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Sepsis Detection using Patient Clinical Data with Multi-Layer Perceptron- A Research

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Introduction:

Sepsis is a real-life threat for humanity as it is one of the serious problems among the medical field. It is a lifethreateningcondition and increases with the severity without detection. As per WHO, it kills more than 6 million people a year. The report says that every year 3 million newborns and1.2 million children suffer from sepsis globally. Due to the resistant pathogens, death rate for neonatal sepsis is estimated as three out of every ten deaths. Maternal sepsis cause deaths associated with pregnancy and childbirth. More than 95% of deaths happen in low and middle income countries due to maternal sepsis. Maternal sepsis causes one million newborn deaths in every year.[1].

Early detection of sepsis can be treated using antibiotics and completely curable and save millions of people. In this scenario the early detection or prediction of sepsis using Machine Learning is a hot area for research. Clinical values or criteria are essential for achieving this type of research. Real values are more important to diagnose Sepsis but it is very difficult to get. Normally Systemic Inflammatory Response Syndrome (SIRS) criteria are used to predict or diagnose sepsis. Another criterion is qSOFA (quick Sequential Organ Failure Assessment) [2].

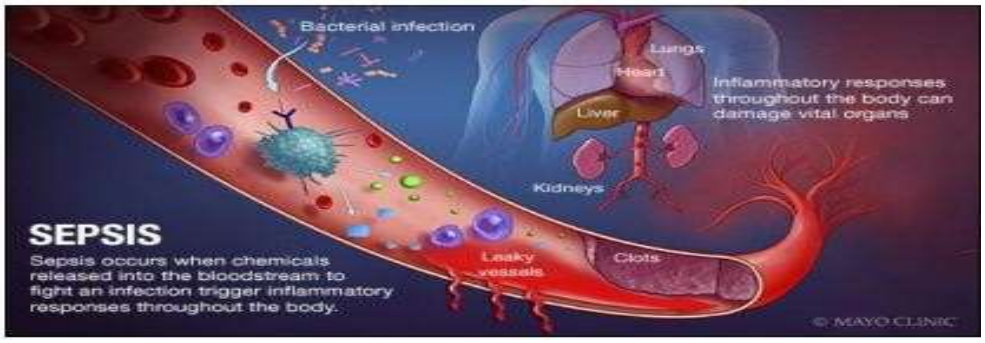

Figure 1: Images of Sepsis Condition.

Sepsis is a hazardous condition that happens when the body's reaction to contamination causes tissue harm, organ failure, or even demise of the person. Generally, the body releases natural synthetics into the circulation system in order to counterbalance the infection which is inside. Sepsis occurs when the body's response to these chemicals is out of balance; this can damage many organ systems. Sepsis is caused by infection and can happen to anyone. It is most common& dangerous for senior citizens, pregnant ladies, kids below one-year-old, persons suffering from chronic conditions, such as diabetes, kidney disease, lung disease, or even cancer, as they have

weak immune systems. This disease is a major health concern for the public in terms of morbidity, health care expenses and mortality. Detecting at early stages, with antibiotic treatment the outcomes can be improved. Though many professional care societies have proposed new methods in recognizing sepsis, the central requirement for early identification and treatment remains neglected. It can be treated if it can be recognized at early stages. Several examinations have demonstrated that delays in finding and treatment of sepsis can prompt high death rates.Our main aim is to detect sepsis as soon as the patient visits the emergency department for the treatment.

Causes of Sepsis

Any infection can trigger sepsis, but the following types of infections are more likely to cause sepsis: **Pneumonia:** It is a type of infection that attacks the lungs one or both lungs canbe affected by bacteria, fungi, and viruses from outside attack lungs. This causes inflammation inthe air sacs called alveoli in the lungs, the bacteria or virus or fungi fills this with fluid which makes breathing difficult.

Abdominal infection: It surrounds a number of infectious processes, including peritonitis, cholecystitis, diverticulitis, pancreatitis, and cholangitis. With help of Empirical treatment, they can identify whether the infection is through community or healthcare-acquired, the organswhich are infected, and to check if the infection is complex or simple.

Kidney Infection: It generally results from an infection in the urinary tract that spreads to 1 or both the kidneys; this can be chronic or sudden. If they are not treated at early stages they can be life-threatening.

Bloodstream Infection: It is an infection that occursAwhen bacteria are in the circulatory system. It generally describes bacteraemia or sepsis. Sepsis is a serious, potentially fatal infection. This infection can cause sepsis to grow rapidly. Brief diagnosis and treatment are basic for treating this infection at the early stages.

Antibiotics via IV in order to fight infection, as the patients suffer from lower blood pressure with help of vasoactive medications in order to increase blood pressure. Insulin is given in order to control the sugar levels in blood. Corticosteroids are used to reduce inflammation caused due to bacteria in the blood. Painkillers are also given in order to bear pains due to treatment. At extreme stages the organs get infected and damaged, in such a case if the kidneys are affected then Dialysis treatment is given in order to sustain.

Motivation

Sepsis is an infection- chronic inflammatory disorder, typically results from the spread of a localized nidus to the systemic circulation, and both with very high deaths and morbidity levels correlated. It is one of the most critical factors of in-hospital deaths. However, a credible way to predict septic origins remains elusive. Early and reliable projections of sepsis will enable further agitation and tailored treatment while antimicrobial stewardship is preserved. Established detection approaches are badly implemented and need laboratory test tests, sometimes overtime. Recently, automated testing has proved to save lives. Tackling and researching enormous physiological observations continuously seen in ICU patients should immediately boost early position estimates, monitoring and essential disease treatment.

Under these conditions, beneficial local inflammatory processes, intervened by specific white platelets, for example, neutrophils and monocytes and the components they produce, and which are ordinarily present to control the spread of the irresistible centre, may grow their circles of movement into perilous fundamental irritation. The course by which a patient advances either to death or medical clinic release is notable and has been portrayed as a continuum from a state named foundational incendiary reaction disorder (SIRS) to progressive conditions of sepsis, serious sepsis, septic stun, numerous endorgan disappointment (MODS) and demise.

The goal of performing this dissertation was to the development of an algorithm for early prediction of Sepsis using routinely available clinical data. Early prediction particularly is potentially a lifesaving, while late or missed predictions are potentially life-threatening, and falsealgorithms might consume hospital resources and erode trust on the algorithm itself. The dataset seems a bit complicated, and hence we will first handle missingness and imbalance in the set as well try to come up with newer features before implementing the algorithm.

The algorithm will be designed at various levels and incorporating the clinical data,

automatically identifying a patient's risk of conceiving Sepsis and also make a positive or negative prediction of at least by six hours and no more than twelve hours before the onset time of Sepsis. To evaluate the algorithm, we have for the time being selected to plot the precision- recall curve with an F1 score that can assess the algorithm and penalize them for wrongly classified data points.

Literature Review:

In 2012, a work is published by E.Gultepe et al. [3] about clustering technique used for extracting features of sepsis. They have done experiments using extracted features with and without lactate levels and evolved a relationship between this using Bayesian networks. They excluded an important parameter - heart rate - from their experiment. Respiratory Rate(RR), White Blood Cells (WBC), temperature, Mean Arterial Pressure (MAP), lactate, length of hospital stay in days (LOS) and sepsis occurrences (SO) are the features used for this study. Among 1492 patient's Electronic medical records, 233 cases of sepsis were used to construct Bayesian network. First network is constructed as BN1 having temperature, RR, WBC, lactate, LOS, SO as parameters and BN2 is the second network with addition of MAP test to the above parameters. Because of the lowest loss function value, BGE scoring criterion was chosen for the learning method of first network BN1. BN2 is learned using BIC and BGE. Having a lower loss function value BIC is used for the final network. BN1 had lower estimated goodness of fit compared with BN2. The relationship between lactate levels and sepsis were obtained for the sepsis patients using Bayesian network. It was shown that lactate levels may be predictive of the SIRS criteria.

Y.Jiang et al. proposed a graphical computational model used for the pathological presentation ofthe sepsis in their paper 2016 called AdapDBN [4]. This computational model captures risk factors of sepsis using dynamic Bayesian network using some screening mechanisms. Physician's knowledge, published clinical research, epidemiological status and patient's data are the input measures used for the construction of AdapDBN. Three conditions were considered for the confirmation of sepsis as initial sepsis, severe sepsis and septic shock. An automaton is constructed with a threshold of onset probability detection and mortality rate monitoring. Each state DBN is attached with the dependency relation with vital signs. When threshold crosses, sepsis is confirmed. Later one is used for AdapDBN model and for screening the system. This helped in shortening the time for syndrome detection and helped to improve the effectiveness of the treatment.

In the work presented by C. Morales et al. [5] in 2016, one of the biggest available multi-centre sepsis database MEDAN is analysed using Conditional Independence Maps method. They explored potential causal relationships between the measured variables and the survival outcome. Then they validated the changes in the new definition of sepsis. Three different subsets are created from the pre-processing steps such as (i) the situation of patients at the time of admission, (ii) 24h later and (iii) 48h later. The authors mainly used the physiological parameters and personal information about the patients' profile. The Causal Independence Maps created by Causal Explorer is used for the experiments with the outcome variable and without the outcome variable. For the experimental setup three different scenarios were used as the time of admission at ICU, 24th and 48th hour after the admission in ICU. Three sets of results were collected using Causal Independence Maps. Authors proved that the peak time of the development of sepsis for the patient's situation is around 24 hours after being admitted at the ICU. The challenges addressed by this research were the remote collection and analysis of outpatient biometrics using commercially available technology. Considering this T.Bui et al. [6] presented a remote monitoring solution for early detection of sepsis for outpatients and published in 2016. In the proposed system, an additional sensor was attached for validating the device. This reduced readmissions in

hospitals, mortality rates and improved the quality of outpatient care. Algorithm developed by the authors marked severe changes in the sepsis risk indicators including heart rate, respiratory rate, temperature, blood pressure and suspected infection. A daily report is generated and sent to the patient care coordinator who makes a better decision about the patient and gives the best response.

Diagnosis of sepsis was done using machine learning techniques. A new learning strategy called chaotic fruit fly optimization (CFOA) was proposed by X.Wang et al. [7] and published their paper in 2018 to increase the performance of kernel extreme learning machine (KELM). The chaotic population initialization and chaotic local search strategy were used as the new mechanisms to improve the performance. Random forest improved fruit fly optimization algorithm-kernel extreme learning machine (RF-CFOA-KELM), was introduced to diagnose sepsis effectively. Methods used for this can be divided into two separate sections such as feature selection and parameter optimization tasks. Using random forest, features are selected and using the parameters of KELM, optimization can be done through 5 fold cross validation by CFOA.

Gas chromatography mass spectrometry (GC-MS) was used for analysing human blood sample data from the hospital. Using sepsis patient's metabolic data, authors achieved a predictive accuracy of 81.6% [7] with the proposed method. For diagnosing sepsis they used SVM, BPN, ANN and nature-inspired algorithm based KELM model for comparison. The proposed RF- CFOA-KELM can achieve more competitive results than other counterparts. The proposed RF- CFOA-KELM is new method consists of two stages as feature selection and parameter optimization. Feature selection is done by Random Forest and optimization of KELM parameters were done by proposed CFOA with five fold cross validation. Result of these two steps was the optimal feature subset and the parameters. The proposed method is used for the evaluation of classification performance. Ten-fold cross validation is done in the outer loop with inputs as optimal Bayesian network. It was shown that lactate levels may bepredictive of the SIRS criteria.

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Nowadays, machine learning (ML) algorithms are widelyimplemented in several biomedical studies including thedetection of the antibiotic susceptibility of bacteria. Therein,ML

algorithms are designed to automate the resistance analysisfor a certain AST. In this context, many applicationswere established to predict antimicrobial MICs [8] or toidentify the bacterial resistance towards a specific antibiotic [9], [10] based on whole genome sequence (WGS) data.

Also, image-based identification was often utilized to detectthe morphological changes in treated bacteria using ML algorithms [11], [12]. Likewise, ML approaches showedquite promisingresults in automating bacteria susceptibilitydetection based on their Raman spectra [13].

Shankar et al[14] implemented six models namely Random Forest, Logistic Regression, Light Gradient Boosting Machine, eXtreme Gradient Boosting, Neural Network and Long Short-Term Memory have been investigated for the classification of patients. The evaluation metrics that have been obtained are unprecedented and can be extremely useful for the timely and accurate prediction of Sepsis. . By comparing the different imputation techniques, it can be concluded that the mixed filling algorithm produces the best results as it selects and integrates the features from the most suitable filling algorithm. Of all the models tested, the LGBM classifier yields the best metrics. This model could play a pivotal role in the early and accurate detection of Sepsis in patients thereby ensuring proper treatment

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