentiment classification approaches
Hai et al. (2014)	Opinion features from online reviews	IEDR	Domain-specific and independent corpus
Stavrianou&Brun (2015)	Product reviews, NLP and fine-grained data like opinion	Improving the recommendation system	Review only particular product.
Agarwal et al. (2015)	Concepts extraction protocol	Semantic relations between words in natural language and Concept Net ontology	Basic problem of SA
Agarwal & Mittal (2016)	Machine learning protocols for SA	Bow representations	High dimensionality of features space
Ahmad et al. (2016)	Sentence-level lexical based domain independent sentiments classification technique	Text level corpus based machine learning techniques	The problem of domain portability

Garg, Bindu, et al. [19] New techniques described in this research produce the highest accuracy with the lowest mean square error among all forecasting-related work. The pioneering dynamic computational algorithm may be used to accurately and reliably estimate and anticipate the frequency of outpatient visits in any territory-care hospital. Health care planning, allocation, and management might benefit from using the model presented in this article. A decision support system for healthcare institutions may be developed using the design of the suggested technique. Such a decision assistance system may significantly impact healthcare service efficiency. The suggested model may be improved using a genetic algorithm in the future to cope with multi-dimensional time-series data.

Gunnarsdottir, Kristin, et al. [20] an efficient technique to categorize sepsis in intensive care units (ICUs) may be to use a generalized linear model. The concept is that the 781 probability model is updated each time a new

measurement is taken and utilized by ICU physicians to understand their patient's clinical status better. Instead of only considering demographic factors, these authors found that including physiological time-series signals improved classification accuracy and specificity. These authors were constrained by the number of patients in the MIMIC II database that could be included in this investigation. Even though these findings are early, they show that GLM can be used to monitor sepsis in real-time.

Liu, Bo et al. [34] MDLats is a method and system for discovering motifs in large-scale time series presented in this work. It utilizes the RP algorithm and the ED to swiftly and precisely locate the motifs, combining the benefits of both approximate and exact techniques. Hadoop is used to construct a production-level system. MDLats' ECG classification findings and real-world use in healthcare prove its usefulness. In the future, these authors want to use MDLats in various other areas, including air pollution, social networks, and logistical optimization and lot of other areas where the system is being use on a large scale.

E. A Survey on Time Series Analysis on General Health Care

Almeida, Rui Jorge, et al. [6] A straightforward method for obtaining medical data summaries in descriptive linguistic form is presented in this paper. Proposals incorporate categorical data and clearly show disparities between patients with distinct class labels from linguistic summary protoforms. These authors propose summarizing data in a new differential form based on a numerical criterion to compare linguistic summaries. Multiple occurrences were detected in the same individuals over long periods in the reviewed data set. Summaries of linguistic features are proposed that offer chronological context for the quantification of characteristics and time

Baldassano, Steven, et al. [8] ICU caregivers are alerted to crucial occurrences in real-time using a configurable platform established in this article. This platform developed and clinically applied open-source techniques for identifying defective EEG electrodes, tracking burst suppression ratios, and detecting problems in neuromonitoring data. When it comes to improving ICU workflow, easing the strain on nurses, and enhancing research data quality, these authors showed how this platform could do all of those things and calculate clinically significant trending indicators. Medical data analytics may greatly impact patient care, and this study provides a framework for understanding a broad range of ICU data streams.

Biem, A et al. [9] These authors introduced STAM as a domain-agnostic, multi-component, generic time-series analysis and management system and exhibited its capabilities via experiments on a real-time, large-scale anomaly detection application and generated tests. The STAM system is created with a specific emphasis on well-defined qualities. STAM is a general plug-and-play system. It gives the capacity to handle multi-dimensional time-series data of nearly any size. The user inputs the data source, and the system executes the processing. STAM stresses simplicity of use: the system needs minimum adjustment from the user and minimal settings to start, save for adding data sources. It also offers sophisticated user control (e.g., sensitivity modification and parameter selection).

TABLE II: COMPARATIVE ANALYSIS OF DIFFERENT HEALTH CARE DATA

Type of Model	Size of Data	Patient Age	Accuracy
Multiple Regression	1 M	> 65	0.66
LassoLarsIC-AIC	2.3 million	All	0.72
Decision Tree Regression	2.3 million	All	0.76

Cao, Xi Hang, et al. [10] Methods for learning continuous-time LDS from MTS with different types of imperfection, such as restricted time points and uneven sample intervals, are presented in this study. These authors used a support vector machine model for classification tasks and a sophisticated LDS kernel formulation.

These authors demonstrated that our suggested technique is successful and superior to other ways based on the outcomes of three diagnostic tasks with varying degrees of imperfection.

Hajihashemi, Zahra and Popescu, Mihail [22]. Elderly people at the highest risk of deterioration and adverse events may be identified using our methods in this research. Automated in-home monitoring systems will use our computational approach to track the health trends of older persons and notify healthcare practitioners so that they may take action before things worsen. The features of TSW are discussed in depth here, followed by the findings of the suggested approach's performance on a benchmark dataset.

This research was constrained by Helander, Elina, et al. [23] because it relied on data from just two healthy patients. However, some findings were consistent with previous research. Behavioral weight loss participants were tracked on average, 28 percent on weekdays and 17 percent on weekends. These two individuals showed a reduction in self-monitoring frequency throughout the weekend. Weight fluctuates during the day and over time. An average daily weight fluctuation of 2% to 3% may be regarded as typical, with daily weight fluctuations being more frequent than day-to-day weight fluctuations

Hochstein, Axel, et al. [25] Using static Bayesian network theory, these authors develop the concept of probabilistic event networks, which describe the relationships between regime shifts in time and their locations. These authors demonstrate how RSVAR inference and learning algorithms must be altered to take higher-order regime dynamics into account.

Lehman, Li-Wei H. et al. [32] This research aims to see whether the SLDS framework can be used to follow the evolution of patients' health status over time. An ICU patient cohort was studied using the framework during the first 24 hours of hospitalization. These authors found that the vital sign dynamics of patients who did not survive their hospital stays evolved differently from those who did. As patients' health improves or worsens, the distribution of their vital sign dynamics likewise changes. These findings confirm our idea.

Liu, junjian et al. [35] Using ontology, these authors developed a real-time monitoring system to monitor patient care flow and compare it to the specified CP treatment requirements. The suggested system's monitoring data is organized and stored in a database, making it easy for the computer to handle and evaluate.

Mei, Jiangyuan, et al. [37] Computer vision and pattern recognition applications rely on accurately measuring and categorizing motion tracking signals (MTS). A new method for measuring MTS has been presented. MTS's local distance is first determined using the Mahalanobis distance, as described in the new technique. The DTW is then used to discover the best route to align MTS out of synchronization or have various lengths. Once this is done, the difference between two MTS may be derived for MTS classification and clustering purposes. Learning the Mahalanobis function for the MTS dataset is another major issue in the proposed MDDTW metric. LogDet divergence-based metric learning with triplet constraints was developed in this study for the MTS example. Our technique was tested on several well-known datasets. The results showed that the recommended strategy was dependable and accurate. An issue with the suggested framework is that it is inefficient in computing.

According to this article, pealat, Clement et al. [41], Respiratory viruses significantly affect emergency departments (ED) in France each winter. To prevent this from happening, it's critical to have the means to monitor the passage of these viruses across the patient population. This is exactly what is being discussed in this paper.

Penfold, Robert B, and Zhang, Fang [42] it is a simple yet effective evaluation of policies and programs. Despite its drawbacks, few statistical techniques are as well-designed or as effective in their effect on the audience as this one

Pierleoni, Paola, et al. [43] When used for Parkinson's disease diagnosis and treatment, this new system presented in this research offers qualities that make it an excellent choice for ambulatory and home monitoring. Tremors may be classified using a basic IMU device and a set of algorithms that can measure the intensity of their symptoms in real-time using the UPDRS scale. The system also provides a mechanism for annotating illness severity and progression to the neurologist. The report, thus, is unaffected by subjective judgments, such as those made by medical experts who alternate in subsequent analyses of a patient.

Rusanov, Alexander, et al. [47] Data-driven, time-series clustering identifies people with managed and uncontrolled diabetes. Other illness factors or long-term medical issues may apply to this strategy.

Sana Imtiaz et al. [48] Using a fitness monitoring app or a wearable device, these authors develop an online system to predict a user's food habits and health statistics. To this end, these authors have developed and deployed a pipeline that can reliably forecast user behavior and utilize commonalities between people to increase model performance while ensuring data privacy. Assuming that the dataset and characteristics are consistent, our predictions are less than 0.025 percent out of whack with reality.

Shi, Yong, et al. [50] Researching the Home Health Care 690 logistics optimization is of major importance in this article since transportation expenses are one of the main kinds of spending in the business.

According to this research, Sindhu Shantha Nair et al. [52] Ethical considerations must be considered when applying these dimensions to the healthcare business. Healthcare businesses must practice these aspects to the letter to achieve a competitive edge. These fields may benefit from more education and training to improve productivity. These perceptions and characteristics of organizational pedestal morally contribute to health care excellence if they are understood, aware, and ready.

Stylianides, Nikolas, et al. [55] The suggested solution's usability and cost-effectiveness are shown in this paper's assessment scenario. As discussed earlier, many research institutions have formed common repositories to share medical data. Researchers may access the data they need to analyze in databases or binary files.

Vasco, Todor, et al. [57] Sensor data streams are modeled using semantics. WSN and WBAN data streams demand that adaptable architectures be designed based on multiagent systems to meet the needs of real-time vital signs monitoring. Semantically-driven sensor data streams are created by the system using the suggested approach. Attributes such as timestamps, vital signs, and values define each reading. Yandong Zheng et al. [61] These authors provide an efficient and privacy-preserving forward algorithm, which these authors then employ to build a healthcare monitoring system. A collection of mutually orthogonal matrices was the first thing these authors offered, and a strategy for building one was presented shortly after.

Zhang, Ying, et al. [64] in Consistent correlation between physiological and clinical events has been shown by this method for synchronized data collection and clinical annotations. Even though hardware capabilities might affect its performance, the system gathered and evaluated patient monitoring algorithms in real-time at the bedside.

III. CONCLUSION

Two things are anticipated to occur in the future growth of technology and healthcare. First, the rising sophistication of computerization and software development will be a potent mix for predicting. Various complicated procedures and strategies now only imaginable may soon be realized and used in actual circumstances. The variances and degrees of complexity are also growing regarding the quantity of data. In addition, the healthcare departments requiring large-scale data forecasting will expand. In the future, there will be rapid growth in using these two technologies, which combine forecasting and data mining. There are various benefits to developing new forecasting methodologies, such as those based on soft computing technologies, which may produce more accurate forecasting results than conventional approaches and more efficient processes. A thorough evaluation of existing time series forecasting approaches is expected to serve as a direction for future field classifications and analysis research.

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