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■ RESEARCH ARTICLE

A Decision Support System on Artificial Intelligence Based Early Diagnosis of Sepsis

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Abstract

Sepsis is the intense reaction of the immune system as a result of a severe infection in any part of the body and damages to organs and tissues. And this disease is commonly fatal and costly. In this study, we perform a comparative study for Sepsis prediction using machine learning algorithms from original laboratory findings. For this purpose, thirty-two different machine learning algorithms including different structures as well as neural network classifiers are evaluated and compared. As a result of experimental studies, SVM (Cubic, Fine Gaussian), KNN (Fine, Weighted, Subspace), Trees (Weighted, Boosted, Bagged) and neural network-based classifiers have achieved a significant success rate in the diagnosis of Sepsis using the new dataset. Thus, it is concluded that it is appropriate to use machine learning algorithms to predict whether a Sepsis patient will be survived. This study has the potential to be used as a new supportive tool for doctors when predicting Sepsis.

Keywords: sepsis, early forecasting, artificial intelligence, decision support systems

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1. Introduction

It is seen that the number of scientific research and artificial intelligence applications in the field of health are increasing rapidly in the world. Hence, almost whole universal artificial intelligence and big data companies focus on medical research and do their work on a large scale from patient services to diagnosis and treatment systems. In this way, it has been possible to develop important applications such as disease diagnosis and diagnosis systems, surgeries performed with artificial intelligence (AI) supported robots, personalized treatments, drug development, hospitalization prediction, and decision support systems. Developments in the health sector, which is one of the sectors most affected by this challenging process, where the pandemic accelerates digital transformation, offer an alternative solution for insufficient human resources. This contributes to the acceleration of routine work that requires faster results in the departments where healthcare professionals cannot follow the process, with AI, and to reduce errors in intense work.

Sepsis, a dysregulated immune-mediated host response to infection, is common, lethal, and costly [1]. Sepsis, often called blood poisoning, is a truly negative result of the body's

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response to an infection, and this response causes organ damage. Identifying those at risk for Sepsis and initiating appropriate treatment before any clinical manifestations will have a significant impact on the mortality and healthcare cost burden of Sepsis. According to World Sepsis Association data, it is estimated that 47-50 million people have Sepsis, and 11 million people die from Sepsis each year, with one death occurring every 2.8 seconds. 1 in 5 deaths worldwide is associated with Sepsis [2]. In addition, 40% of Sepsis cases are in children under 5 years old. 20% of all deaths in the world are associated with Sepsis, depending on the country, the mortality rate ranges from 15% to 50%. Sepsis has a higher mortality rate in the world than the most common diseases of breast cancer, prostate cancer, and HIV-AIDS combined. Sepsis-related deaths have a higher rate than cancer-related deaths, as reported by the World Health Organization in 2018. The highest death rate of Sepsis is in poor and developing countries. However, it can also be caused by infections with seasonal influenza viruses, dengue viruses, and highly contagious pathogens of public health concern. Sepsis often presents as a clinical worsening of common and preventable infections such as respiratory, gastrointestinal, and urinary tract or wounds and skin as shown in Figure 1.

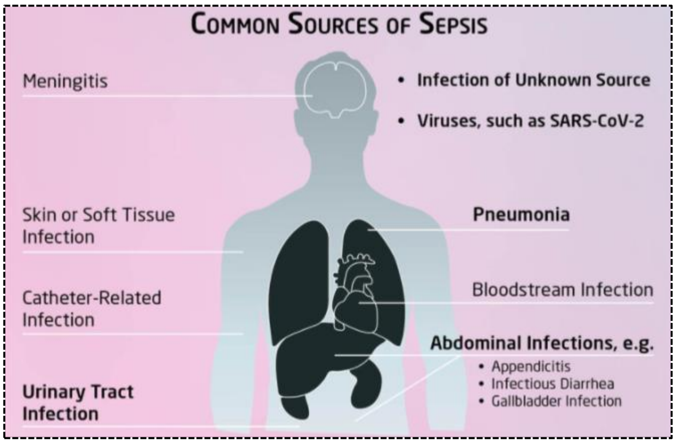

Figure 1. Common sources of Sepsis.

Sepsis-related mortality (death rate) risk factors vary depending on the size and development of the health center. It causes 20-50% mortality in affected patients and significantly reduces the quality of life in patients who recover. In a large multicenter epidemiological study conducted in our country, mortality rates due to Sepsis and septic shock were found to be unacceptably high (55% and 70%). The significant increase in mortality and annual health care expenditures (affected by the increased length of stay) have made Sepsis treatment and research a critical area in medical internet research and medical informatics, resulting in a recent surge in the relevant literature.

Early Sepsis prediction can help doctors intervene and diagnose early to improve treatment and patient outcomes. Most of the existing methods for Sepsis diagnosis and early prediction use only structured data stored in the electronic medical records (EMR) system. Clinical decision support tools can help identify those at the highest risk for Sepsis. Existing studies on EMR and laboratory data look improving. Detecting Sepsis at an earlier stage can save lives and reduce financial expenses for the patient. The diagnosis of Sepsis is often delayed because it is difficult to distinguish from other high-risk conditions, and this delay can cause the patient to deteriorate rapidly. A potentially transformative approach to this problem would leverage the vast amount of information from patients' Electronic Health Records (EHR) to derive Clinical Decision Support

Systems. With the widespread use of artificial intelligence in the field of medicine, these methods allow early prediction and treatment of many diseases.

Artificial neural networks, which are one of the most popular algorithms of machine learning methods today, are deduced that will be used in estimating the early stages of Sepsis disease and determining the level of Sepsis, considering their reasoning and decision-making abilities.

Various studies have been conducted to detect Sepsis in patients and to develop early prediction models. Due to advances in machine learning and artificial intelligence, these fields also have great applications in the medical field. Machine learning algorithms are used to predict Sepsis and help people take appropriate medications. Different machine learning algorithms can diagnose or predict Sepsis and thus prevent the progression of Sepsis.

Artificial intelligence, whose importance has emerged once again in the Covid-19 process, can be briefly defined as the technology that makes computers do the work that requires human intelligence. Considering the point that artificial intelligence technology has reached today; it can make a medical diagnosis, offer personalized health solutions, and offer practical solutions in many areas of our lives. In the digitalization process accelerated by the Covid-19 pandemic, health technologies are at the forefront of the focal points of artificial intelligence technologies, which we have seen superior success in many sectors.

2. Related Works

Several studies in the literature have compared the performance of different AI techniques for detecting Sepsis using different datasets and pediatric patients [10-18]. Because these studies were not conducted using the same datasets, it is not accurate to directly compare performance with our study. For this reason, similar studies have been focused on in the literature. Some studies in the literature on the use of machine learning methods in Sepsis can be summarized as follows:

Umut Kaya et al. in their study in 2018, proposed a model that uses multilayer artificial neural networks (Levenberg Marquardt and Feed forward) to help diagnose Sepsis. Using the data of intensive care patients aged 18-65 in Istanbul, the risk of catching Sepsis was tried to be estimated with the help of artificial neural networks. In this model, 99% training, testing and accuracy values were obtained [3].

In 2014, Gültepe et al. aimed to develop a decision support system to identify patients at high risk for hyperlactatemia based on routinely measured vital signs and laboratory studies. In this AI-based study, they concluded that, given the temporal nature and variability of patient data, effective estimates of lactate levels and risk of death can be obtained with several clinical variables [4].

In 2016, Desautels et al. used the machine learning-based InSight application to examine and validate a Sepsis prediction method for new Sepsis-3 definitions in retrospective data. The classification system 'InSight', which uses multivariate combinations of Glasgow Coma Score and age, is effective for predicting the onset of Sepsis. They concluded that it is a tool and performs well even with random missing data [5].

Fleuren et al. evaluated the performance of real-time models to predict Sepsis by conducting a systematic review and meta-analysis in their work in 2020. In this study, he concluded that individual machine learning models can accurately predict the onset of Sepsis early [6].

In 2012, Gültepe et al. proposed a Bayesian network using an electronic medical record (EMR) database of 1492 patients, including 233 Sepsis cases. This study reveals a clear relationship between lactate levels and Sepsis. In conclusion, Bayesian networks showed that Sepsis patients were able to capture the relationship between lactate levels and Sepsis [7].

In 2014, Stanculescu et al. evaluated late-onset premature Sepsis as one of the most important clinical concerns in which premature babies are kept in the intensive care unit for the early diagnosis of Sepsis. They evaluated the efficacy of the autoregressive latent Markov model for diagnosing Sepsis with data from a neonatal intensive care unit [8].

Guillen et al. aimed to identify early predictors for the prediction of severe Sepsis using clinical laboratory values and vital signs collected from adult patients in intensive care. For this purpose, they used logistic regression models, supporting vector machines and logistic model trees. They showed that models developed and based on this framework can be recommended for clinical decision support in and outside intensive care settings [9].

When these studies were examined, although the machine learning methods were used on different datasets taken from the international database, not so many algorithms as we suggest were tried. In addition, when the performance parameters of these studies in the literature are examined, it is seen that there is an improvement in terms of our study's results. It is understood that this makes a significant contribution to the literature in this regard.

3. Metarials and Methods

3.1. Dataset Description

This section will present details of the basic components of the used dataset, the description, and an overview of the various machine learning algorithms and proposed approaches.

Many types of infections can play a role in the formation of Sepsis. The most common of these are urinary tract infections, respiratory tract infections, pneumonia, intra-abdominal infections, wounds and burns, meningitis, and skin infections. Children under the age of 1, pregnant women, people with chronic diseases, and elderly individuals are in the risk group for Sepsis. The incidence of Sepsis is higher than the incidence of other known diseases such as heart, cancer, and stroke. More people die from Sepsis than deaths from colon and breast cancer combined.

According to the recently published Sepsis-3 criteria, it is formally defined as an acute increase in the Sequential Organ Failure Assessment (SOFA) score of ≥2 points due to a suspected or proven infection [1]. Overall, the new definition offers better performance than the previous one for identifying septic patients at high risk of mortality in intensive care units (ICUs) [1]. Sepsis is also used to screen rapid SOFA (qSOFA) patients with the worst Sepsis outcomes." Septic Shock is the subset of Sepsis in which the underlying circulatory and cellular/metabolic abnormalities are profound enough to significantly increase mortality [19].

Severe Sepsis and septic shock are still the leading causes of death in Intensive Care Units (ICUs), and timely diagnosis is crucial for treatment outcomes. Considering that Sepsis management is very time-sensitive, early estimation of Sepsis is very important in preventing mortality (death rate). The advancement of electronic medical records (EMR) offers the possibility to store large volumes of clinical data that could facilitate the development of AI in medicine.

The high-risk group of Sepsis; include adults aged 65 and over, people with chronic diseases such as diabetes, cancer, lung, liver, and kidney disease, those with weakened immune systems, people with previous Sepsis, and children younger than one year old [20].

The clinical findings used in the diagnosis of Sepsis, which we used in this study, are as follows.

1. Fever
2. Hypothermia (low body temperature)
3. Heart rate
4. Tachypnea (rapid breathing)
5. Mental status change
6. Hyperglycemia
7. Leukocytosis (Increased Leukocyte)
8. Leukopenia (Reduction of Leukocytes)
9. Immature form white blood cell count leukocyte
10. Plasma C-reactive protein (CRP)
11. Plasma procalcitonin
12. Hypotension
13. Hypoxemia (Decreased oxygen)
14. Saturation
15. Creatinine increase
16. Coagulation disorder
17. Thrombocytopenia (Decreased Platelet)
18. Hyperbilirubinemia
19. Lactate elevation [21]

The eighteen features in the dataset are numeric. Only mental status is not numerical. In binary categorical (binary) features, "0" indicates that the mental state is closed, and "1" indicates that the mental state is open. The mental state was converted in binary to make the dataset used for the classification task.

3.2. Machine Learning Algorithms

Machine learning is one of the most widely used sub-branches of artificial intelligence science today. AI-based systems constantly learn and train to behave like humans and develop self-reasoning and problem-solving abilities. Properly trained systems using the AI approach can seamlessly solve complex problems without a higher degree of mathematical manipulations. Therefore, the AI approach has become a promising alternative to various traditional problem-solving techniques. Machine learning is the ability of machines to learn and perform actions of making decisions and recognizing patterns similar to the thoughts of human intelligence with artificial intelligence algorithms. Algorithms adaptively improve their performances as the number of existing samples for learning increases [22]. Machine learning is basically to predict the future from past experiences [23]. The algorithms, which are used for plenty of aims such as classification, estimation, forecasting forming [24], and can make an effective and errorless estimation, consist of software design, which can learn rules from data, adapt to changes, and improve its performance with experience. The field of machine learning in computer programming by engaging with how to form computer programs that develop automatically with experience and by using sample data or experience to optimize performance [25]. When a machine improves its performance through experiences, it is considered that the machine has learned; the learning mentioned here requires computer models that keep the data and reveal beneficial samples [26].

There are numerous algorithms used in the literature for classification in machine learning suchlike as the Decision Tree Classifier Algorithm, Naive Bayes Classifier, Artificial Neural Networks, Support Vector Machine, and k-Nearest Neighbor Algorithm. The purpose of classification, also known as an inference from samples, is to develop a classifier that will obtain samples that have not been introduced to the algorithm before, with the highest accuracy, after the concept definition is obtained [27].

The use of artificial intelligence and machine learning applications in the field of health is carried out in many sub-activity areas such as medical diagnosis and disease tracking, cost estimation, imaging analysis, resource planning and emergency management, and processing of unstructured data. Machine learning provides the solution to both reduce the rising cost of healthcare services and helps build a better patient-doctor relationship. Recently, a large amount of data has become available in healthcare. This includes EMRs with structured or unstructured data. Structured health data is information that is easy to categorize in a database; patient weights, temperatures, headache, stomachache, etc. may include a range of statistics and categories, including but not limited to general symptoms such as most medical data is unstructured data in the form of various notes, reports, images, audio, and video recording. However, regarding the use of artificial intelligence in the field of health; Data management, the accuracy of clinical data, and ethical and legal processes related to data protection limit the use of artificial intelligence in the field of health.

In this study, some blood test values (PCT, PLT, WBC, Glucose (fasting), creatinine (blood), Lactic Dehydrogenase (LDH), INR, CRP, Prothrombin Time, Bilirubin, PCO2), and Classifier models with different structures were developed using the machine learning toolbox of the MATLAB programming language to predict the early diagnosis of Sepsis by looking at its features such as vital signs (blood pressure, pulse, fever, saturation, etc.). These models are Decision Tree Classifier Algorithm, Naive Bayes Classifier, Artificial Neural Networks (ANN), Support Vector Machine (SVM), and k-Nearest Neighbor Algorithm (KNN) methods detailed below. All numerical results were obtained using MATLAB R2021b on an Intel processor under Windows 10 operating system.

3.2.1 Artificial Neural Networks (ANN)

Artificial neural networks (ANNs), one of the most common machine learning methods, are systems formed by the combination of simple information processing units called neurons. ANNs are quite capable of learning nonlinear relationships between variables and recognizing high-order relationships. The power of ANNs to model complex relationships consists not in complex mathematical models, but the interactive assembly of large numbers of simple neurons. ANNs are models that can be fully applied to supervised, unsupervised, and reinforcement learning algorithms.

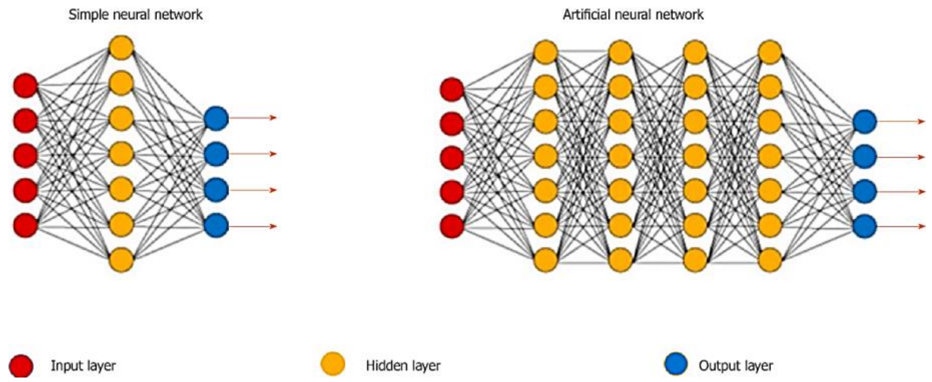

Figure 2. Artificial neural network model

3.2.2 Support Vector Machine (SVM)

While the support vector machine was originally used to separate the two classes, it has been developed over time and has been successfully used in regression, classification, and outlier detection problems with nonlinear systems. It is a supervised parametric machine learning algorithm based on statistical learning theory. To separate the two classes in the SVM algorithm, a parallel line/hyperplane is drawn between the data that makes up the classes. The structure used to separate classes is represented as a line in two-dimensional space, and as a plane in three-dimensional space. The data closest to the hyperplane are called support vectors. The margin between the support vectors of opposite classes is maximized, thus making it more durable [28].

3.2.3 k-Nearest Neighbor Algorithm (KNN)

K-NN is known as one of the simplest and oldest non-parametric supervised classification approaches among machine learning algorithms in the literature. By defining a special number k in the total data set, the mean/mode classes of the nearest neighbors are obtained, and the new object is assigned to the class closest to its neighbors. The distances of the new object to its neighbors can be calculated with functions such as Euclid, Manhattan, Minkowski, and Chebyshev. It has a robust structure against training data provided the k-number is large enough. When the data set and k size increase, the processing time increase considerably, and in this approach, all these distance calculations must be kept in memory [29]. Therefore, the choice of k value is extremely important.

3.2.4 Decision Tree Classifier Algorithm

The decision tree algorithm falls under the category of supervised learning. They are used to solve both regression and classification problems. The decision tree uses tree representation to solve the problem where each leaf node corresponds to a class label and the attributes are represented at the inner node of the tree. Statistics is one of the predictive modeling approaches used in data mining and machine learning. Tree models in which the target variable can take a discrete set of values are called classification trees; in these tree structures, leaves represent class labels and branches represent combinations of properties that give rise to these class labels. Decision trees where the target variable can take continuous values are called regression trees. In indecision analysis, a decision tree can be used to represent decisions visually and clearly. The decision tree method is the classification process for all elements to have the same class label by dividing the input data into groups with the help of an algorithm. First, the entropy for the data set is calculated with H method shown in Equation 1. Entropy which is symbolized as H(S), is the measure of the amount of uncertainty in the set of data. S is the existing set which is used to calculate the entropy. In S, C = {True, False}, is the classes set. The P function is the ratio of the number of elements in class "c" to the number of elements in the set [30].

$$H(S) = \sum_{c \in C} -\mathrm{p(c)} \log_2 \mathrm{p(c)} \quad (1)$$

3.2.5 Naive Bayes

Naive Bayes is a classification model which is a statistical approach, is based on the Bayes theorem as seen in Equation 2, the NB classifier supposes that the effect of a specific attribution in the class is independent of the other attributes. Indeed, if these attributes are connected, they're estimated as an independent. This supposition facilitates the computation and is called naive for this reason. This supposition is also called class conditional independence [31].

Likelihood Class Prior Probability

$$P(c \mid x) = \frac{P(x \mid c) P(c)}{P(x)} \quad (2)$$

Posterior Probability Predictor Prior Probability

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

4. Experimental Study

This section demonstrates the early detection prediction performance of recommended machine learning algorithms. Evaluation of prognostic prediction performance is performed on the dataset of patients with Sepsis.

In this section, we estimate the early diagnosis of patients with Sepsis by evaluating the artificial neural network results according to the classification accuracy. For this purpose, a data set containing 19 features (18 Inputs - 1 Output) and 977 samples were used. Traditional validation and the k-fold cross-validation approach were used to evaluate the performance of the proposed algorithms. Sepsis diagnostic data was tested with many different machine learning techniques to demonstrate the success of the study. For this purpose Fine Tree, Medium Tree, Coarse Tree, Linear Discriminant, Quadratic Discriminant, Logistic Regression, Gaussian Naive Bayes, Kernel Naive Bayes, Linear SVM, Quadratic SVM, Cubic SVM, Fine Gaussian SVM, Medium Gaussian SVM, Coarse Gaussian SVM, Fine KNN, Medium KNN, Coarse KNN, Cosine KNN, Cubic KNN, Weighted KNN, Boosted Trees, Bagged Trees, Subspace Discriminant, Subspace KNN, RUSBoosted Trees, Narrow Neural Network, Medium N. Network, Wide N. Network Bilayer N. Network, Trialayer N. Network, SVM Kernel shapes were checked and classification performance results were obtained with different classifiers by using all of the features (with or without PCA) are shown in Table 1.

Table 1. Machine learning techniques for comparison (%)

Machine Learning Models	**TV**		**3-Fold CV**		**5-Fold CV**		**10-Fold CV**	
	PCA Disable	**PCA Enable**	**PCA Disable**	**PCA Enable**	**PCA Disable**	**PCA Enable**	**PCA Disable**	**PCA Enable**
Fine Tree	96.1	96.5	82.2	71.5	81.1	75.9	81.5	75.6

Medium Tree	87.5	82.3	81.5	70.7	81.5	74.2	79.9	73.0
Coarse Tree	78.4	73.9	75.1	72.6	76.8	70.8	75.3	71.8
Linear Discriminant	75.4	74.0	73.1	73.4	74.4	72.7	74.3	73.2
Quadratic Discriminant	76.4	73.7	75.6	72.5	75.4	72.4	74.5	72.2
Logistic Regression	74.7	73.5	73.0	72.5	74.2	72.3	74.3	72.6
Gaussian Naive Bayes	70.2	69.6	68.9	68.9	69.2	69.9	69.4	68.5
Kernel Naive Bayes	85.5	80.5	77.7	74.3	80.2	74.7	79.1	75.3
Linear SVM	74.0	73.2	73.0	73.4	73.0	72.4	73.2	71.7
Quadratic SVM	91.3	87.6	83.2	82.4	84.4	82.7	86.1	82.9
Cubic SVM	<u>100</u>	98.5	<u>87.8</u>	<u>85.7</u>	89.0	86.0	88.4	86.7
Fine Gaussian SVM	<u>100</u>	99.6	75.8	77.3	78.9	80.4	79.8	81.6
Medium Gaussian SVM	90.8	87.7	85.3	82.4	86.6	83.3	86.4	83.8
Coarse Gaussian SVM	73.4	73.5	71.9	70.4	72.5	72.5	72.7	73.0
Fine KNN	<u>100</u>	<u>100</u>	87.4	83.2	89.9	85.1	90.5	85.7
Medium KNN	89.5	88.2	83.3	83.4	84.7	83.6	84.3	84.4
Coarse KNN	77.4	76.3	73.7	72.3	74.5	73.7	76.2	75.0
Cosine KNN	89.7	87.4	83.5	83.2	84	83.4	85.3	83.2
Cubic KNN	88.8	86.8	80.6	82.5	81.8	82.8	82.9	83.8
Weighted KNN	<u>100</u>	<u>100</u>	85.9	84.4	87.8	87.1	89.3	87.4
Boosted Trees	<u>100</u>	94.2	86.7	79.2	88.2	78.8	88.0	78.9
Bagged Trees	<u>100</u>	99.9	87.1	81.5	89.7	81.6	89.9	82.9
Subspace Discriminant	73.4	73.0	73.0	72.5	73.1	72.5	73.2	72.0
Subspace KNN	<u>100</u>	<u>100</u>	88.6	86	<u>90.5</u>	<u>87.3</u>	<u>90.8</u>	<u>87.6</u>
RUSBoosted Trees	89.7	88.0	85.7	78.2	83.9	75.5	84.0	78.4
Narrow Neural Netw.	<u>100</u>	92.5	80.7	78.8	83.4	79.3	83.4	79.9
Medium Neural Netw.	<u>100</u>	<u>100</u>	84.1	83.2	85.2	83.5	85.6	81.9
Wide Neural Netw.	<u>100</u>	<u>100</u>	85.5	83.1	87.3	84.5	88.9	84.1
Bilayer Neural Netw.	<u>100</u>	<u>100</u>	83.1	79.5	83.0	77.9	84.0	77.9
Trialayerde Neural Netw.	<u>100</u>	<u>100</u>	81.7	77.6	82.5	79.4	84.6	81.1
SVM Kernel	93.9	90.8	83.0	79.4	84.4	82.2	85.6	81.2
Logistic Regression Kernel	87.5	86.4	78.6	77.2	80.5	77.9	80.5	81.0

For the same dataset, the accuracy performance of the methods proposed in this study was more successful than other machine learning methods in the literature, and an effective decision support system was designed that could successfully determine the early diagnosis of patients with Sepsis. Despite the imbalance in the dataset, the Cubic SVM, which showed the best performance in risk estimation, Fine Gaussian Algorithms SVM, Fine KNN, Boosted Trees, Bagged Trees, Subspace KNN, Narrow Neural Network, Medium Neural Network, Wide Neural Network Bilayer Neural Network and Trialayer Neural Network achieved a successful prediction score (100%). Also, the PCA method is used to try different parameter variations and the best results are shown in the table. When we examined these results, we found no significant performance impact.

A confusion matrix represents most successful and unsuccessful algorithms implemented. Machine learning uses a confusion matrix to interpret the performance of the classification model used. Figure 3 and Figure 4 show a confusion matrix comparing the predicted and actual values of the target attribute.

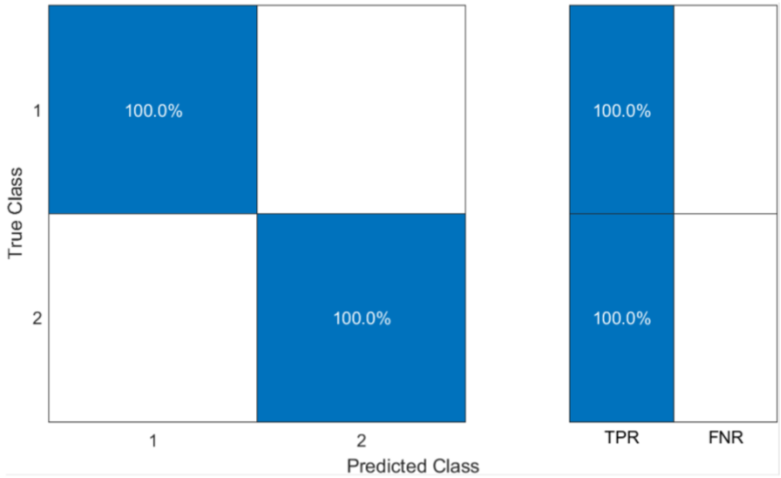

Figure 3. Confusion Matrix for the most successful Fine KNN algorithm.

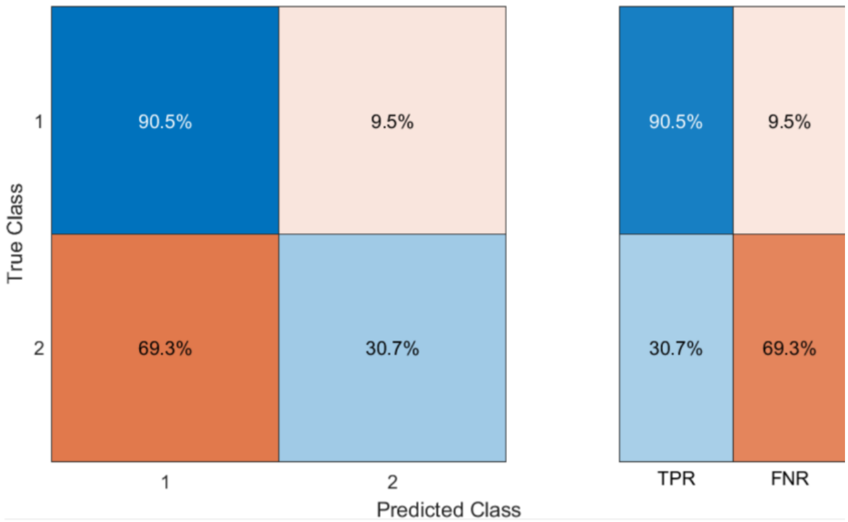

Figure 4. Confusion Matrix for the worst successful Gaussian Naive Bayes **algorithm.**

As can be seen in Figure 3, the Fine KNN algorithm confusion matrix, out of 977 samples, it was determined that 977 Sepsis patients would live and 0 would not. As seen in Figure 4, the Gaussian Naive Bayes algorithm confusion matrix was determined as 678 of 977 samples would survive the Sepsis patient and 299 would not.

The receiver operating characteristic (ROC) curve is a graph showing the ability of a binary classifier system to classify as the discrimination threshold changes. ROC curve obtained as a result of determining algorithm performances. The ROC curves for the best performing Fine KNN algorithm and the worst performing Gaussian Naive Bayes algorithm are shown in Figure 5 and Figure 6, respectively.

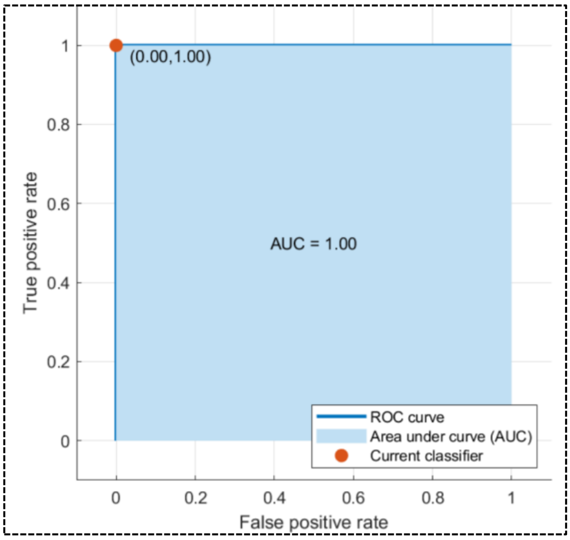

Figure 5. ROC curve for the best performing Fine KNN algorithm.

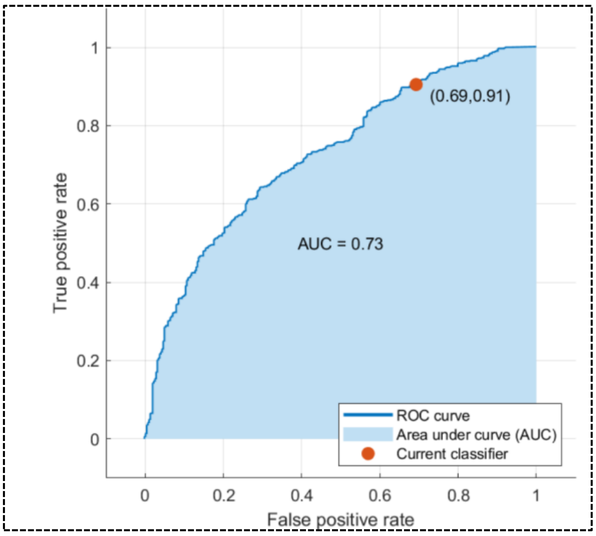

Figure 6. ROC curve for the worst-performing Gaussian Naive Bayes algorithm.

When the results obtained are examined, it is understood that the artificial neural network methods mentioned above have extraordinary success in predicting the early diagnosis of a Sepsis patient. Thus, it is concluded that the study with this current situation is promising and successful. Further, it is appropriate to use machine learning algorithms to predict an early diagnosis of patients and this study has the potential to be used as a new support tool for physicians when predicting the early diagnosis of a Sepsis patient.

As a result, 32 different machine learning techniques were applied to Sepsis on our original dataset, and it was seen that 12 different methods achieved 100% accuracy performance. The success rates of other methods vary between 68.9% and 96.1% and cannot be underestimated. When these performances are examined, it is seen that machine learning algorithms can be integrated into applications such as Sepsis decision support systems. It is recommended to use artificial intelligence methods to predict Sepsis-related death-survival due to their high accuracy predictive ability.

5. Conclusion

Sepsis patients have a very high mortality rate, and doctors need reliable prognostic estimates to be able to diagnose early and properly administer drugs to make informed decisions. In our original research, which is considered the application of information sciences in the health sector, predictive learning models and decision support systems that learn from data were produced on the data set used to diagnose Sepsis. These models aim to contribute to science by evaluating the early prediction of the disease.

In this study, all the features in the data set were classified by machine learning methods and estimated with 100% accuracy for a controlled classification problem in terms of early estimation of Sepsis. Accordingly, our study has shown that machine learning can be used effectively in the dual classification of health records of patients with Sepsis.

For comparison, different types of machine learning methods were tried with different variants and classification accuracy was obtained between 69% and 100%. It has been observed that the performance of Cubic SVM, Fine Gaussian SVM, Fine KNN, Boosted Trees, Bagged Trees, Subspace KNN, Narrow Neural Network, Medium Neural Network, Wide Neural Network Bilayer Neural Network, and Trialayer Neural Network methods is maximum.

As a limitation of the current study, it should not be overlooked that the data set (977 patients) is small and unstable for classification.

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