International Research Journal of Engineering and Technology (IRJET) Volume: 07 Issue: 03 | Mar 2020 www.irjet.net

Accuracy Prediction and Classification using Machine Learning Techniques for Sepsis

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Abstract - Sepsis is estimated to affect more than 30 million people worldwide every year, potentially leading to 6 million deaths. It is estimated that 3 million newborns and 1.2 million children suffer from sepsis globally every year. One in ten deaths associated with pregnancy and childbirth is due to maternal sepsis with over 95% of deaths due to maternal sepsis occurring in low- and middle-income countries. Early prediction of sepsis is a challenging problem. The aim of this study is to develop an artificial intelligence-based prediction system to control sepsis-associated hospital mortality. The concept of neural network algorithm is used to predict the onset of Sepsis as early as possible using the clinical data of ICU patients aiding in the reduction of hospitalmortality ratio.

Key Words: Sepsis, Artificial Intelligence, Clinical Data, Prediction, Machine learning, Neural Network.

1. INTRODUCTION

Sepsis is a medical complication not a disease. It is a lifethreatening organ dysfunction[3]. A life-threatening organ dysfunction caused by a dysregulated host response to infection. It has a high mortality rate .Sepsis treatment resulted in an estimated \$27 billion or 5.2 percent of the total cost for all hospitalizations making it one of the most expensive treatments. Early detection of sepsis has the potential to reduce mortality by facilitating timely implementation of evidence-based interventions [1]. According to World Health Organization (WHO) data, 27,000,000 cases of sepsis develop annually[3]. Predictive models have been used to improve care in critical care settings, such as the Intensive Care Unit (ICU), and can potentially be used for earlier detection of patients at risk of becoming septic, allowing for earlier treatment [4].

A variety of symptoms are considered for the prediction process early symptoms include fever and feeling unwell, faint, weak, or confused., heart rate and breathing are faster than usual. If it's not treated, sepsis can harm the organs, make it hard to breathe, and gives diarrhea, nausea, and mess up thinking capacity. It's rare, but sepsis can happen during pregnancy shortly after pregnancy due to infection.

Early prediction of sepsis is a challenging problem. The aim of this study is to develop an Machine learning based system which reduces sepsis-associated hospital mortality.

2. DATASET

The data consists of a combination of vital sign attributes, lab values, and static patient descriptions. In particular, the data contained 40 clinical variables: 8 vital sign variables, 26 laboratory variables, and 6 demographic variables; Table 1 describes these variables.

1 HR - Heart rate (beats per minute)
2 O2Sat - Pulse oximetry (%)
3 Temp - Temperature (deg C)
4 SBP - Systolic BP (mm Hg)
5 MAP - Mean arterial pressure (mm Hg)
6 DBP - Diastolic BP (mm Hg)
7 Resp- Respiration rate (breaths per minute)
8 EtCO2 - End tidal carbon dioxide (mm Hg)
9 BaseExcess - Excess bicarbonate (mmol/L)
10 HCO3 - Bicarbonate (mmol/L)
11 FiO2 - Fraction of inspired oxygen (%)
12 рН – рН
13 PaCO2 - Partial pressure of carbon dioxide from
arterial blood (mm Hg)
14 SaO2 - Oxygen saturation from arterial blood (%)
15 AST - Aspartate transaminase (IU/L)
16 BUN - Blood urea nitrogen (mg/dL)
17 Alkalinephos - Alkaline phosphatase (IU/L)
18 Calcium - Calcium (mg/dL)
19 Chloride - Chloride (mmol/L)
20 Creatinine - Creatinine (mg/dL)
21 Bilirubin direct - Direct bilirubin (mg/dL)
22 Glucose - Serum glucose (mg/dL)
23 Lactate - Lactic acid (mg/dL)
24 Magnesium - Magnesium (mmol/dL)
25 Phosphate - Phosphate (mg/dL)
26 Potassium -Potassiam (mmol/L)
27 Bilirubin total - Total bilirubin (mg/dL)
28 TroponinI - Troponin I (ng/mL)
29 Hct - Hematocrit (%)
30 Hgb- Hemoglobin (g/dL)
31 PTT - Partial thromboplastin time (seconds)
32 WBC - Leukocyte count (count/L)
33 Fibrinogen - Fibrinogen concentration (mg/dL)
34 Platelets - Platelet count (count/mL)
35 Age - Age (years)
36 Gender - Female (0) or male (1)



Volume: 07 Issue: 03 | Mar 2020

www.irjet.net

e-ISSN: 2395-0056 p-ISSN: 2395-0072

37 Unit1 - Administrative identifier for ICU unit
(MICU); false (0) or true (1)
38 Unit2 - Administrative identifier for ICU unit
(SICU); false (0) or true (1)
39 HospAdmTime- Time between hospital and ICU
admission (hours since ICU admission)
40 ICULOS - ICU length of stay (hours since ICU
admission)

Table 1

3. LITERATURE SURVEY

This chapter reviews already published works, found to be relevant and related to the taken-up research problem.

A Prediction system is build using an ML algorithm to predict severe Sepsis and septic shock and evaluate impact on clinical practice and patient outcome [1]. To assess clinician perception of ML based EWS to predict severe sepsis.[2]

Early detection and antibiotic treatment of sepsis are also modeled by POMDS for improving sepsis prediction for improving sepsis outcome in times to treatment where each hour of delayed treatment has been associated with roughly an 4-8% increase in mortality[3] .In this paper Sepsis-3 defention was used to build 3 predictive models of sepsis in ICU patients using Logistic model tree(LMT), Support Vector Machine (SVM), Logistic Regression(LR) were used to predict onset of sepsis in adult intensive care unit patients using vital signs and blood culture results.[4].

A new learning strategy was proposed to boost the performance of Kernal Extreme Learning Machine(KELM), known as, Chaotic fruit fly optimization(CFOA) was proposed to diagnose sepsis using patient data. [5] and Feasibilty of utilizing CNN in the task of predicting the suspected late onset neonatal sepsis [6] Hierarchical analysis of Machine Learning algorithms is also used to improve prediction. This method could be incorporated into the current clinical workflow as a decision support system and provide useful information [7] Attention based RNN to predict sepsis from multi varaiate time series of clinical lab measurements [8] and Investigating the possibility of predicting the clinician's treatment towards the pre term infants in ICU [9] Open source algorithm for early detection of sepsis from clinical data. These Data are extracted from the Electronic Medical Record (EMR) underwent a series of pre-processing steps prior to formal analysis and model development. All patient features were condensed into hourly bins simplifying model development and testing.[10]

4. METHODOLOGY



In this study we use PNNs in order to make predictions using clinical data. A PNN is an implementation of a statistical algorithm called kernel discriminant analysis in which the operations are organized into a multilayered feed forward network with four layers.

4.1 Input layer

The input layer contains the notes with a set of measurements. Each neuron in the input layer represents a predictor variables. In categorical variables, N-1 neurons are used when there are N number of categories. It standardizes the range of the values by subtracting the medion and dividing by the interquartile range. Then the input neurons feed the values to each of the neurons in the hidden layer.

4.2 Pattern layer

The pattern layer consists of the Gaussian functions formed using the given set of data points as centres. This layer contains one neuron for each case in the training data set. It stores the values of the predictor variables for the case along with the target value. A hidden neuron computes the Euclidian distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma value.

4.3 Summation layer

The summation layer performs a sum operation of the outputs from the second layer for each class.

4.4 Output layer

The output layer performs a vote, selecting the largest value. The associated class label is then determined.

5. RESULT AND DISCUSSION



In this paper the accuracy prediction and classification using Artificial Intelligence techniques for Sepsis has been discussed. The Probabilistic Neural Network algorithm has been used to achieve this process. Using this mechanism we can predict the presence of sepsis on an ICU patient efficiently.

6. CONCLUSION

In this paper we discussed the feasibility of utilizing the PNN (probabilistic Neural Network) algorithm in the task of predicting the disease onset as early as possible using the vital signs of patients.

However, there are a few shortcomings with our approach which we seek to address in our future work. First of all, it is important to consider evaluating other methods to handle the missing data and improve the overall efficiency

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