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Edge of Automated Intelligence in Healthcare for Detection and Prediction of Sepsis

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Abstract

As Sepsis is being responsible for emergency mortality rates in hospitals and is accountable for the longest, most costliest, emergency stays in the United States. The crave for new treatment strategies to arrest sepsis are greatly needed to boost survival and longevity of human life. Blood culture which is a highest standard to analyze sepsis is tedious and takes about 48-72 hours. To preserve time, forecast models or screening tests are utilized to start antibiotic treatments. As the ultimate responsibility for a patient's care remains in human hands however, our automated helpers insured by leading edge AI, are going to be genuinely helpful in saving and enhancing human livesas sepsis is being confused by the other symptoms caused within the body.As physicians are struggling to come to a decision to define few standards and definitions that could aid them identify sepsis in early stages as they aren't able to detect this disease on time which is leading the patients, to lose one or more organs of their body parts, or directly going to the ICU's or to death bed because of sepsis. Nonetheless, most of past models have depended on an obsolete definition of sepsis dependent on fundamental incendiary reaction condition(SIRS).

Hence, this examination tried to manufacture predictive models of sepsis utilizing the latest meaning of sepsis, Sepsis-3. The vast majority of the prediction models require obtrusive boundaries to anticipate sepsis. However, provincial regions of developing nations need laboratory centers which are rarely found. In this manner, these prediction models can be equipped in these regions. The main objective of this paper is to help medics identify sepsis in early stages and if we predict sepsis hours before clinicians suggestion or before blood culture test reports using machine learning models with the help of supervised learning algorithms, such as Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Trees (DT), Random Forest (RF), etc we can save thousands of lives of people all over the world. We in this investigation, made an effort of identifying which among the classification modelswe could achieve the highest accuracy, ROC curves and Classification report in detecting and predicting sepsis and we discovered that the Decision Tree with Bagging gave 95% of train accuracy, 82% of test accuracy with best ROC AUC curve of 82% and also along with f1 scores. It is also flexible to be used anytime and deployed in hospital settings as it can save many lives of patients suffering from sepsis.

Keywords: Arrest Sepsis, boost survival, early prediction, Supervised Learning Models, Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Trees (DT), Random Forest (RF).

INTRODUCTION

Can your immune system fight an infection too hard?

- Yes? then you are perfectly fit and fine.
- No? Little confused! Not sure, then there can be a possibility of an disease called sepsis. Get checkup.

Our body releases chemicals to battle an infection caused by bacteria, viruses, or fungi. Sepsis is defined as a body's outrageous response to a disease which triggers a chain response all through the body which frequently releases chemicals within our circulatory system to battle any outside infection. Sepsis happens when the body's reaction to these outsider chemicals is no longer working or functioning properly, it is a life-threatening condition as it rapidly destroys our normal body functional activities one by one which makes hard to spot in early stages as it shows no symptoms [1]. Several cases of sepsis without on time treatments pave way to severe sepsis or even septic shock (three stages of sepsis). Delayed detection and diagnosis of sepsis rapidly lead to tissue damage, organ failure, and eventually progressing to deaths. It is also sometimes addressed as “Blood Poisioning”. It is estimated to affect more than 30 million people worldwide every year, potentially leading to 6 million deaths [1] worldwide because of sepsis only and the bitter and hard truth of it is whoever survives, most among them will have of face post-sepsis syndrome which includes physical and mental health issues for the rest of their lives (symptoms).

Fig-1: Statistics about Sepsis[5]

1.1 Who is in danger by sepsis?

Sepsis doesn't differentiate irrespective of age, sex, lifestyle choices, etc. But the most effected ones are infants less than 1 year, children below 5 years, elderly Individuals, pregnant ladies, neonates, hospitalized patients, and individuals with AIDS/HIV, cancer, liver cirrhosis, kidney infection, immune system infections and no spleen, are at higher chance [3].

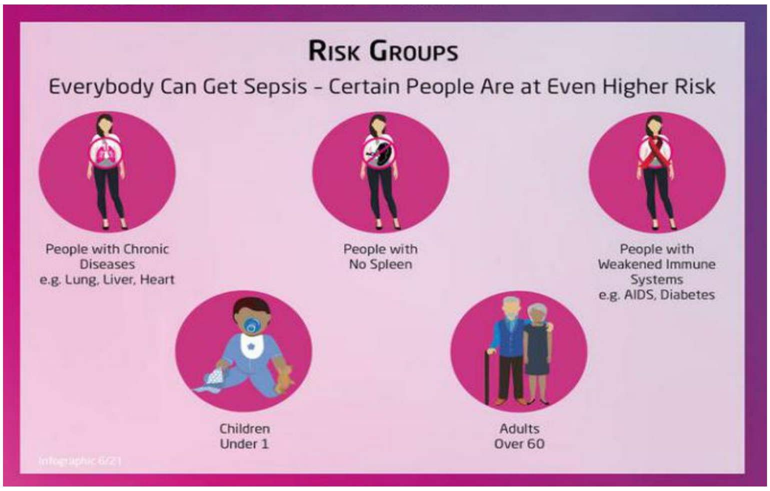

Fig-2: People who are in Crisis by Sepsis[5]

1.2 Sepsis norm?

As sepsis is a worldwide medical emergency and number one primary cause of deaths in ICU, most of the medics aren't aware of how to treat and identify sepsis in early stage or on time. There are many [4], [5] among which few of the warning signs are shown in Fig-3:

Fig-3: Sepsis Symptoms[5]

Along with these few other EHR records to consider are as follows:

Fever ⚇more than 100.4°F (38°C) or less than (36°C)

Heart rate ⚇more than 90 beats per minute

Respiratory rate ⚇more than 20 breaths per Minute or arterial carbon dioxide tension (PaCO2) of less than 32 mm Hg

WBC ⚇having greater than 12000/mm3 or less than 4000/mm3

White blood cell counts ⚇abnormal, etc.

BACKGROUND AND LITERATURE REVIEW

A. Changing Definitions of Sepsis

Sepsis by no meansis a particular ailment but instead a disorder partnered with an uncertain pathobiology and absence of gold standard diagnostic tests. accordingly, few effortswere made to arrest pathobiology and the study of disease transmission of sepsis to describe the disease. First meaning of sepsis was developed at 1991 Consensus Conference [7] that characterized sepsis as a systemic inflammatory response syndrome (SIRS). Four SIRS models were distinguished, to be specific; tachycardia (pulse >90 beats/minute), tachypnea (respiratory rate >20 breaths/minute), fever or hypothermia (temperature >38 or <36 C) and White platelet tally >12000mm3, <4000mm3, 10% juvenile groups [7]. This definition, neverthless, failed to describe sepsis from other straightforward diseases thatpresented themselves with similar symptoms and basically failed to characterize what sepsis is[7]. The conference likewise also coined definitions for extreme sepsis and septic shock; characterizing severe sepsis as sepsis confounded by organ dysfunction and septic shock as sepsis-prompted hypotension persevering in spite of sufficient liquid revival[7]. A 2001 team presented increasingly analytic models however the center meaning of sepsis, as characterized by the 1991 consensus conference gathering stayed unaltered as a result of an absence of a superior comprehension of the pathobiology. With significant headways in the information on pathobiology of sepsis, another meaning of sepsis was authored by at the Third Worldwide Consensus in 2016, after almost two decades [7]. Sepsis is currently characterized as a life-threatening organ dysfunction caused by a dysregulated host response to infection. The sequential organ failure assessment (SOFA)score is utilized in the ICU to decide the degree of an individual's organ work or on the other hand rate of failure. An individual with suspected infection can be speedily distinguished at the bedside utilizing the qSOFA (brisk Couch) score which requires two of the accompanying models to be fulfilled

• Systolic arterial blood pressure ≤ 100 mmHg

• Respiratory rate ≥ 22 breaths/min

• Altered mentation (Glasgow Coma Scale ≤ 14)

B. Bedside Monitoring: qSOFA versus SIRS

Few examinations have begun utilizing the qSOFA parameters for building predictive AI models.[9] discovered qSOFA score to have a higher prognostic accuracy for mortality and organ failure than SIRS measures. [10]presumed that qSOFA given a greatly improved segregation than SIRS for anticipating mortality and without ICU days. [11] and [12] discovered solid proof to help the utilization of SOFA and qSOFA over SIRS models. Nonetheless, a few studies have proposed the opposite and expressed that qSOFA displays defectiveperformance in mortality expectation. [13], [14] and [15] found that qSOFA displayed faulty performances and took much more time than SIRS to recognize patients with sepsis which further postponed the presentation of clinical intercessions, in that way, putting the patient at a higher danger of creating septic shock.

On account of these unmistakabledifferentiations in the aftereffects of predictive modeling utilizing qSOFA parameters; we chose to make a stride back and investigate the qSOFA paramaters, and its quality and interrelation. Multicollinearity among parameters regularly prompts model overfitting and adversely impacts the generalizability of discriminant capacities [8]. This further suggests that little deviations in the information can prompt enormous changes in the model, in any event, prompting the adjustment in indication of boundary gauges [8].

Hence we came up with this technology were we use ML models and can make predictions based on the EHR records available of that particular patient and we can make early detection of sepsis hours before the blood culture tests or medics suggestions.

MOTIVATION

Early identification is pivotal, as a suitable treatmentintended to forbid further detoriation in organ failure diminishes mortality by 15% [8]. However, sepsis must be precisely analyzed by the presence of a positive blood culture for a known pathogen. This infection is generally not discovered on time. When a patient is declared that he/she has sepsis they are admitted to ICU's immediately. As sepsis is being confused by the other symptoms caused within the body, they are struggling to come to a decision to define few standards and definitions that could aid the doctors identify the sepsis during an ICU stay, as they aren't able to detect this disease on time which is leading the patients, to lose one or more organs of their body parts, or directly going to the ICU's or to death's because of sepsis. Henceforth, doctors require the help of AI to increase the prediction of sepsis (using word prediction as this is classification problem to predict if patient has sepsis or no) in early stage so as to treat the patients in early stages or on time saving millions of lives each year from the dreaded epidemic.

Foreseeing sepsis in non-sepsis patients or anticipating sepsis right off the bat in sepsis patients consumes limited hospital resources. distinguishing and not thinking little of the signs and side effects, alongside the detection of some biomarkers (foe example, procalcitonin), which are pivotal components for early diagnosis of sepsis and in this manner the apt establishment of its appropriate clinical administration. After early recognition, diagnostics to help distinguish a causal pathogen of infection resulting in sepsis also are crucial to guide targeted antimicrobial treatment. Antimicrobial resistance (AMR) can endanger clinical administration of sepsis in light of the fact that experimental anti-toxin treatment is normally required.

Accordingly, realization of the epidemiology of AMR within the local setting is vital. Once the source of infection is detected, the source control like drainage of an abscess is additionally critical.Early fluid resuscitation is important within the initial phase of sepsis management. Additionally, vasopressors could also be in need to enhance and preserve tissue perfusion. Frequent examination and diagnostics, including monitoring vital signs, will guide the acceptable management of sepsis with time.

Fig-4: Awareness of sepsis[5]

PROPOSEDSYSTEM

Dataset taken:

The datasets utilized is sourced from hospital's ICU patients and was obtained online from physio-net challenge 2019 in kaggle website [16]. The size of complete dataset is 232 MB which consists of 40,336 records in total. It consists of 41 columns where the last column is the outcome of sepsis prediction which says with Sepsis-label "with_sepsis (1 value) or a person without_sep sis (0 value)" assigned. The dataset consists of clinical and laboratory track records of a single patient on an hourly base, which helps the doctors to scrutinize the details of the patient without any rerun of the tests. It also had NaN values in the table which describes that those measurements were not recorded at that time of interval.

Data extraction and attribution:

Initially the raw dataset was in PSV file format (pipeline separated values) as mentioned in [16]. As the collected data was a raw data, brought to light of finding missing values in few of the rows and columns in it. As the raw dataset collected had 8 vital signs which few among them are Heart Rate, Temperature, Blood Pressure, Respiratory rate. The laboratory records were 26 in number which few among them are Platelet Count, Glucose, Calcium, Magnesium, Potassium, Hemoglobin, etc and also had 6 demographics details like Age, Gender, Hospital admin time, ICU length of stay and soon to list a few. As observed from the original data collected, more of laboratory values were missing.

Featuring Selection and Preprocessing

In order to train the data with the models, made sure that any features with more than 92% missing values were deleted. Then feature engineering and label encoding was done by taking into consideration of the parameters of all the features.

Ex: The new feature designed for temperature takes intothree categories:

- Body temperature for any healthy person (child, adult and senior alike) is 'normal' when found between 36 Deg C to 38 Dec C.
- Anything above or below this range is labeled as 'abnormal'
- 'Missing' is a null or nan case is observed.

and filled the missing values by considering them as normal assuming doctor's didn't measure those parameters which were normal which is why they were blank. After the datasets were been preprocessed and feature engineered, next we performed normalization.

Dealing with Imbalanced Data:

To perform this step, there are three steps:

- Under sampling
- Oversampling or
- Using a good algorithm

we equalized the data evenly to calculate whether a person had sepsis or not using normalization method i.e by under sampling the data. Next step we performed the bellow action.

Splitting the data to apply ML Models

Here we split the data into 2 types, firstly for training the data and secondly for testing the data. The data was splinted into ratio 7:3 which in-turn means training dataset of 70% and testing dataset of 30%. Analyzing each row independently we were able to predict if a patient was with or without sepsis without any preclinical history of the patient which was more robust.

MODEL DESIGN

We performed prediction of sepsis using the supervised machine learning algorithms as we know the input(X) and the output(Y) but need to predict the rule to find out the mapping perform from the input to the output.

$$Y=f(X)$$

Which means that whenever we pass a new data to the machine as input(X), the inputs here are all the features (40 columns), we need to predict the output value(Y) as the output feature here is the sepsislabel column (last column) which says 0(no) or 1(yes) with the help of some function(f). Hence to get more accuracy results than any other papers, we are using most of the classifier models to consider that model which has more accuracy values and then pass them through hyper parameter tuning or ensemble learning. We here are using supervised classifier models because we already have all the labeled values and just have to predict to which category it belongs to when a new data is passed to the machine to predict as it's a known fact that we get more correctness compared to unsupervised models.

Henceforth, as there are many classifier models how do we know that which is the best fitted model is? Here just having a high accuracy rate and having low recall rate is considered to be a bad prediction model. Not just having high accuracy values but also to have few metrics which are accuracy, precision and recall is necessary. In order to get more accuracy rates than these classifier models we used the Ensemble learning models to achieve good and high prediction model.

The algorithms used to evaluate best fit model among all are as shown below as follows:

Table -1: Results of the applied classifier models

MODEL NAME	TRAINING %	TESTING %	ACCURACY %	ROC%
SVM	87	59	59	57
LR	68	67	67	67
LDA	68	67	67	67
SGD	65	64	64	64
Gaussian	67	66	66	66
MLP	71	71	71	70
Decision Tree	91	72	72	72
KNN	98	74	74	74
Random Forest	**94**	**80**	**80**	**80**

From the above table, we can observe that the Random forest gave us the best accuracy results when compared to other classifier models as shown below along with the classification report.

```
Train Accuracy:  0.9411561571931764
Test Accuracy:  0.8039136690647481
ROC AUC Score= 0.8033287084385277
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.83      0.81      8912
           1       0.81      0.78      0.80      8463

    accuracy                           0.80     17375
   macro avg       0.80      0.80      0.80     17375
weighted avg       0.80      0.80      0.80     17375

The score for Random Forest Classifier is 80.09208633093525% with [100, 500] estimators.
```

Fig-5: Random Forest results obtained

Table -2: Appling Ensemble Learning Models
(for more Accurate and stable results)

MODEL NAME	TRAINING %	TESTING %	ACCURACY %	ROC%
RF	**88**	**77**	**77**	**77**
AdaBoost	72	71	71	71
Gradient Boost	73	72	72	72
Extra Tree	81	73	73	73
XGBoost	73	72	72	72
CatBoost	80	75	77	77

From the above table-1, as we can observe that the Random Forest again by applying Ensemble learning gives us the best results the below figure is attached to have a view on it.

```
ROC AUC Score= 0.7716160797417675
Classification Report:
              precision    recall  f1-score   support

           0       0.76      0.82      0.79      8912
           1       0.79      0.73      0.76      8463

    accuracy                           0.77     17375
   macro avg       0.77      0.77      0.77     17375
weighted avg       0.77      0.77      0.77     17375

Random Forest:
> Accuracy on training data = 0.8848
> Accuracy on testing data = 0.7728
```

Fig-6: Results of Random Forest by applying Ensemble Learning.

Table-3: Applying default hyper parameter tunning on bagging

MODEL NAME	TRAINING %	TESTING %	ACCURACY %	ROC%
Bagging on Decision	99	79	79	78

```
Checking different metrics for bagging model with default hyper parameters:

Training accuracy:  0.9912927653486594
Testing accuracy:  0.7852661870503597
Confusion Matrix:
 [[7447 1465]
 [2266 6197]]
ROC AUC score:  0.7839305748160066
Classification Report:
               precision    recall  f1-score   support

           0       0.77      0.84      0.80      8912
           1       0.81      0.73      0.77      8463

    accuracy                           0.79     17375
   macro avg       0.79      0.78      0.78     17375
weighted avg       0.79      0.79      0.78     17375
```

Fig-7: Result of bagging model with default hyper parameter

From the results obtained as we can observe though having training accuracy of 99% and testing accuracy of 79%, but as the classification report shows us the difference of 11% in prediction result with bagging, hence we just evaluate the results by applying bagging model on Decision Tree to see if we can have more accurate results.

Table-4: Using bagging classifier model(for above best model)

MODEL NAME	TRAINING %	TESTING %	ACCURACY %	ROC%
Bagging on decision	95	82	82	82

```
Train Accuracy:  0.9472166586090199
Test Accuracy:  0.824115107913669
ROC AUC Score= 0.8240362698776871
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.83      0.83      8912
           1       0.82      0.82      0.82      8463

    accuracy                           0.82     17375
   macro avg       0.82      0.82      0.82     17375
weighted avg       0.82      0.82      0.82     17375

Accuracy of bagging classifier on test set: 0.82
```

Fig-8: Bagging applied on Decision tree

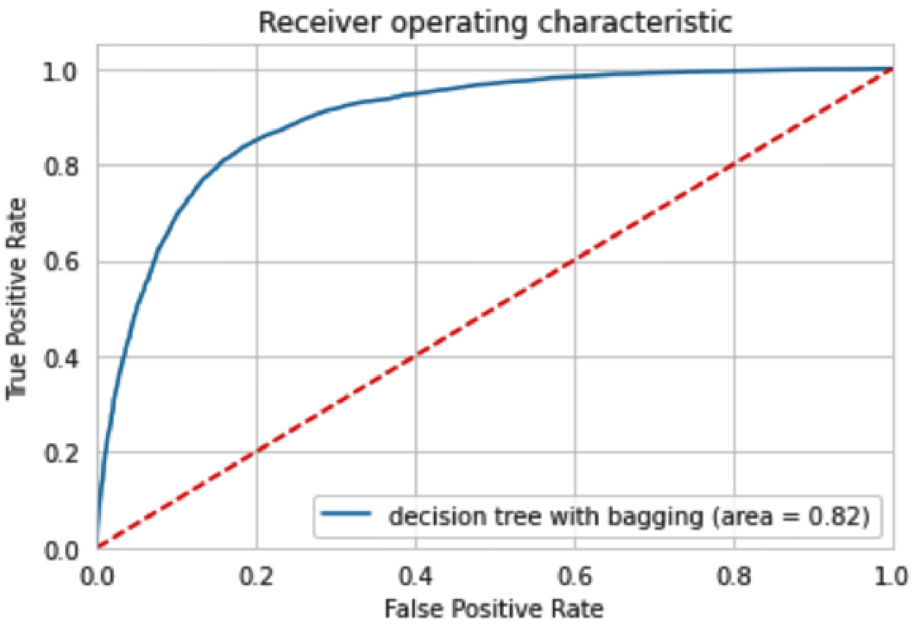

Fig-9: Decision tree with bagging results

Thus from the results obtained from table-4, we could see that we obtained the best training, testing as well as classification report which is why i conclude that this paper has predicted the best accuracy results on prediction of sepsis so far when compared to others.

CONCLUSION

Sepsis must be treated as crisis and this developing Innovation is for quick analysis of microbial diseases without culture. By 2030, endurance rates from sepsis for youngsters (counting neonates) and grown-ups will have improved by a further 20% from their levels in 2020. This will be checked and exhibited through the foundation of territorial and national sepsis offices, and through information sharing encouraged by WHO Regional Offices and different agencies. We aimed to predict the sepsis and so the machine was able to classify most of them accurately. As it's supervised problem we observed that when applied all the classifier models, we obtained highest accuracy and other metrics rate in Decision trees (random forest) with

94% training accuracy, 80% testing accuracy, 80% accuracy rate, 80% ROC AUC accuracy, with 78 out of 83 recall score.

Then, when we applied Ensemble learning model on decision tree to grain more accuracy and we found out that applying bagging on decision tree classifier we obtained results of 95% training accuracy, 82% testing accuracy, 82% accuracy rate, 82% ROC AUC accuracy, with 82 out of 83 recall score.

Then on Ensemble learning model, Applying default hyper parameter tunning on bagging decision tree to grain more accuracy and we found out results of 99% training accuracy, 79% testing accuracy, 79% accuracy rate, 78% ROC AUC accuracy, with 73 out of 84 recall score.

Not just the accuracy rate but also with other metrics we have proved that this research gives the best results when compared with other existing models and also can be readily integrated and used in hospitals.

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