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SPESIS DETECTION USING MACHINE LEARNING

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ABSTRACT

Sepsis is a potentially fatal medical disorder that needs to be identified and treated right away to avoid fatalities. It must be quickly identified and treated in order to stop it from developing into severe sepsis, septic shock, and multiorgan failure. Sepsis remains a significant problem for doctors despite advancements in medical technology and treatment methods. The beginning of the disease has been successfully predicted by machine learning models in recent years, but due to their black-box character, it is challenging to interpret these predictions and comprehend the underlying illness mechanisms. In this research, we propose a comprehensible AI method for sepsis analysis that combines machine learning with clinical knowledge and expertise in the domain. Our method allows clinicians to understand and verify the model's predictions based on clinical expertise and preexisting beliefs,in addition to providing precise predictions of the onset of sepsis.

Keywords-Sepsis, Artificial Intelligence, Machine Learning, Explainable AI, Sensitivity Analysis.

I. INTRODUCTION

As the world continues to embrace technology, the potential of artificial intelligence (AI) in healthcare is becoming increasingly evident. One area where AI holds great promise is early detection of sepsis, a disease that affects millions of people each year. Sepsis, a medical condition, develops when the body's immune system reacts to pathogens that can damage its tissues and organs. Any infection can cause sepsis, including pneumonia, urinary tract infections, or skin infections. Sepsis is a very serious illness that requires immediate hospital treatment [1]. Treatment may include antibiotics, antibiotics, and oxygen therapy. Early diagnosis and prompt treatment increases the chance of a full recovery.

Artificial intelligence (AI) has emerged as a promising tool for the early detection and diagnosis of sepsis . By analyzing large amounts of patient data, including vital signs, lab results, and medical history, machine learning algorithms can identify patterns that may indicate the onset of sepsis. This allows healthcare providers to intervene early and prevent the condition from becoming severe. There have been several studies done by researchers in building a machine-learning algorithm for early detection [2]. In addition to early detection,AI can also help healthcare providers make more accurate and timely diagnosis There is one major drawback to black box algorithm, as our machine learning models continue to advance to achieve greater accuracy, it becomes difficult or impossible to understand how these models arrive at their decisions or predictions. This can pose challenges in healthcare, where decisions made by AI models can have serious consequences for patient health and well-being [3].

XAI (Explainable Artificial Intelligence) is an emerging field that aims to solve this problem. A collection of concepts and techniques called Explainable Artificial Intelligence (XAI) makes AI models openended and explainable. XAI helps solve translational problems in clinical practice and sepsis by allowing doctors to understand how models make decisions or predictions. This knowledge helps build trust and acceptance of the model, facilitating more informed decision making by healthcare professionals. XAI can also improve communication between doctors and patients [4]. By providing clear explanations and descriptions of how AI models make decisions, patients can participate in their own care and better understand the logic behind decisions. Our goal is to solve these problems by providing a clear and easy-to-understand intelligence model.

Our approach integrates clinical knowledge and AI into machine learning processes, allowing clinicians to understand and apply predictive models. This method not only increases confidence in the cognitive model, but also provides physicians with useful information for the diagnosis and treatment of sepsis [5].

MOTIVATION

A growing number of studies are using machine learning to improve early prediction of sepsis through digital biomarker discovery, but this review highlights several shortcomings of current methods, including low comparability and reproducibility.

II. RELATED WORK

In this paper[1],The Sequential Organ Failure Assessment (SOFA) score is used to assess organ dysfunction, where an increase of 2 points indicates a greater than 10 percent.

The main goal of this study[2] is to develop a method for early sepsis detection using a Random Forest Classifier First, the data is pre-processed using a resampling technique. Then, the importance of different features is calculated using methods like log plots and Yeo Johnson transformation. Finally, the Random Forest Classifier is applied to detect sepsis.Prediction of sepsis within 24 hours before clinical suspicion of sepsis was performed using the negative Bayes algorithm on a maximum posteriori basis.

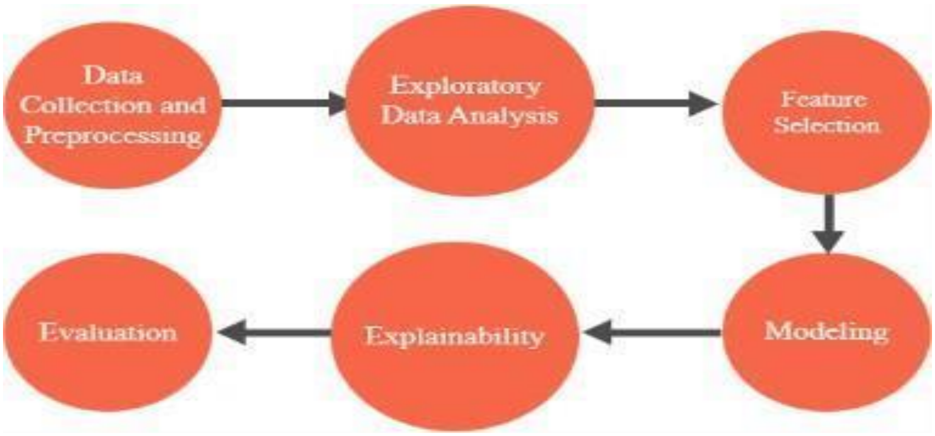
This study[3] also preserves valuable information. It is less time consuming and less likely to be entered incorrectly than studies that use a grid to record important characters.

From[4] 34 features used by machine learning, 7 values are selected among 6 quantitative products. The physicochemical prediction model is built with decision tree based SVM classifier. The proposed LSTMRNN and SVM data analysis techniques are implemented using ACNN classifier and two intelligent candidates.

The aim of this study [5]was to develop the description of a sepsis prediction algorithm using the continuous signal of the electrocardiogram (ECG) with the aim of applying it to patients in the intensive care unit (ICU) monitoring center.

III. METHODOLOGY

We aimed to develop a model that could accurately predict sepsis in hospital patients using readily available clinical variables. To achieve this goal, we obtained a large dataset consisting of 155,221 patient records from a hospital. The dataset contained information on 43 variables, including demo graphic information, vital signs, laboratory results, and comorbidities. Before using the dataset for analysis, we conducted a thorough data cleaning pro- cess. We first identified missing values in the dataset and determined the proportion of null values for each variable. Some variables had more than 90.



IV. EXPLORATORY DATA ANALYSIS

Evaluate the model performance using confusion matrices and statistics. The confusion matrix shows the number of good, bad, negative and negatives. From the confusion matrix we can see that the sample is divided into 18,692 sepsis negative and 18,643 sepsis positive samples. However, it is not correct to classify 864 samples as positive when they are negative and 840 samples as negative when they are positive. Distribution 95.64.

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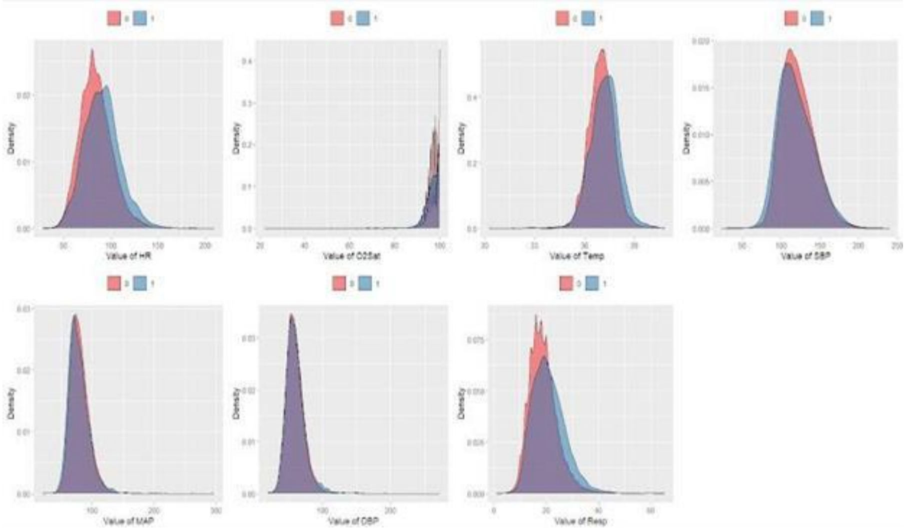

The kappa statistic is 0.9127 and measures the agreement between model predictions and actual outcomes, including expected agreement over time. A kappa of 1 indicates perfect agreement, while a kappa of 0 means the agreement is worse than chance. Distribution. The specificity is 0.9570, which is the percentage of negative samples from which the sample was excluded. The positive predictive value (PPV) is 0.9569, which is the percentage of positive predictions that are correct. The negative predictive value (NPV), which is the percentage of negative predictions, is 0.9558. The kappa statistic is 0.9127 and measures the agreement between model predictions and actual outcomes, including expected agreement over time. A kappa of 1 indicates perfect agreement, while a kappa of 0 means the agreement is worse than chance. Distribution. The specificity is 0.9570, which is the percentage of negative samples from which the sample was excluded. The positive predictive value (PPV) is 0.9569, which is the percentage of positive predictions that are correct. The negative predictive value (NPV), which is the percentage of negative predictions, is 0.9558.

V. FUTURE SCOPE

A) Improved accuracy : While our model is fairly ac- curate at predicting sepsis, there is always room for improve- ment. In the future, we may explore more machine learning algorithms or integrations to improve the accuracy of our models.

B) Point-of-care monitoring : Our models currently run on static data which prevents them from being useful in managing patients with sepsis. In the future, we may work to develop models that can monitor patients regularly and notify healthcare providers when sepsis is detected.

C) Responsible AI: As with all applications of machine learning in healthcare, it is important to ensure that our standards are ethical and responsible. In the future, we can work to create standards that are more transparent, explainable, and do not cause complaints and inconsistencies in treatment

VI. CONCLUSION

An XAI-based system for early detection of sepsis has been developed, which holds significant potential in improving patient outcomes and reducing mortality rates. The system utilizes machine learning algorithms and interpretable models to analyze a wide range of patient data and provide early warning signs of sepsis. Although this technology is still in its initial stages, it has shown promising results in terms of accuracy and speed of diagnosis. Further research and development are required to improve the system's performance and expand its capabilities, but the potential impact of XAI in healthcare and the early detection of sepsis is undeniable. This study represents an important step forward in the application of XAI to address pressing medical issues and highlights the importance of continued research in this area.

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