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# Design a modified fly anatomy and support vector machine-based heart disease prediction system

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**Abstract**

A previous heart disease diagnosis system relied on Interval Type-2 Fuzzy Logic System (IT2FLS), but it had poor recognition accuracy and training time. This research proposes an efficient heart disease prediction system using modified firefly algorithm based radial basis function with support vector machine (MFA and RBF-SVM). In smart healthcare AI systems, the decision support component acts as a watchdog or adviser to cut down on medical mistakes, which include patient errors. There are two primary versions of this component. The prediction of CVD makes use of a number of ML and DL methods. On the other hand, a fully clinical setting is ideal for these approaches. However, a new need for improved prediction systems that are suited to real-time monitoring and illness prediction has arisen as a result of technological advancements. To minimizes computing cost and boost prediction system performance, the ideal subset of attributes is selected using the PSO algorithm and an attribute reduction approach based on Rough Sets (RS).

**Keywords:** Support vector machine, heart disease, prediction**,** healthcare and artificial intelligence

## Introduction

Smart healthcare makes extensive use of a number of AI algorithms for a variety of purposes, including cancer diagnosis, cardiac arrest prediction, and risk assessment for suicidal thoughts and behaviors. Convolutional neural networks (CNNs), RNNs (including LSTMs), and support vector machines (SVMs) are commonly used in medical image recognition. CNNs show great promise in this field, while RNNs and LSTMs are good at handling time-series data like electrocardiograms and medical notes. SVMs are also popular because they are easy to explain and use, and they are effective in areas like disease prediction and medical diagnosis

To find valuable trends and patterns in health data, the predictive analytics part of smart healthcare does sophisticate data analysis. Thanks to these discoveries, doctors are better able to foretell how patients will do in the future. In many cases, the predictive analytics part helps with chronic illness management, identifying high-risk patients early on, and anticipating disease outbreaks.

In smart healthcare AI systems, the decision support component acts as a watchdog or adviser to cut down on medical mistakes, which include patient errors. There are two primary versions of this component: one that uses machine learning and statistical conclusions, and another that makes use of advanced rule-management subsystems in electronic health record systems.

For artificial intelligence (AI) systems in smart healthcare to continually learn, increase efficiency, and boost accuracy, the feedback and optimization component is vital. This entails keeping an eye on how the app is doing in real time, taking user input into account after each action, and then feeding that data into optimization algorithms to make the app even better.

Discussions on artificial intelligence (AI), in which computers are able to carry out activities often associated with human intellect, are happening right now in almost every scientific and technical field. Computers may reach human-like competency in picture identification, according to major scientific contests like ImageNet Large Scale Visual identification Challenges. Advancements in voice recognition and natural language processing have also been made possible by AI. Concerns about how these skills might supplement or improve human health and healthcare decision making have been raised by all of these advancements. At least in very limited contexts, two prominent research articles published recently shown that AI can do clinical diagnoses on medical pictures on par with seasoned physicians.

**Literature Review**

These days, healthcare decision-making, early illness detection, and service optimization are all positively impacted by the application of artificial intelligence (AI) technology. Artificial intelligence may be used with many different types of data. In this article, we have covered the most recent news on AI healthcare applications, technology, advantages, disadvantages, and ethical concerns. It has also highlighted the importance of AI in enhancing prediction, individualized therapy, and diagnostics. This study's findings suggest that AI-ethics in healthcare will be a hot topic for the next decade or more, depending on how the industry chooses to regulate AI in healthcare

Yousef Shaheen *et al*. (2021) [1]. With its ability to anticipate, understand, learn, and take action, artificial intelligence is enhancing and transforming contemporary healthcare. This is true whether the technology is used to control surgical assistance robots or to discover new connections between genetic codes. It has the ability to see subtle patterns that others would miss. The many current uses of artificial intelligence (AI) in healthcare are examined and debated in this research. The research focuses in on two of the fastest growing subfields within AI-enabled healthcare: clinical trials and patient care, as well as AI-led drug development.

Abbas *et al*. (2023) [2]. With its many potential uses, artificial intelligence (AI) is quickly becoming a game-changer in the healthcare sector. This article delves into the many uses of artificial intelligence (AI) in healthcare, including topics such as diagnostic aid, administrative simplification, individualized therapy, and predictive analytics. While artificial intelligence (AI) has tremendous promise in healthcare, there are also many obstacles to overcome, including concerns about patient data privacy and ethics as well as regulatory red tape and the difficulty of integrating AI into preexisting systems. Despite these obstacles, artificial intelligence (AI) has great promise for the future of healthcare, with the ability to improve treatment quality, lower costs, and increase patient outcomes. Hello there!

Chan *et al*. (2023) [3]. Artificial intelligence (AI) has been rapidly used by healthcare organizations because to the COVID-19 epidemic. There has been a shift in emphasis toward artificial intelligence (AI) technologies that may enhance healthcare delivery and patient outcomes in response to the growing need for fast diagnosis and treatment and the popularity of remote care and monitoring. Screening and diagnostics, drug research, and vaccine development have all benefited from the use of AI-powered technologies including computer vision, natural language processing, and predictive analytics. Remote patient triage and treatment has also made use of chatbots and virtual assistants driven by artificial intelligence. Although there have been many positive outcomes from using AI in healthcare, there are still certain obstacles that must be overcome.

Hasan *et al*. (2023) [4]. The interdisciplinary study of health informatics (HI) focuses on how AI, data analytics, and IT can improve patient care. Artificial intelligence has brought about a sea change in healthcare by introducing novel methods of handling and interpreting health information for the benefit of patients, researchers, and administrators. This research made use of health information systems, clinical images, and academic jargon that is dense, complicated, and sometimes unstructured. Data that is neither organized nor structured has proliferated due to the rise of artificial intelligence applications and their incorporation into healthcare systems, further complicating research efforts. In order to improve AI applications, this research evaluates HI thoroughly.

**Research Methodology**

The prediction of CVD makes use of a number of ML and DL methods. On the other hand, a fully clinical setting is ideal for these approaches. However, a new need for improved prediction systems that are suited to real-time monitoring and illness prediction has arisen as a result of technological advancements. In this chapter, we will learn how to employ neural network techniques and neutrosophic sets to build a healthcare sector prediction model. The presentation of a neutrosophic approach to detect the onset of a heart attack and alert the doctor in advance was made. In order to find all potential interactions among predictable variables, a predictive model is developed for the complex link between the dependent and independent variables. Diagnostics via web-based healthcare monitoring necessitated prediction models and categorization techniques, which were already existent in the interaction between the stored information and the service providers.

Such a decision-making process will improve and simplify the job of medical experts. But doctors and nurses have a hard time putting their faith in decision-making processes, therefore they don't always accept or use them. The decision-making system facilitates better processing and enables medical professionals to understand the system's operation. The proposed research is noteworthy since it offers a reliable technique for multi-classifying cardiac data pertaining to the patient's pulse rate. Moreover, in order to discover the confusion matrix with high-performance parameters, it is essential to compare its results with other fuzzy algorithms and methods.

**Data Analysis**

These days, heart disease is a leading cause of mortality worldwide. Doctors have a hard time making accurate predictions about heart disease The input dataset for this method has three types of attributes: input, key, and prediction. Principal Component Analysis (PCA) is used for feature extraction after normalization, while FA is used for attribute reduction. At last, RBF-SVM is categorized as either healthy or having cardiac issues.

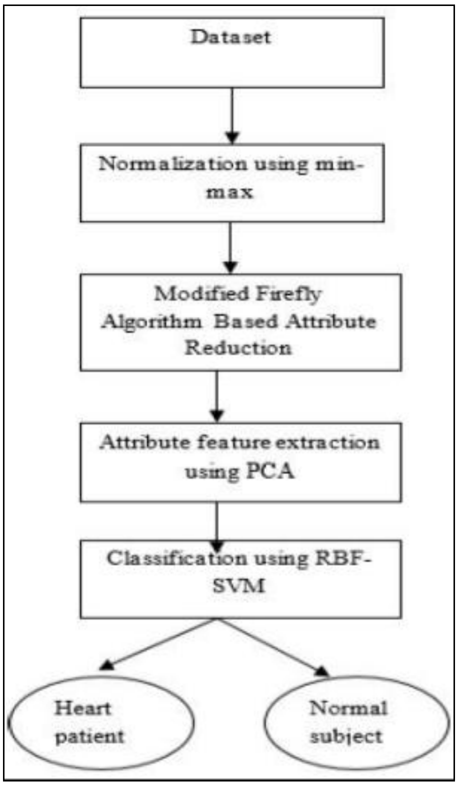


**Fig 1:** Flow Diagram of Proposed Methodology

Firefly blazing light is controlled by bioluminescence techniques. There are a lot of theories on the meaning of glimmering, but most of them center on the mating stage.
According to the inverse square rule, the intensity of the light I, which is proportional to the distance r, keeps decreasing up to a certain point. I 1/r2. After that, the data is sent to a smart gateway via Bluetooth and then uploaded to a server in the cloud for further processing. After that, the physicians, doctors, consultants, and professionals in the field use the MADM method in conjunction with IvTNN and WASPS to ascertain the stage of the cardiac disease. The doctor is able to send the patient an electronic health record after the diagnosis Having said that, the categorization result it produces is far from good in this study, Zero-Score (Z-Score) is used for data normalization in order to decrease data redundancy and increase data integrity.
To minimizes computing cost and boost prediction system performance, the ideal subset of attributes is selected using the PSO algorithm and an attribute reduction approach based on Rough Sets (RS). Last but not least, the RBF-TSVM classifier is used for the prediction of cardiac illness. The Gaussian component, which is based on RBF, transforms the space of the lower dimensions into an unfathomably high-dimensional space. Unidentifiable highlights that are projected into three-dimensional space always end up being vividly visible.

$$KF(x^{""}, x_i^{"}) = (-\gamma\|x^{""}, x_i^{"}\|)^2 : \forall$$

The $\gamma$ is responsible for adjusting the Gaussian ringer mold's width. The smaller the estimate, the wider the curve, and vice versa. When the RBF component is combined with SVM, the final result is a step closer to becoming

$$f(x^{"} = \sum_{i=1}^{m} \alpha_i e^{(-\gamma\|x^{"}, x_i\|)} + b$$

The RBF-based support vector machine (SVM) has two categories: normal subjects (NS) and heart patients (HP).
In this study, Zero-Score (Z-Score) is used for data normalization in order to decrease data redundancy and increase data integrity. To minimizes computing cost and boost prediction system performance, the ideal subset of attributes is selected using the PSO algorithm and an attribute reduction approach based on Rough Sets (RS). Last but not least, the RBF-TSVM classifier is used for the prediction of cardiac illness.

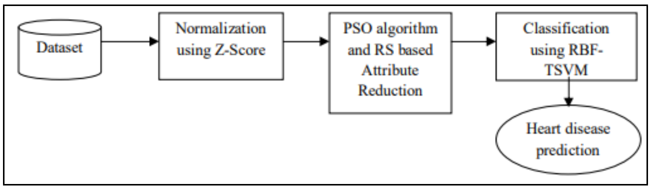


**Fig 2:** Block diagram of the proposed methodology

There are three main phases to the comprehensive design of a system for diagnosing heart disease: Classification, feature extraction, attribute reduction, and normalization.
It is possible to combine the proposed broadcast data of unlabeled examples with well-prepared tests since TSVM computations make use of the potential of transudative adaptation effectively. When the pre-set estimate of N is significantly different from the actual number of tests with positive marks, the TSVM calculation's presentation becomes very weak, and the calculation's grouping accuracy cannot be effectively guaranteed.

$$(x_1,y_1),\ldots.(x_n,y_n), x_i \in R^m, y_i \in \{\ 1, \mid 1\}$$

with an additional set of unlabeled samples from the corresponding sharing,

$$x_1^*, x_2^*, x_3^*, \ldots, x_k^*$$

$$(y_1^*, \ldots y_k^*, w, b, \xi_1, \ldots, \xi_n, \xi_1^*, \ldots \xi_k^*)$$

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i + C^*\sum_{j=1}^{n}\xi_j^*$$

Subject to:

$$\forall_{i=1}^{n}: y_i t[w.x_i + b] \geq 1 - \xi_i$$

$$\forall_{j=1}^{k}: y_j^*[w.x_j^* + b] \geq 1 - \xi_j^*$$

$$\forall_{i=1}^{n}: \xi_i \geq 0$$

$$\forall_{j=1}^{k}: \xi_j^* \geq 0$$

## Training in TSVM

Classify the test examples using <~w;b>. The num+test examples with the highest value of $\vec{w} * \vec{x}_j^* + b$ are assigned to class $+(\vec{y}_j^* := 1);$ ;The remaining test examples are assigned to class $-+(\vec{y}_j^* := -1);$ $C_-^* := 10 - 5;//$ some small number

$$C_-^* := 10 - 5 * \frac{num+}{k-num+};$$

$$\text{While } ((C_-^* < C^*) || (C_-^* < C^*)) \quad \{$$

//Loop1

$(\overrightarrow{w}, b, \vec{\xi}, \vec{\xi} *) :=$
$solve\_sum\_qp([(\overrightarrow{x\,1}, y1), \dots, (\overrightarrow{x\,n}, yn)], [(\vec{x}_1^*, \vec{y}_1^*), (\vec{x}_k^*, \vec{y}_k^*)], C, C_-^*, C_+^*)$
;

1) While $(\exists m, 1: (y_m^* * y_1^* < 0) \& (\xi_m^* > 0) \& (\xi_1^* > 0) \& (\xi_m^* * \xi_1^* > 2))$

{

Loop2

$y_m^* := -y_m^*;$ //take a positive and a negative test

$y_1^* := -y_1^*;$ // example, switch their labels, and retrain

$(\vec{w}, b, \vec{\xi}, \vec{\xi} *) :=$
$solve\_sum\_qp([(\overrightarrow{x\,1}, y1), \dots, (\overrightarrow{x\,n}, yn)], [(\vec{x}_1^*, \vec{y}_1^*), (\vec{x}_k^*, \vec{y}_k^*)], C, C_-^*, C_+^*)$
;

}

$C_-^* := \min(C_-^* * 2, C^*);$

## TSVM training Algorithm

**Input:** -training examples $(\overrightarrow{x\,1}, y1), \dots, (\overrightarrow{x\,n}, yn)$

-test examples $\vec{x}_1^*, \dots \dots \vec{x}_k^*$

**Parameters:** -C, $C^*$**:** parameters from OP (2)
-num+: number of test examples to be assigned to class+

**Output:** - anticipated labels for the sample data

$$\vec{y}_1^* - \vec{y}_k^*(\overrightarrow{w}, b, \vec{\xi}, \quad) := solve\_sum\_qp([(\overrightarrow{x\,1}, y1), \dots, (\overrightarrow{x\,n}, yn)],$$

The x-axis represents the dataset size, while the y-axis represents the specificity. Results comparing the proposed MFA and based RBF-SVM classification method to the current system demonstrate greater specificity across all dataset sizes.

**Table 1:** Results of MFA-RBF-SVM and IT2FLS

| Data Size (Bytes) | Accuracy | | Sensitivity | | Specificity | |
|---|---|---|---|---|---|---|
| | **IT2FLS** | **MFA and RBF-SVM** | **IT2FLS** | **MFA and RBF-SVM** | **IT2FLS** | **MFA and RBF-SVM** |
| 1000 | 91.5 | 92 | 87 | 89 | 91 | 92 |
| 2000 | 92 | 93 | 89 | 91 | 92 | 93 |
| 3000 | 94 | 95 | 91 | 93 | 93 | 94 |
| 4000 | 95 | 96 | 94 | 95 | 95 | 96 |
| 5000 | 96 | 97 | 95 | 97 | 96 | 97 |

## Conclusion

A PSO-RBF-TSVM approach has been designed to predict heart disease intelligently and efficiently. After the normalization process, the unpleasant sets based characteristic decrease utilizing PSO calculation is acquainted with find ideal decrease which along these lines diminishes the excess and improves execution of classifier and attribute features are also extracted through. Finally, the classification is performed by using RBF-TSVM, to predict the heart diseases. Additional evaluations are carried out by dispatching an ambulance to the patient in cases of severe or very serious conditions. Predicting cardiac problems using a radial basis function and support vector machines was the focus of the prior. Smart healthcare makes extensive use of a number of AI algorithms for a variety of purposes, including cancer diagnosis, cardiac arrest prediction, and risk assessment for suicidal thoughts and behaviors.

## References


1. Shaheen MY. Applications of Artificial Intelligence (AI) in healthcare: A review [Internet]. 2021 [cited 2021 May 14]. Available from: https://doi.org/10.14293/S2199-1006.1.SOR-.PPVRY8K.v1
2. Abbas A, Cheng L, Raza F. AI in Healthcare: Applications, Challenges, and Future Prospects. 2023.
3. Chan CYT, Petrikat D. Strategic Applications of Artificial Intelligence in Healthcare and Medicine. J Med Health Stud. 2023;4(3):58–68. Available from: https://doi.org/10.32996/jmhs.2023.4.3.8
4. Hasan M, Islam M, Islam M, Chen D, Sanin C, Xu G. Applications of Artificial Intelligence for Health Informatics: A Systematic Review. J Artif Intell Med Sci. 2023. Available from: https://doi.org/10.55578/joaims.230920.001
5. Pallavi T, Rao AL, Talasila B, Murthy TG. Artificial Intelligence: Applications in Healthcare Industry. Int J Res AYUSH Pharm Sci. 2022;6(5):622–627. Available from: https://doi.org/10.47070/ijraps.v6i5.136
6. Datta S, Barua R, Das J. Application of Artificial Intelligence in Modern Healthcare System. 2019. Available from: https://doi.org/10.5772/intechopen.90454
7. Alloghani M, Al-Jumeily O, Aljaaf A, Khalaf M, Mustafina J, Tan SY. The Application of Artificial Intelligence Technology in Healthcare: A Systematic Review. 2020. Available from: https://doi.org/10.1007/978-3-030-38752-5_20
8. Sharma R. Artificial Intelligence in Healthcare: A Review. Turk J Comput Math Educ. 2020;11(1):1663–

7. Available from: https://doi.org/10.61841/turcomat.v11i1.14628 turcomat.org

9. Shah A, Hakim K, Luqman S. The Role of Artificial Intelligence in Healthcare: Current Applications and Future Prospects. 2023.
10. Manne R, Kantheti S. Application of Artificial Intelligence in Healthcare: Chances and Challenges. 2023.
11. Bohr A, Memarzadeh K. The Rise of Artificial Intelligence in Healthcare Applications. In: Bohr A, Memarzadeh K, editors. Artificial Intelligence in Healthcare. Academic Press; c2020. p. 3–10. Available from: https://doi.org/10.1016/B978-0-12-818438-7.00002-2