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A Novel Medical Decision Support System Using Swarm Intelligence Based Bayesian Learning Algorithm

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Abstract: The use of Machine Learning (ML) methods may be beneficial at the clinical and diagnostic levels of medical decision-making. A foundation for ML is provided by feature selection algorithms. In a medical setting, feature selection may be used to rapidly and efficiently identify the health-related qualities that are most distinctive from the original feature collection. The two primary objectives of feature selection algorithms are to determine the properties of data classes that are most relevant and to enhance classification performance. In addition to assisting lower the general measurement of the dataset, feature selection also aids in determining which features are most important. Therefore, we provide a unique ML-based approach in this study. The dataset is first gathered and prepared using the min-max normalization approach. The features are selected using principal component analysis (PCA). Using a novel swarm-optimized Bayesian learning approach (SOBLA), accuracy is used to evaluate the effectiveness of various feature subsets. Experimental results show that the performance of the proposed method performs better when compared to conventional methods. The outcomes of this study suggest interventions with the potential to enhance the quality of healthcare decision-making about certain healthcare procedures.

Keywords: *Medical decision support system (MDSS), min-max normalization method, principal component analysis (PCA), swarm-optimized Bayesian learning approach (SOBLA)*

1. Introduction

A medical decision is a process through which doctors, nurses, and other medical staff decide on the best course of action for a patient's diagnosis, treatment, or continued medical treatment. Using the patient's medical history, symptoms, diagnostic test results, and pertinent research findings, this process determines the most beneficial course of treatment. Decisions in medicine include a broad spectrum, from selecting an appropriate course of therapy to deciding whether surgery is required, from drug selection to behavioral counseling [1]. The patient's health, interests, and values need to be included in risk and benefit evaluations to be complete. Ethics must be considered in medical decisions. The well-being and autonomy of the patient must take priority over other considerations, such as the patient's capacity to comprehend and take part in the decision-making process, the influence on their quality of life, and the limitations imposed by laws or cultures [2]. The MDSS is intended to help medical professionals and other members of a patient's medical professionals showed up for more reliable treatment and diagnosis plans by using the healthcare data and knowledge that is available at their disposal. It is designed to act as a supplement for healthcare practitioners by giving them a source of information that is up to date, observations that are relevant to their job, and suggestions that may be implemented. This data includes healthcare records of patients, outcomes of tests, literature on medicine, and therapy recommendations. These are but a few examples of the many different kinds of medical data that are handled by MDSSs [3]. To better assist doctors in making diagnoses, deciding on treatments, and checking up on patients, these technologies can efficiently analyze and understand large data sets, spot trends, and produce useful insights. MDSS's capacity to decrease mistakes and increase patient safety is a major benefit. MDSSs can identify possible medication mistakes, inform healthcare practitioners about drug interactions or contraindications, and offer practical alternatives by cross-referencing patient data with significant medical knowledge and standards of care. Due to this, lives may be spared, treatment results can be improved, and bad medication responses can be avoided [4]. MDSSs are intended to supplement medical staff rather than replace them. The physician is ultimately responsible for making the call after examining all relevant information about the patient and using his or her professional judgment. Healthcare practitioners may benefit greatly from medical decision support systems since they are cutting-edge solutions that integrate medical expertise, data analytics, and technology. Healthcare providers would be hard-pressed to do their professions without medical decision support systems. These systems increase diagnostic accuracy, patient safety, and evidence-based treatment by using cutting-edge technology and integrating huge volumes of medical data and expertise [5]. This research provides recommendations

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for treatments that may enhance the timeliness, quality, and accuracy of healthcare decisions.

2. Related Work

The paper [6] described the Decision Support System (DSS) to assist a psychiatrist in developing a treatment strategy in light of the transfer matrix that represents the dynamics of a patient's mental state. The study [7] identified and highlighted a CDSS's potential for use in the diagnosis, care, and prevention of COVID-19. The goal of the cross-sectional study was to describe how CDSS is used for COVID-19 diagnosis, treatment, and prevention. The study [8] presented a DSS using ML methods for diabetes prediction. They analyzed the differences and similarities between deep learning and traditional ML. The study [9] delivered further into the present state of ontology used in Clinical DSS (CDSS) rule management. When it comes to enhancing the quality and safety of healthcare delivery, CDSS plays a crucial role. CDSS guidelines dictate how CDSS operates. The ontology may encourage the sharing and reuse of CDSS rules, which has not been done consistently. The study [10] provides a medicinal agent-based DSS equipped to manage the whole radionics procedure. Medical agents that can anticipate the effects of therapy for patients by making use of the vast amounts of data presently accessible for each patient are gaining popularity as part of the personalized medicine paradigm. The research [11] demonstrated how efforts to eliminate bias from ML decision-support systems for medical diagnosis obscure the hermeneutic character of such decisions and the beneficial function that bias may play. To demonstrate how the use of ML systems modifies medical diagnosis. The paper [12] suggested a critical examination of existing methods for supporting diagnostic decisions, most of which involve giving practitioners access to either guidelines or, more rarely, full-fledged diagnosis suggestions. To avoid interfering with the decision-makers competence and authority, decision analysts face difficult problems in this situation. The research [13] created a CDSS to direct the first treatment for Low Back Pain LBP in the community pharmacy context and to assess the prototype's usability and acceptability from the pharmacists' perspective. There is a lack of evidence-based care for people with LBP in the community. People with LBP may greatly benefit from the first-line treatment provided by community chemists because of how readily accessible. The study [14] developed a mobile-based DSS for COVID-19 to assist medical professionals in collecting information, evaluating risk, screening, administration, and follow-up during the COVID-19 outbreak. The research [15] aimed to determine what features a CDSS should have to be useful in the primary care setting in West Africa, what would stand in the way of its successful adaptation and deployment, and how to best secure its long-term viability. The research [16] created a fuzzy logic-based CDSS for the diagnosis of colorectal cancer (CRC). One of the world's worst illnesses, CRC is the most common form of cancer affecting the digestive tract. Given CRC's dismal outlook, improving our ability to forecast the disease's progression is crucial. The study [17] improved upon the performance of current fuzzy and intuitionistic fuzzy similarity measures by adapting them for use in the cognitive domain. Numerous fuzzy similarity measures have been refined into intuitionistic fuzzy similarity measures for use in a variety of contexts. The research [18] provided a framework for an integrated information model-based intelligence algorithms networking atmosphere, or CDSS, which would allow for the easier creation and dissemination of such systems. The CDSS is widely acknowledged as a tool that improves both clinical efficiency and patient safety. However, it has not lived up to its full promise because of the lack of standardized clinical data and compatible systems. To evaluate nutrition-related aspects (symptoms) and calculate the probability of health hazards associated with four syndromes in elderly patients, the explainable artificial intelligence-based (XAI) clinical decision support system (CDSS) is proposed in the study [19].

3. Proposed Methodology

These systems make employing a wide variety of approaches and procedures. then pre-processed using the Min-max Normalization and feature selection for Principal Component Analysis (PCA). We propose an innovative SOBLA technique for classification. The suggested block diagram is shown in Fig. 1.

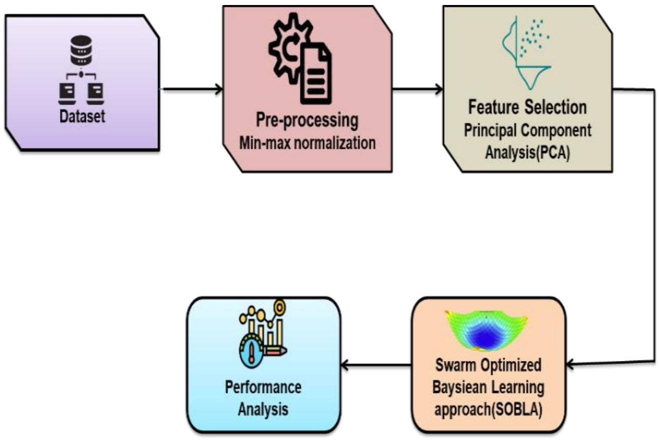

Fig.1. Block diagram of proposed

3.1. Data collection

The creation and selection of characteristics from the medical dataset are the main objectives of this study. The data was collected from "(https://www. kaggle.com/datasets/fedesoriano/stroke-prediction-dataset)" rows and columns stand in for the tabular data that makes up the picture. There are 5110 and 12 in the rows and columns, respectively. Table 1 displays a description of the dataset.

Table 1. Description of the dataset

ID	Gender	Age	Heat-disease	Hypertension	Work-type	Ever-married	Brni	Residence-type	Avg-gulcose-level	Stroke
60182	Female	48	1	1	Private	Yes	35.5	Urban	172	2
1665	Female	78	1	2	Self-employed	Yes	25.1	Rural	175	2
9046	Male	68	2	1	Private	Yes	36.7	Urban	228	2
51676	Female	62	1	1	Self-employed	Yes	NaN	Rural	203	2
31112	Male	81	2	1	Private	Yes	33.6	Rural	107	2

3.2. Pre-processing of Z-score normalization

Data pre-processing is the handling of initial information to prepare it for additional data analysis activities. This has traditionally been an essential phase before starting the data analysis process. A technique for linearly converting data at the start of a range is called min-max normalization. This method preserves the link between different pieces of information. For correctly fitting information, established bounds with predetermined boundaries are a crucial method. Every value in the feature under consideration is mapped to a new normalized value using the following equation [1].

$$R_{new} = \frac{R - \min(R)}{\max(R) - \min(R)} * \ (\mathrm{U} - \mathrm{L}) + \mathrm{L} \quad (1)$$

Y_{new} = Min-Max data, and [L, U] is one of the boundaries
Y=outdated value
Max(Y) = Dataset's highest possible value
Min(Y) = Dataset's lowest possible value

3.3. Features Selection using Principal Component Analysis (PCA)

PCA is a technique that may be used to minimize the number of dimensions that raw feature data are represented by removing all or some of the fewest principal components and replacing them with a lower-dimensional projection, all while maintaining the greatest degree of variation in the original data. Orthogonal linear projecting is used to convert one space into another in this case. Here is an overview of the PCA technique.

$$LZ = WD \quad (2)$$

With $Z \in \mathbb{Q}^{T\times T}$ includes the planned data matrix O primary Elements of W with $O \leq M$. Locating the projection matrix, therefore, is the critical step $D \in \mathbb{Q}^{M\times O}$, a process that is equal to determining the eigenvectors of the covariance matrix of W, alternatively, resolving a problem using singular value decomposition (SVD) for W.

$$W = V\Sigma U^{S} \quad (3)$$

where $V \in \mathbb{Q}^{T\times T}$ and $U \in \mathbb{Q}^{T\times T}$ are the matrix orthogonal in the row and column dimensions of W, and Σ represents single values as a diagonal matrix, $\lambda_{m,}$ for $m = 0, \cdots, M - 1$, gradually not laying on the diagonal. Matrix for projecting D derived from the initial O columns of U with

$$U = [U_1, \dots, U_M] \quad (4)$$

Besides

$$D = [D_1, \dots, D_O] \quad (5)$$

Where $U_m \in \mathbb{Q}^{M\times 1}$is the n_{th} correct particular path of W, and $d_m = U_m$

In reality, each of the unique values in Σ in (3) are the dispersion measures of W along the primary axes of the region covered by the rows of C. Consequently, λ_m^2turns into a measure of dispersion across the nth principal component of W's projection. The amount of information that a particular aspect adds to the overall depiction of the data is thought to be a good proxy for its variance. One approach is to calculate the accumulated variation explained proportion between the principal components, assumed as

$$Q_{dfu} = \frac{\sum_{m=1}^{O} \lambda_m^2}{\sum_{m=1}^{M} \lambda_m^2} \quad (6)$$

The results show that retaining only a few major components may preserve more than 90% of the total variance or information of W. In the following analysis, we compare the results obtained by using a range of different numbers of primary components.

3.4. Swarm Optimized Bayesian Learning Approach (SOBLA)

A potent method for tackling challenging optimization issues in medical applications is the combination of SOBLA. By leveraging the swarm's collective intelligence and Bayesian learning's probabilistic reasoning, it may improve decision-making, diagnose patients more accurately, optimize treatment regimens, and improve patient outcomes.
A directed acyclic graph is used to depict BLs. Random variables are represented by vertices, while the probability of interaction between them is shown by the edges. BL was named after the well-known Bayes theory. The joint probability in a BL is denoted by the following formula.

$$o(w_1, w_2, \dots. w_m) = \prod_{j=1}^{m} o\left(w_j \middle| \pi_j\right) \quad (7)$$

Where, $w_1, w_2, \ldots\ldots w_m$ are variables and π_j denotes the parents of the variablew_j.

Structured ML methods, such as the search-and-scoring algorithm, are used by BLs. The program then attempts to find a framework that optimizes this score, which is an assessment of the framework's appropriateness given the data. The most common method of scoring takes into account the following chances for the arrangement given the data. A proposed Bayesian learning structure BS's posterior probability may be calculated using the Bayes rule.

$$o(B_s|C) = \frac{o(C|B_s)o(B_s)}{O(C)} \quad (8)$$

where $O(C|B_s)$ is the data's likelihood given BLs structure BS, $O(B_s)$ is the prior probability of BS, and P(D) is the probability of the observed data C. Since the data probability $O(C)$ is a fixed, unchanging number no matter which BS model is used, we may disregard it. If all of the possible hypothetical model's BS have the same prior probability$O(B_s)$, then the likelihood of the data given the model BS, $O(C|B_s)$, will uniquely identify the model's posterior probability, $O(C|B_s)$.

$$O(C|B_s) = \prod_{j=1}^{m} \prod_{i=1}^{rj} \frac{(q_j-1)!}{(M_{ji}+q_j-1)!} \prod_{l=1}^{q_j} M_{jil}!. \quad (9)$$

$$M_{ji} = \sum_{l=1}^{q_j} M_{jil.} \quad (10)$$

SOBLA is a method of computational evolution that takes its cues from the cooperative behaviors of wildlife swarms like bird flocks and fish schools. SOBLA has a basic theoretical framework and can be easily developed and implemented on a computer. SOBLA also has a strong capability for exploring new areas; it searches for the best possible solutions incrementally. As a result, SOBLA has become more popular and has found several uses in modern society. This includes the BLs learning issue, which SOBLA has been used to address. In a d-dimensional search space, the location and speed of each particle are expressed as $W_j = (w_{j1,}w_{j2,} \ldots\ldots w_{jc})$and , $U_j = (u_{j1,}u_{j2}, \ldots\ldots, u_{jc})$respectively ($c = 1,2, \ldots. M$). There is an optimal location for every particle $W_{best,j} = (w_{best,j1}w_{best,j2}, \ldots., w_{best,jc})$ stands for the best particle discovered at the t-th iteration for the whole swarm as a whole. Where M is the total number of optimization variables and O is the total number of particles in the swarm. Here's how you can figure out how fast each particle is going now:

$$u_{jc}(s+1) = x.u_{jd}(s) + d_1.q_{1.}\left(w_{best,jc}(S) - w_{jc}(s)\right) + d_2.q_{2.}\left(w_{global-best,c^{(s)}} \text{-} w_{jc}(s)\right) j = 1 \ldots. O, c = 1 \ldots, M \quad (11)$$

$$w_{jc}(s+1) = w_{jc}(s) + u_{jc}(s+1) \quad (12)$$

Exploration and exploitation on both a global and local scale are balanced by the inertia weight x. With a greater w, the elements retain high speeds, whereas, with a lower w, they hold low speeds. Smaller x promotes particles to use the identical search space region, whereas greater w may prevent particles from being stuck in local optima. To determine whether particles xi prefer traveling towards a $w_{best,j}$ location or an $w_{global-best}$, j position, the variables d_1 and d_2 are utilized. Particles with low values of them may wander far from the target locations before being pulled back. High numbers, on the other hand, cause sudden movement towards or beyond the objective. , x was typically set by beginning at .9 and ending at .4. The speeds and constants are predicted based on historical data d_1 and d_2 were often adjusted at 2.0. The random functions $q_{1.}$ and $q_{2.}$ fall between [0, 1].

The SOBLA method employs a collaborative swarm of particles, with each particle representing a possible solution to the optimum challenge of concern, to probe the space of solutions. The fitness should be checked at each optimization step. Several different formulae may be used to determine the fitness function, each tailored to a certain practical context in equation 12. Compare the health value of each particle's present location to the health value of its prior best position, $w_{best,j}$. Update $w_{best,j}$ with the present rate and position if the present value is superior. Update Xglobal_best with the present rate and place of the present particle if the fitness rate is greater than the fitness rate of the global best position, $w_{global-best}$. According to Equ. 5 and Equ. 6, adjust each particle's place and speed. $w_{global-best}$ and its A fitness rating is generated if a threshold stopping condition is achieved; otherwise, the evaluation process continues.

4. Performance analysis

4.1. Results

In this part, the suggested system's effectiveness is evaluated. The performance indicators used for assessment are accuracy, sensitivity, specificity, and f1-measure. Fuzzy Neural Classifier (FNC), XGBoost, and Logistic Regression (LR) are the existing methods used for comparison [20].

4.1.1. Accuracy

A difference between the result and the true number is caused by inadequate precision. The percentage of actual outcomes reveals how balanced the data is overall. Accuracy is assessed using an equation (13). In the context of MDSS, accuracy refers to a system's capacity to provide accurate recommendations or projections for choices on medical diagnosis or treatments. It assesses how well the MDSS conforms to actual or acceptable results. In Table 2, the accuracy of the suggested technique is contrasted with the existing methods. In comparison to existing methods, the suggested approach offers a high level of accuracy. Fig 2 shows the Evaluation measures between the suggested and current approaches

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (13)$$

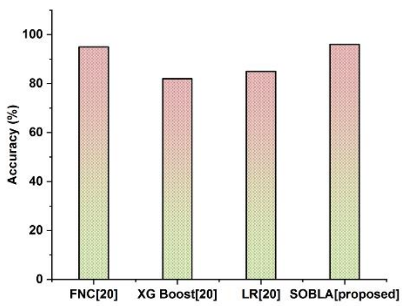

Fig.2 Accuracy between the suggested and current approaches

Table 2. Comparison of Accuracy

Methods	Accuracy (%)
FNC[20]	95
XG Boost[20]	82

LR[20]	85
SOBLA[proposed]	96

4.1.2. Sensitivity

Sensitivity is measured as the fraction of correct diagnoses relative to the sum of correct diagnoses and false negatives. It shows the percentage of real positive instances that the test or model successfully recognized. With greater sensitivity, the test or model is more accurate in identifying positive cases because there are fewer false negatives. Sensitivity is a crucial factor that plays a role in deciding how well MDSS operates and how well it runs overall. An MDSS is a medical decision support system that assists medical professionals in making clinical choices by providing evidence-based ideas, analyzing information about patients, and making recommendations for probable diagnoses or treatments. Fig 3 displays the sensitivity of the suggested procedure. Table 3 displays the implemented method's outcomes. In comparison to conventional methods, the suggested methodology offers superior sensitivity.

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP + FN}} \tag{14}$$

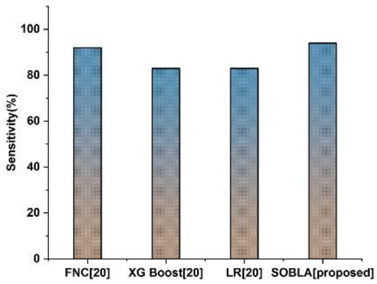

Fig.3. Sensitivity between the suggested and current approaches

Table 3. Comparison of Sensitivity

Methods	Sensitivity(%)
FNC[20]	92
XG Boost[20]	83
LR[20]	83
SOBLA[proposed]	94

4.1.3. Specificity

The level of specificity describes how well a measurement, examination, or diagnostic tool classifies people who do not have a certain ailment or feature as negative. Specificity is a common metric used to assess the reliability of diagnostic tools. It assesses a test's capacity to properly classify as negative those people who are clear of a certain illness or condition. A reliable identification of those without the ailment as negative is indicated by a high specificity, which also suggests that the test has a low number of false positives. The ratio of true negatives to the total of true negatives and false positives is often used to assess specificity. The proposed technique provides a high degree of specificity in contrast to current approaches. In comparison to existing methods, the suggested approach offers a high level of specificity. The following is the formula (15) for specificity: Fig 4 presents a comparison of the success rate to existing method. Table 4 displays the implemented method's outcomes.

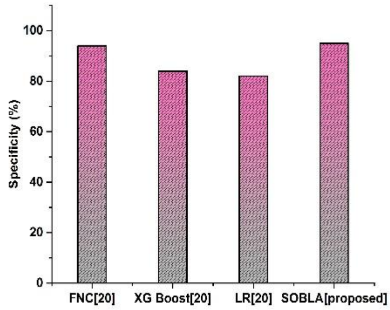

Fig.4. Specificity comparisons between the suggested and current approaches

Table 4. Comparison of Specificity

Methods	Specificity (%)
FNC[20]	94
XG Boost[20]	84
LR[20]	82
SOBLA[proposed]	95

4.1.4. F1-Score

The F1- score is often used while assessing information. It is possible to alter the F1- score so that accuracy is prioritized above recall, or vice versa. The recommended technique has a higher level of F1- score when measured against the currently used methods. The F1 score is a common evaluation measure that is used in MDSS to assess the efficacy of categorization algorithms. This score is used in situations when there is erroneous information or if there is a large disparity in the costs of inaccurate results and false negatives. The F1 score is a fair evaluation of a model's efficacy since it incorporates both accuracy and recall. In Fig 5 and Table 5, the F1-score of the suggested method is contrasted with the traditional methods. The proposed method performed better than the current results with an F1-score of 98%.

$$F1 = \frac{2 * (precision * recall)}{(precision + recall)} \tag{16}$$

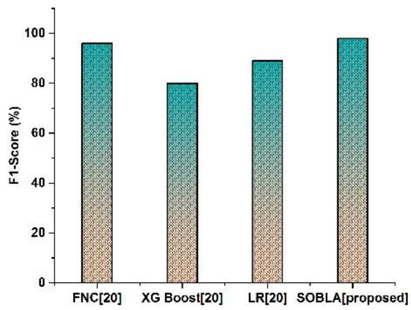

Fig.5. F1-Score comparisons between the suggested and current approaches

Table 5. Comparison of F1-Score

Methods	F1-Score (%)
FNC[20]	96
XG Boost[20]	80
LR[20]	89
SOBLA[proposed]	98

5. Conclusion

In conclusion clinical decision-making with precise and fast data, MDSS shows the potential in enhancing the quality of treatment provided to patients. We may anticipate future improvements and refining of these systems to better serve patients and healthcare professionals as technology progresses and more research is undertaken on this subject. In this research, we provide SOBLA, a novel ML-based feature selection strategy. Normalization is applied to the dataset after it has been collected and cleaned. The characteristics are extracted using PCA, and the recommended approach is utilized to choose the most important ones. We tested the recommended method to use for the test on healthcare data sets. As a result, we introduced the SOBLA for the recognition of spoken emotion. Performance metrics like accuracy, sensitivity, specificity, and f1-measure, are evaluated and compared with existing technologies like FNC, XGBoost, and FR. The development of innovative categorization algorithms and the acquisition of more healthcare information in the future are both crucial to our efforts to improve performance.

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