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Time Series Forecasting with Machine Learning: Applications in Healthcare

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Abstract: This paper explores the application of machine learning techniques in time series forecasting within the healthcare sector. The primary objective is to evaluate the effectiveness of various machine learning models in predicting healthcare-related outcomes, such as patient admission rates, the spread of infectious diseases, and patient outcomes in critical care settings. Through an extensive review of existing literature, this paper compares traditional time series forecasting methods with modern machine learning approaches, highlighting the advantages of machine learning in handling complex, non-linear healthcare data. Key findings indicate that machine learning models, particularly deep learning architectures like Long Short-Term Memory (LSTM) networks, offer superior accuracy and flexibility compared to traditional methods. However, challenges such as data quality, model interpretability, and ethical considerations regarding patient data privacy are also addressed. The paper concludes by discussing future directions, including the integration of machine learning models with electronic health records (EHRs) for real-time forecasting and the potential for broader applications across the healthcare industry.

Keywords: Long Short-Term Memory (LSTM) networks, electronic health records (EHRs), machine learning

Introduction

Background and Motivation

Time series forecasting plays a pivotal role in various sectors, enabling organizations to make informed decisions by predicting future trends based on historical data. In healthcare, the stakes are particularly high, as accurate forecasting can directly influence patient outcomes, resource allocation, and overall public health strategies. The ability to predict patient admission rates, disease outbreaks, or the demand for healthcare services allows for better planning, improved patient care, and more efficient use of resources.

Traditionally, time series forecasting in healthcare has relied on statistical methods such as Auto-Regressive Integrated Moving Average (ARIMA), Holt-Winters exponential smoothing, and Seasonal Decomposition of Time Series (STL). These methods are well-established and provide a straightforward approach to modeling temporal data. However, they are often limited by their assumptions of linearity and stationarity, which may not hold true in the complex and dynamic context of healthcare data. Moreover, traditional methods can struggle with large, high-dimensional datasets, often resulting in less accurate forecasts that fail to capture the nuances of real-world healthcare scenarios.

The healthcare industry is characterized by data that is often noisy, nonlinear, and influenced by a multitude of factors, including patient demographics, environmental conditions, and evolving medical practices. This complexity demands more sophisticated forecasting tools. Machine learning (ML) offers a powerful alternative to traditional methods by leveraging its ability to model complex, non-linear relationships in data. Machine learning models, particularly those based on deep learning architectures like Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), have shown promise in capturing intricate patterns within time series data that traditional methods might miss.

The potential of machine learning in healthcare time series forecasting is significant. For instance, ML models can improve the prediction of patient inflows in hospitals, allowing for better staffing and resource management. They can also be used to forecast the spread of infectious diseases, providing crucial insights for public health interventions. Additionally, in critical care settings, ML-driven forecasts can help predict patient deterioration, enabling timely and potentially life-saving interventions.

However, the adoption of machine learning in healthcare forecasting is not without challenges. One of the primary concerns is the quality and quantity of data required to train effective machine learning models. Healthcare data is often fragmented across different systems and may suffer from inconsistencies, missing values, or biases. Additionally, the "black box" nature of many machine learning models raises concerns about interpretability and trustworthiness, which are crucial in a field where decisions can have life-or-death consequences. Furthermore, the use of patient data in machine learning models introduces ethical and privacy concerns, particularly regarding the protection of sensitive health information.

Despite these challenges, the potential benefits of applying machine learning to healthcare time series forecasting are compelling. With advancements in data integration, model interpretability, and privacy-preserving techniques, machine learning has the potential to revolutionize how healthcare providers anticipate and respond to future challenges. This paper aims to explore these possibilities, providing an in-depth analysis of the current state of machine learning in healthcare forecasting, comparing it with traditional methods, and identifying areas where machine learning can make the most significant impact.

Literature Review

Traditional Time Series Forecasting Methods

Time series forecasting has a long history of application in various fields, including finance, economics, and healthcare. Among the most commonly used traditional methods are the Auto-Regressive Integrated Moving Average (ARIMA) model and the Holt-Winters exponential smoothing method.

ARIMA is a powerful tool for modeling time series data by combining auto-regression, moving average, and differencing to make non-stationary data stationary, which is a prerequisite for accurate forecasting. The ARIMA model is particularly useful for univariate time series data where past values are used to predict future outcomes. Despite its widespread use, ARIMA has notable limitations in healthcare applications. Healthcare data often exhibit non-linear patterns and are influenced by multiple external factors, such as patient demographics, environmental variables, and medical practices, which ARIMA models struggle to capture effectively (Box & Jenkins, 1976).

Holt-Winters exponential smoothing is another traditional method that is widely used for forecasting seasonal time series data. This method extends simple exponential smoothing by adding components to capture trend and seasonality. Holt-Winters can be particularly useful for short-term forecasts where seasonality plays a significant role. However, its reliance on the assumption that future patterns will closely resemble past trends makes it less effective in the healthcare context, where sudden changes and unpredictable events are common (Holt, 1957).

Both ARIMA and Holt-Winters are effective for time series data that exhibit relatively stable and linear patterns. However, the inherent complexity of healthcare data, which often involves multiple variables, non-linear relationships, and dynamic patterns, limits the effectiveness of these traditional methods. They also require manual tuning of parameters and assumptions about the data that may not hold true in practice. Consequently, these models may fail to provide accurate forecasts in healthcare settings, leading to potential inefficiencies in resource allocation and patient care.

Machine Learning Approaches

Machine learning (ML) has emerged as a powerful alternative to traditional time series forecasting methods, particularly in handling complex, high-dimensional, and non-linear data. Unlike traditional models, which rely heavily on assumptions about data distribution and relationships, machine learning models learn patterns directly from the data, making them more flexible and capable of capturing intricate relationships.

Linear Regression is one of the simplest machine learning techniques used for time series forecasting. It models the relationship between a dependent variable and one or more independent variables. While linear regression is easy to implement and interpret, it is limited by its assumption of linearity, which may not hold in healthcare data (Makridakis et al., 1983).

Support Vector Machines (SVM), on the other hand, are capable of modeling more complex relationships by finding the hyperplane that best separates the data points in a high-dimensional space. SVMs are particularly effective in scenarios where there is a clear margin of separation between different outcomes, but they require careful tuning of parameters and can be computationally expensive, especially for large datasets (Smola & Schölkopf, 2004).

Random Forests, an ensemble learning method, combines multiple decision trees to improve predictive accuracy and control overfitting. Random Forests are robust to noise and can handle a large number of input variables, making them well-suited for healthcare applications where the data may be complex and multifactorial. However, the interpretability of Random Forest models can be a challenge, especially in a clinical context where understanding the reasoning behind predictions is critical (Breiman, 2001).

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) designed specifically to handle time series data with long-term dependencies. LSTMs are capable of learning and remembering patterns over long sequences, making them highly effective for healthcare time series forecasting, such as predicting patient outcomes or disease progression. The main drawback of LSTMs is their complexity, which requires significant computational resources and expertise to implement effectively (Hochreiter & Schmidhuber, 1997).

When comparing traditional methods with machine learning approaches, it is evident that ML models offer greater flexibility and the ability to capture non-linear relationships and complex patterns in data. Machine learning models, particularly deep learning architectures like LSTMs, can outperform traditional methods in terms of predictive accuracy, especially in healthcare applications where data complexity is high. However, challenges such as model interpretability, data requirements, and computational cost need to be carefully considered when choosing between traditional and machine learning approaches.

Applications in Healthcare

Machine learning techniques have been increasingly applied to time series forecasting in healthcare, with promising results. Several studies have demonstrated the effectiveness of machine learning models in improving forecast accuracy and supporting better decision-making in healthcare settings.

One area where machine learning has shown significant promise is in predicting **patient admission rates**. For instance, a study by Tsai et al. (2018) utilized Random Forest models to predict patient admissions in emergency departments, achieving higher accuracy compared to traditional methods. The ability to accurately forecast admission rates allows hospitals to allocate resources more efficiently and improve patient care during peak times (Tsai et al., 2018).

Another important application is the **forecasting of infectious disease outbreaks.** Researchers have used LSTM networks to model the spread of diseases such as influenza, dengue fever, and Ebola. For example, Yang et al. (2019) developed an LSTM-based model that significantly improved the prediction of influenza trends compared to traditional ARIMA models. Such predictions are crucial for public health planning and intervention strategies (Yang et al., 2019).

Machine learning has also been applied to **predict patient outcomes in** critical care settings. For example, a study by Harutyunyan et al. (2019) applied deep learning techniques to predict mortality rates among ICU patients using time series data from electronic health records (EHRs). The study found that deep learning models outperformed traditional logistic regression models in predicting patient outcomes, highlighting the potential of ML in critical care forecasting (Harutyunyan et al., 2019).

These studies demonstrate the potential of machine learning to transform time series forecasting in healthcare. By leveraging the ability of ML models to handle complex, multi-dimensional data, healthcare providers can achieve more accurate predictions, ultimately leading to better patient outcomes and more efficient use of resources.

Methodology

Theoretical Framework

Time series forecasting involves predicting future values based on previously observed data points. The theoretical foundation of time series forecasting is grounded in the assumption that historical data patterns can provide insights into future trends. This concept is particularly relevant in healthcare, where understanding past events, such as patient admissions or disease outbreaks, is crucial for planning and decision-making.

Traditional time series models, like ARIMA, are based on the principles of autoregression, moving averages, and differencing to make data stationary, which is necessary for accurate forecasting. These models rely on the linear assumption, meaning they predict future values based on a weighted sum of past observations. While these models are mathematically elegant and interpretable, they struggle with non-linear relationships and complex interactions among variables, which are often present in healthcare data.

Machine learning models, on the other hand, are data-driven and can model complex, non-linear relationships without requiring explicit assumptions about the underlying data distribution. These models use algorithms that learn from the data by adjusting their internal parameters to minimize prediction error. The learning process is iterative, allowing models to improve as more data becomes available.

In healthcare, the application of machine learning models to time series forecasting is particularly powerful due to the complex and multifactorial nature of medical data. For example, patient outcomes can be influenced by a variety of factors, including demographic characteristics, comorbidities, treatment protocols, and external environmental conditions. Machine learning models can capture these intricate patterns and interactions, providing more accurate and nuanced predictions than traditional statistical methods.

Furthermore, machine learning models, particularly deep learning architectures, can process vast amounts of data from different sources, such as electronic health records (EHRs), medical imaging, and wearable devices. This capability is crucial in healthcare, where data is often heterogeneous and high-dimensional. By leveraging the ability to learn from large, complex datasets, machine learning models can offer predictive insights that are not feasible with traditional methods.

Machine Learning Models

Several machine learning models are particularly relevant to time series forecasting in healthcare. Below is a detailed exploration of some of the most commonly used models, along with their strengths and limitations in healthcare applications.

1. Linear Regression

Linear regression is one of the simplest and most interpretable machine learning models used in time series forecasting. It models the relationship between a dependent variable (e.g., patient admission rates) and one or more independent variables (e.g., time, day of the week). The simplicity of linear regression makes it easy to implement and interpret, which is beneficial in healthcare where understanding the factors driving predictions is crucial. However, its major limitation is the assumption of linearity, which often does not hold true in the complex, non-linear data typical of healthcare settings (Makridakis et al., 1983).

2. Support Vector Machines (SVM)

Support Vector Machines are effective in capturing non-linear relationships by mapping data into a higher-dimensional space where a linear separator can be applied. This makes SVMs particularly useful in healthcare when there is a need to classify patient outcomes or disease states based on a set of features. However, SVMs require careful tuning of hyperparameters and can be computationally intensive, especially with large datasets common in healthcare. Additionally, the model's predictions are not as easily interpretable as simpler models, which can be a drawback in clinical settings (Smola & Schölkopf, 2004).

3. Random Forests

Random Forests are ensemble learning models that aggregate the predictions of multiple decision trees to improve accuracy and reduce overfitting. This method is robust to noise and capable of handling large datasets with many variables, making it well-suited for healthcare applications such as predicting patient admissions or disease progression. The key strength of Random Forests lies in their ability to handle both categorical and continuous data and to provide estimates of feature importance, which is valuable for understanding the factors driving predictions. However, Random Forests can be computationally expensive and may require significant computational resources for training, particularly with very large datasets (Breiman, 2001).

4. Long Short-Term Memory (LSTM) Networks

LSTM networks, a type of recurrent neural network (RNN), are specifically designed to handle sequential data, making them highly effective for time series forecasting. LSTMs are capable of learning long-term dependencies, which is crucial in healthcare contexts where events may be influenced by factors occurring far in the past. For instance, predicting patient outcomes may depend on long-term medical history, which LSTMs can incorporate into their forecasts. The primary advantage of LSTM networks is their ability to model complex temporal patterns and interactions. However, they are also among the most complex and resource-intensive models to train and require significant expertise in neural network design and tuning (Hochreiter & Schmidhuber, 1997).

5. Convolutional Neural Networks (CNNs)

While traditionally used in image processing, Convolutional Neural Networks (CNNs) have been adapted for time series forecasting by treating time series data as a one-dimensional image. CNNs are particularly good at detecting local patterns in data and can be used to forecast short-term trends in healthcare time series. For example, CNNs can be used to predict the onset of an epidemic by analyzing trends in disease incidence data. The strength of CNNs lies in their ability to automatically learn relevant features from raw data, reducing the need for manual feature engineering. However, like LSTMs, CNNs are computationally demanding and require large amounts of data to perform well (LeCun et al., 1998).

6. Hybrid Models

Hybrid models combine multiple machine learning techniques to leverage the strengths of each. For instance, a hybrid model might use a CNN to extract features from time series data and then feed these features into an LSTM network for forecasting. Such models can be particularly powerful in healthcare, where data is complex and multi-dimensional. Hybrid models can improve accuracy and robustness but at the cost of increased complexity and computational requirements. These models also require careful design and tuning to ensure that the different components work well together (Zhang, 2003).

Strengths And Limitations in Healthcare Applications

Each of these machine learning models offers unique strengths and comes with specific limitations when applied to healthcare time series forecasting. The choice of model depends on the specific application, the nature of the data, and the need for interpretability versus accuracy. For instance, while LSTMs may provide highly accurate predictions, their complexity and "black-box" nature may not be suitable for all healthcare applications where transparency is crucial. Conversely, simpler models like linear regression, while easier to interpret, may not capture the complexity needed for accurate predictions in many healthcare scenarios.

In conclusion, machine learning models offer powerful tools for improving time series forecasting in healthcare. However, their implementation must be carefully considered, balancing the trade-offs between accuracy, interpretability, computational cost, and the specific needs of the healthcare context.

Case Studies and Applications

Case Study 1: Predicting Patient Admission Rates

Description of the Problem and Methodology:

Accurately predicting patient admission rates is critical for hospital operations, as it directly influences resource allocation, staffing, and bed management. Traditional methods, such as seasonal autoregressive integrated moving average (SARIMA) models, have been commonly used to forecast patient admissions based on historical data. However, these models often fall short in capturing the complex patterns and non-linear trends present in healthcare data.

A study by Amin and Shaban (2019) explored the use of machine learning models to predict emergency department (ED) admission rates. The authors applied a Random Forest model to time series data, which included variables such as historical admission rates, weather conditions, and public holidays. The Random Forest model was chosen for its ability to handle non-linear relationships and interactions between variables, which are common in healthcare data.

Synthesis of Findings and Implications for Hospital Operations:

The study found that the Random Forest model outperformed traditional SARIMA models, achieving higher accuracy in predicting daily admission rates. The machine learning model's ability to incorporate multiple variables and capture complex interactions resulted in more reliable forecasts, especially during periods of high variability, such as flu season.

The implications for hospital operations are significant. By improving the accuracy of admission forecasts, hospitals can better manage staffing levels, ensure sufficient bed availability, and reduce patient wait times in the emergency department. This can lead to enhanced patient care, more efficient use of resources, and reduced operational costs (Amin & Shaban, 2019).

Case Study 2: Forecasting Infectious Disease Spread

Overview of Approaches Used in Literature and Outcomes Reported:

Forecasting the spread of infectious diseases is a crucial component of public health planning. Traditional models, such as compartmental models (e.g., SIR models), have been widely used to predict the dynamics of disease transmission. However, these models often require predefined assumptions about transmission rates and other parameters, which may not accurately reflect real-world conditions.

In a study by Yang, Santillana, and Kou (2015), the authors applied a Long Short-Term Memory (LSTM) network to forecast the spread of influenza across different regions in the United States. The LSTM model was trained on historical influenza incidence data, along with supplementary information such as weather conditions and social media trends, to capture the temporal and spatial dynamics of the disease.

Discussion on the Impact of These Forecasts on Public Health Planning:

The LSTM model demonstrated superior predictive performance compared to traditional compartmental models, particularly in capturing the non-linear and complex patterns of influenza spread. The model's ability to incorporate real-time data and adapt to changing conditions allowed for more accurate and timely forecasts.

The impact of these forecasts on public health planning is profound. Accurate predictions of disease spread enable public health officials to allocate resources more effectively, implement targeted interventions, and communicate risks to the public more efficiently. This can lead to more effective containment of outbreaks, reduced healthcare burden, and ultimately, saved lives (Yang, Santillana, & Kou, 2015).

Case Study 3: Predicting Patient Outcomes in Critical Care

Explanation of Forecasting Methods Used in Studies and Their Integration with Healthcare Practice:

In critical care settings, predicting patient outcomes, such as mortality or length of stay, is essential for improving patient care and optimizing resource utilization. Traditional scoring systems, like the Acute Physiology and Chronic Health Evaluation (APACHE) score, have been used to assess patient risk based on clinical parameters. However, these systems are often static and do not fully capture the dynamic nature of patient conditions.

A study by Harutyunyan et al. (2019) applied deep learning techniques, specifically a bidirectional LSTM network, to predict patient outcomes using time series data from electronic health records (EHRs). The model was trained on a large dataset of ICU patient data, including vital signs, laboratory results, and treatment information, to capture the temporal dynamics of patient conditions.

Analysis of How Improved Forecasting Could Benefit Patient Outcomes:

The bidirectional LSTM model outperformed traditional scoring systems in predicting patient mortality and length of stay. The model's ability to continuously update predictions based on the latest available data allowed for more accurate and timely assessments of patient risk.

Improved forecasting in critical care can significantly benefit patient outcomes. By providing clinicians with accurate, real-time predictions, healthcare providers can make more informed decisions about patient care, such as adjusting treatment plans or allocating resources to high-risk patients. This can lead to better management of ICU resources, reduced patient mortality, and more personalized care (Harutyunyan et al., 2019).

Discussion

Comparison with Traditional Methods

The comparative analysis between machine learning models and traditional forecasting methods reveals several key distinctions that influence their effectiveness in healthcare applications. Traditional methods, such as ARIMA and Holt-Winters, have been the backbone of time series forecasting due to their simplicity and ease of interpretation. However, these models are often constrained by their assumptions of linearity and stationarity, which can limit their applicability in the complex, non-linear environment of healthcare data. For instance, ARIMA models are effective for short-term, stable time series but may fail to capture sudden changes or non-linear trends in patient data (Box & Jenkins, 1976).

In contrast, machine learning models, particularly those based on deep learning architectures like LSTMs, offer significant advantages in handling the multi-dimensional, non-linear nature of healthcare data. Studies have shown that LSTMs and Random Forests can outperform traditional methods in predicting patient admissions, disease outbreaks, and patient outcomes by capturing more complex patterns and relationships in the data (Hochreiter & Schmidhuber, 1997). However, the increased complexity of machine learning models comes with trade-offs, such as higher computational costs and the need for large datasets for training, which are not required by traditional methods.

Challenges and Limitations

Despite the advantages of machine learning models, several challenges and limitations have been identified in the literature. One of the primary challenges is data quality. Healthcare data is often incomplete, inconsistent, and noisy, which can adversely affect the performance of machine learning models. Missing data, in particular, can lead to biased predictions if not properly handled (Smola & Schölkopf, 2004).

Model interpretability is another significant challenge. Machine learning models, especially deep learning models, are often described as "black boxes" because their internal workings are not easily understood by humans. This lack of transparency can be problematic in healthcare, where understanding the rationale behind a prediction is crucial for clinical decision-making. Efforts to improve model interpretability, such as the development of explainable AI (XAI) techniques, are ongoing but not yet fully integrated into many healthcare applications (Rudin, 2019).

Privacy concerns also pose a major limitation in the application of machine learning to healthcare. Patient data is highly sensitive, and the use of such data in machine learning models raises issues related to data security and patient consent. Ensuring that patient data is anonymized and protected while still being useful for predictive modeling is a complex challenge that requires careful consideration of both ethical and legal frameworks (Price & Cohen, 2019).

Ethical Considerations

The ethical use of patient data in machine learning is a critical concern in healthcare. As machine learning models increasingly rely on large datasets, there is a growing need to ensure that these models are developed and deployed in ways that respect patient privacy and autonomy. One of the key ethical issues is obtaining informed consent from patients whose data is used in machine learning models. This is particularly challenging in situations where data is aggregated from multiple sources or where the use of data for secondary purposes, such as research, was not initially disclosed to patients (Price & Cohen, 2019).

Additionally, the potential for bias in machine learning models must be carefully managed. Bias can arise from imbalanced training data or from the way models are designed and deployed. In healthcare, biased predictions can lead to disparities in care, where certain patient groups may receive less accurate predictions or less favorable outcomes. Ensuring fairness and equity in machine learning applications is an ongoing area of research and ethical debate (Char et al., 2018).

Conclusion

Summary of Findings

This paper has explored the application of machine learning models in time series forecasting within the healthcare sector, highlighting their advantages over traditional methods, particularly in handling complex, non-linear data. Case studies have demonstrated the effectiveness of machine learning models in predicting patient admissions, disease outbreaks, and patient outcomes, providing valuable insights that can enhance healthcare operations and patient care.

Implications for Healthcare

The integration of machine learning models into healthcare forecasting has the potential to significantly improve patient care and operational efficiency. By providing more accurate predictions, these models can help healthcare providers anticipate and respond to future challenges more effectively, ultimately leading to better patient outcomes and more efficient use of resources.

Final Thoughts

The potential of machine learning in healthcare is vast, but realizing this potential requires addressing several challenges, including data quality, model interpretability, and ethical considerations. Continued research and development in this field are essential to overcome these challenges and fully harness the power of machine learning to transform healthcare.

References

[1]. Amin, M., & Shaban, K. (2019). Machine learning-based hospital admission prediction for resource-limited environments. IEEE Access, 7, 52336-52344.

[2]. Box, G. E. P., & Jenkins, G. M. (1976). Time series analysis: Forecasting and control (Revised ed.). Holden-Day.

[3]. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.

[4]. Char, D. S., Shah, N. H., & Magnus, D. (2018). Implementing machine learning in health care—addressing ethical challenges. The New England Journal of Medicine, 378(11), 981-983.

[5]. Goldstein, B. A., Navar, A. M., Pencina, M. J., & Ioannidis, J. P. A. (2017). Opportunities and challenges in developing risk prediction models with electronic health records data: A systematic review. Journal of the American Medical Informatics Association, 24(1), 198-208.

[6]. Harutyunyan, H., Khachatrian, H., Kale, D. C., Ver Steeg, G., & Galstyan, A. (2019). Multitask learning and benchmarking with clinical time series data. Scientific Data, 6(1), 1-18.

[7]. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.

[8]. Holt, C. C. (1957). Forecasting seasonal and trends by exponentially weighted averages. ONR Research Memorandum, 52, 1-23.

[9]. Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., ... & Wang, Y. (2017). Artificial intelligence in healthcare: Past, present and future. Stroke and Vascular Neurology, 2(4), 230-243.

[10]. Kamila, S., Nitesh, V. C., & Kalpana, R. (2017). Medication adherence prediction using machine learning. International Journal of Pharma and Bio Sciences, 8(4), 73-81.

[11]. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

[12]. Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1983). Forecasting: Methods and applications (2nd ed.). John Wiley & Sons.

[13]. Pan, S. J., & Yang, Q. (2010). A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345-1359.

[14]. Price, W. N., & Cohen, I. G. (2019). Privacy in the age of medical big data. Nature Medicine, 25(1), 37-43.

[15]. Smola, A. J., & Schölkopf, B. (2004). A tutorial on support vector regression. Statistics and Computing, 14(3), 199-222.