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Artificial Intelligence (AI) in Healthcare Prediction Systems: Potential uses

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Abstract: The advancement of predictive algorithms that improve early diagnosis, treatment planning, and patient management is one area where artificial intelligence (AI) is having a profound impact on healthcare. Accurate forecasts of illness start, development, and treatment results are made possible by AI algorithms that leverage enormous datasets from medical imaging, wearable devices, and electronic health records. These algorithms are able to detect patterns and correlations beyond what humans are capable of. In particular, AI-driven predictive healthcare systems are improving the management of chronic diseases, the prediction of patient deterioration, and the optimisation of clinical resource allocation. On top of that, AI makes personalised medicine a reality by customising treatment plans to each patient's unique profile, which boosts efficiency and happiness. There are a number of obstacles to implementing AI in healthcare, such as worries about data privacy, algorithmic bias, and the necessity for regulatory supervision, despite the technology's enormous promise. However, AI-powered prediction systems have the potential to promote data-driven, proactive medicine and radically alter the healthcare system with further development and ethical regulation.

Keywords: Artificial Intelligence, Healthcare prediction, Potential

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INTRODUCTION

Many modern-day sectors generate massive amounts of data on a regular basis. Hardware that can manage this data and derive meaningful insights has been steadily improving, fuelling the rapid expansion of AI in many domains. One reason for the widespread application of AI in healthcare is the rising demand for services and the corresponding strain on healthcare resources brought about by the world's constantly growing population (Naqvi, 2023). This combination has led to the development of applications such as diagnostic imaging, personalised treatment planning, and the prediction and prevention of sickness. "Smart healthcare" encompasses all of these applications, and the concept was first introduced by IBM's "Smart Planet" in Armonk, NY, USA. A similar fundamental idea supports the many AI uses in this field: post-data acquisition, ML (DL) methods give predictive analytics.

Using AI to refocus attention from specialists to patients is one manner in which smart healthcare deviates from traditional medicine. A smart healthcare system focused on patients' needs, experiences, and engagement is built by combining state-of-the-art intelligent healthcare technology. There have been a lot of fruitful commercial smart healthcare projects. Merative L.P.'s smart healthcare solutions are used by nine out of ten top hospitals in the US. The number of American academic medical institutes that collaborate with Tempus exceeds fifty percent. Aidoc analyses two million patients per month (Samajdar, 2025). Using Path AI, nine of the top 10 biopharma companies are reshaping pathology. Consequently, a lot of research has focused on the possibilities and challenges of smart healthcare. Some see a dark future for smart healthcare due to the challenges of transforming data into insight. A number of scholars have hypothesised that smart healthcare would solve problems including an ageing population, high healthcare costs, and a shortage of doctors and nurses, all while promoting long-term economic growth. Three opportunities for smart healthcare are presented by artificial intelligence (AI): first, predictive healthcare modelling; second, knowledge discovery from structured and unstructured data; and third, cross-domain insights, research and innovation facilitation, and resource utilisation enhancement (Sharma, 2023). The first two areas involve large-scale data processing and analysis, pattern recognition, anomaly detection, dynamic prediction, and decision-making support, respectively.

Artificial Intelligence

Computer scientists use the term "artificial intelligence" (AI) to describe programs that can learn to think and solve problems in ways that humans can. We try something, make a mistake, and then maybe (with any luck) figure out how to do it better next time. Similarly, an AI (Artificial Intelligence) system should take on a problem, make a few blunders while solving it, and then use those blunders to improve itself. To rephrase, it's very similar to a game of chess (Shuford, 2024).

"Artificial intelligence" (AI) refers to a subfield of computer science that aims to program computers to mimic human intellect in areas such as language understanding, sophisticated analysis, and user input response. Humans are universally acknowledged as being the most intelligent and perceptive species on Earth. This honour is due to their exceptional reasoning, comprehension, logic, application, and autonomous judgement abilities. Additionally, they are capable of planning, inventing, and solving problems. Starting with the invention of fire and continuing all the way to the landing on Mars, man has produced a great deal for the benefit of his fellow humans. One such invention is the computer, which has considerably decreased human labour while simultaneously solving several complex mathematical and logical problems. The limit to what scientists can uncover, however, has been proven again and time again (Islam, Md Mafiqul. 2024). Their goal in experimenting with AI systems was to create a link between the computer world and the "man-made homoserine" species; these systems are both artificial and capable of independent thought. A system is said to have artificial intelligence (AI) if it can learn, reason, develop itself (via experience learning), understand language, and solve problems. Artificial intelligence (AI) has found uses across many industries, especially in the information technology industry, and is projected to provide an additional 2.3 million jobs by 2020.

The future of AI in healthcare

If you ask Dr. Jehi, the field of artificial intelligence that has the highest chance of succeeding in research is the one dealing with healthcare.

"After this process, I really believe that AI still has so much to teach us," she says.
Dr. Jehi is an authority in the field of epilepsy surgery, and he investigates the ways in which machine learning has changed the discipline.

Patients whose epilepsy symptoms continued after medication had stopped working were formerly thought to have the highest chance of a successful surgical intervention. As part of the surgical procedure, the surgeon would identify the region of the brain that is responsible for the seizures, make sure it isn't necessary for their function, and then safely remove it (Nkhoma, 2024).

"Back in the day, when we were making those decisions, we would conduct a battery of tests, record brainwaves, take a picture of the brain, review the radiologist's or EEG doctor's interpretation of the results, and then, we would take the results," according to her. Our decision to go through with the treatment would be grounded in our personal experiences as people. But our ability to learn from one another was severely limited.

Dr. Jehi concludes by stating that the medical field was essentially functioning independently. It was challenging to anticipate the optimal surgical strategy for first-time patients without taking the larger context into account, even though their years of expertise had been advantageous individually.

Now that machine learning has centralised all this patient data, we can fill in the gaps in our understanding. With everything in one place, clinicians may learn more about the patient's health, evaluate the effectiveness of different therapies, and make more informed judgements (Adrah, 2024).

Applications of AI IN Healthcare

Some of the many uses of AI in medicine include the following:

- **AI for Drug Discovery**

Pharmaceutical companies are now able to find new medications more rapidly because to the usage of artificial intelligence (AI) in healthcare. However, target identification is also automated by it. Medication repurposing is another area that AI in healthcare 2021 may assist with by assessing off-target compounds. Thus, AI drug discovery benefits the healthcare and AI industries by enhancing efficiency and doing away with manual processes (Francis, 2023).

Several medicines created by leading biopharmaceutical companies are at your disposal. Agrawal (2018) states that Pfizer is working with IBM Watson, a machine learning system, to find new immuno-oncology medications. Genentech, a subsidiary of Roche, is employing an artificial intelligence system created by GNS Healthcare of Cambridge, Massachusetts, to identify potential cancer treatments, while Sanofi has pledged to use Ex Scientia's AI platform to discover medications for metabolic disorders. The vast majority of major biopharma companies have internal research or collaborations like this one (Kejriwal, 2022).

The proponents of these methods claim that AI and ML will usher in a new era of faster, cheaper, and more efficient drug discovery. The majority of experts, despite initial doubt, believe these tools will become increasingly crucial in the future. Because of this shift, researchers face new obstacles and opportunities, particularly when these approaches are integrated with automation.

- **AI for clinical trials**

Taking part in a clinical research is one approach of learning about the efficacy of a recently created medication. A lot of time and energy has gone into this. Having said that, it's not that effective.

This means that AI and healthcare have both benefited from clinical trial automation. Moreover, healthcare and AI collaborate to do away with tedious Kindly reference this most current version: Shaheen, Muhammad Y. (2021). The medical uses of artificial intelligence software surveyed. four methods for evaluating data utilisation. On top of that, clinical trials that use AI to their advantage handle enormous amounts of data and provide very accurate findings (Saxena, 2024).

LITERATURE REVIEW

Pandya, Hetal (2023) There are several clinical uses for artificial intelligence (AI), which can detect significant associations in a dataset and is capable of generating predictions, treating patients, and diagnosis. Many AI-based healthcare and research applications are now in operation or are in the testing phase. These include AI-powered illness diagnostics, AI-powered chronic condition management, AI-powered health service delivery, and AI-powered drug development. In this article, we will discuss the current healthcare system's usage of AI and the challenges it has encountered. This chapter explains the inner workings of various AI devices and how they accomplish their tasks. Alginate is a polymer found naturally in brown algal cell walls. It is employed in tissue engineering because to its biocompatibility, low cost, and easy gelation. It is made up of guarulonic and manuronic acid. Improving cell-material interaction and regulated breakdown can be achieved by adding additional polymers to alginate. With alginate as an example, we discuss the function of AI in tissue engineering.

Kwong, Jethro (2024) Much of the growth and development in AI may be attributed to the pursuit of more advanced machine learning techniques for handling massive amounts of health data. While AI may appear to be an independent system when considering algorithms and learning techniques, in order to process data in a variety of forms, it really requires the integration of many machine learning methodologies. The use of AI to the field of medicine is being covered in more and more journals. Furthermore, medical AI research makes use of techniques such as neural networks, deep learning, support vector machines, and convolutional neural networks. In the fields of neurology, early cancer detection, medical imaging, and stroke diagnosis and treatment, support vector machine is the algorithm of choice. When compared to human approaches, AI is superior at risk prediction and diagnosis, the paper claims. While artificial intelligence has made great strides and has a promising future, there are still challenges in the data and regulation sectors.

Tak, (2024) The introduction of AI has the ability to radically impact the medical industry, particularly in regards to patient evaluation, diagnosis, and treatment. This article provides a comprehensive analysis of AI in healthcare, covering its uses, advantages and disadvantages, and potential future developments. From its beginnings to the present day, this article traces the history of AI in healthcare, emphasising important milestones along the way. Medical imaging, medication development, personalised treatment plans, illness prediction, and diagnostics are some of the areas that artificial intelligence (AI) in healthcare is now focussing on. Data privacy and security, integration with current systems, ethical concerns, and patient acceptability are some of the issues and constraints highlighted in this article about the use of artificial intelligence in healthcare. Finally, the research delves into limitations and problems, possible AI healthcare breakthroughs, AI interaction with other tech, implications on healthcare staff, and more. Taking everything into account, the report emphasises the need for more research and development to fully fulfil the revolutionary potential of AI in healthcare.

Haleem, (2019) Artificial intelligence (AI) has become an integral part of contemporary life due to its fast growth. The emerging discipline of "smart healthcare" is directly related to the integration of AI into medical practice. Smart healthcare has both possibilities and challenges. A comprehensive overview of the development and present status of this area is provided on this page. First, we'll give you the rundown on what "smart healthcare" is and how it operates. Our second objective is to survey the many potential applications of AI in smart healthcare. Our third section delves into the fundamentals of ten distinct AI use cases in smart healthcare. Finally, for each of the ten main problems that these apps face, we go over the existing fixes.

Frank, (2024) The healthcare sector is seeing a remarkable transformation as a result of AI's advanced algorithms and machine learning. This transformation is characterised by enhanced diagnostic accuracy, personalised medicines, and simplified administrative operations. Surgical procedures, patient monitoring, drug research, personalised medicine, diagnostic imaging, and medical imaging are just a few of the areas that artificial intelligence (AI) is influencing, as this study explores. Artificial intelligence's ability to comprehend intricate medical data enhances clinical decision-making, patient outcome prediction, and operational optimisation in hospitals. Decreased healthcare expenditures and diagnostic mistakes are two of AI's many advantages. Possible advancements in artificial intelligence for healthcare include robots assisting surgeons during operations, remote consultations for virtual patient care, and better health monitoring via wearable tech. Because AI enhances patient outcomes, modifies medical research, and simplifies administrative processes, it will lead to a global increase in healthcare accessibility and efficiency. In order to maximise the benefits of AI while upholding ethical standards and safeguarding patients, ongoing research and regulatory oversight are essential.

METHODOLOGY

It uses RBF-based TSVM support classification for heart disease prediction. Prior to this, we reviewed the essentials of the RBF method.

Because TSVM calculations efficiently utilise the potential of transductive adaptation, it is feasible to merge the suggested broadcast data of unlabelled instances with well-prepared tests. while compared to the normal assist vector machine approach, the grouping accuracy is improved while utilising TSVM for calculation. However, TSVM computations still have a few flaws. For TSVM computations, the unlabelled samples' number of positive name tests must be presented misleadingly, and a decent estimate of N worth could be difficult to calculate.

If we compare the ratio of positive tests to all named tests, we may get a good idea of how many unlabelled cases there are. We then utilise this ratio as an estimate of N in TSVM computations. In any case, given a small number of graded tests, it becomes more challenging to obtain a more accurate estimate of N using this technique. As the presentation of the computation degrades and the pre-set estimate of N differs significantly from the actual number of tests with positive marks, there is no way to guarantee the grouping accuracy of the TSVM calculation.

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

in conjunction with a second set of unlabelled samples obtained through the related 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:

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

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

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

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

Curriculum for TSVM

Sort the test cases by using <~w;b>. The number of test cases with the maximum value of $\vec{w} * \vec{x}_j^* + b$ find themselves enrolled in $+(\vec{y}_j^* := 1);$;

Students are given the remaining test cases to complete in class. $-+(\vec{y}_j^* := -1);$

$C_-^* := 10 - 5;//$ some small number

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

While $((C_-^* < C^*)||(C_-^* < C^*))$ {

//Loop1

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

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

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

}

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

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

}

return $(\vec{y}_1^* - \vec{y}_k^*)$;

A TSVM training algorithm mostly consists of the following:

Algorithm for training TSVM

Input: - demonstrations of skills $(\overrightarrow{x\ 1}, y1), \ldots, (\overrightarrow{x\ n}, yn)$

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

Parameters: - C, C*: OP(2) parameters

--num+: the total number of test cases that will be assigned to class+

Output: - expectations for the data samples' labels

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

Stage 1: With all the provided examples, finish the foundational learning via inductive picking up, and build a unique classifier before locating C and C*. Find a model in the unlabelled set that has a positive name and give it a projected value of N.

Stage 2: Apply the first classifier to all of the unlabelled segments to find out how much their choice capacity costs. Mark N. thinks all but one of the models that incorporate his real judging abilities are bad. Determine a C_tmp^* short-term achieve factor.

Stage 3: Retraining the support vector machine is usually the best course of action. To get the best possible estimate of the target capacity decrease for the newly built classifier, change the names of many named unlabelled representations according to a given guideline. This procedure will be repeated until no two models can be built that meet the exchange criteria.

Stage 4: Retraining the support vector machine is usually the best course of action. To get the best possible estimate of the target capacity decrease for the newly built classifier, change the names of many named unlabelled representations according to a given guideline. This procedure will be repeated until no two models can be built that meet the exchange criteria.

Use cases for the RBF-based TSVM in classification include the prediction of cardiac ailment incidence.

RESULTS

When it comes to identifying heart issues, prediction is key. On the basis of accuracy, specificity, and sensitivity, we evaluate the existing method (IT2FLS) in comparison to the proposed modified FA and RBF-SVM approach.

False Positive Rate (FPR)

How often an image's mosaic appearance belied its actual broken state.

$$FPR = \frac{FP}{FP + TN}$$

False Negative Rate (FNR)

Picture segmentation speed in comparison to the non-cancerous area.

$$FNR = \frac{FN}{FN + TP}$$

(i) Accuracy

Accurate measurement enables weighted ratio-based tumour component image segmentation. This is how it is depicted,

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} X100$$

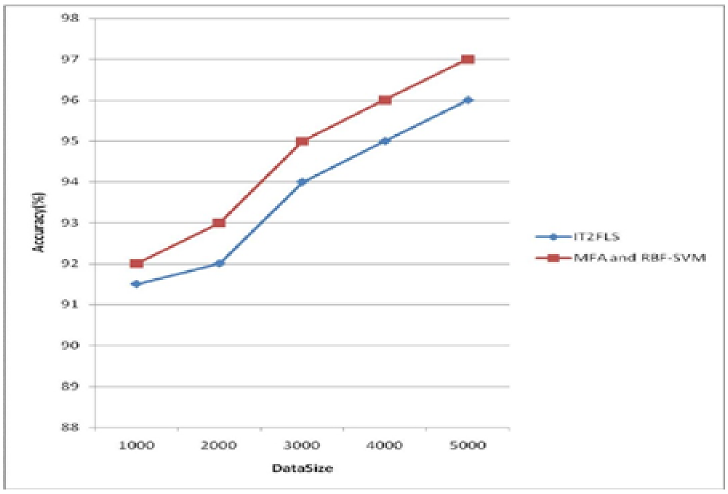

Figure 1: Accuracy

The accuracy of the proposed MFA and RBFSVM based classification technique is compared to the existing IT2FLS based methodology in the picture above. On the one hand, we have accuracy, and on the other, dataset size, represented by the X-axis. Applying MFA to decrease characteristics allowed the suggested strategy to achieve better accuracy. No matter the size of the dataset, the results show that MFA and based RBF-SVM classification methods provide good results.

(ii) Sensitivity

Many well-recognized good qualities are shown by an individual with a high level of affectability. It must identify with the test's border in order to perceive positive findings.

$$Sensitivity = \frac{numberoftruepositives}{numberoftruepositives + numberoffalsenegatives} X100$$

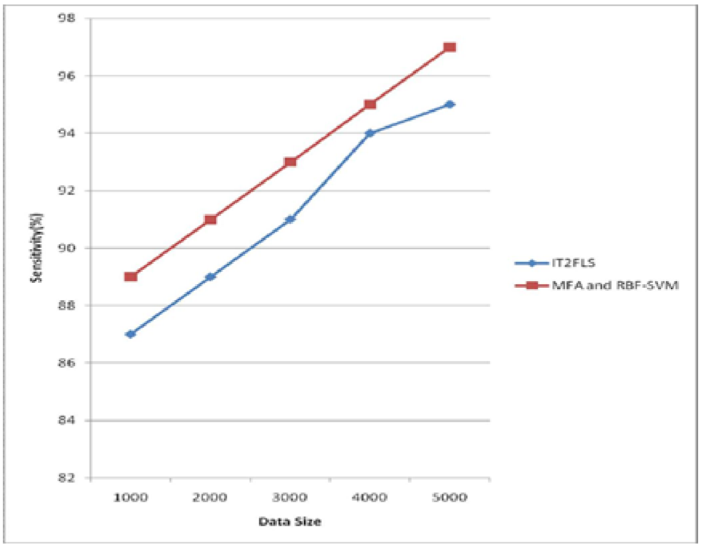

Figure 2: Sensitivity Comparison

The picture shows how the current IT2FLS based classification technique compares in terms of sensitivity to the suggested MFA and RBF-SVM based approach. On the X-axis, you can observe the size of the dataset, and on the y-axis, the sensitivity. The proposed research makes use of the min-max algorithm for normalisation in an effort to boost the system's overall performance. Also, RBF-SVM has good results when it comes to categorisation. It raises the rate of true positives. When compared to the suggested MFA and based RBF-SVM classification method, the current system demonstrated good sensitivity results across all dataset sizes.

(iii) Specificity

Examining the ratio of correctly identified negatives is one approach to find specificity. The test's ability to detect adverse outcomes is linked to it.

$$Specificity = \frac{numberoftruenegatives}{numberoftruenegatives + numberoffalsepositives} X100$$

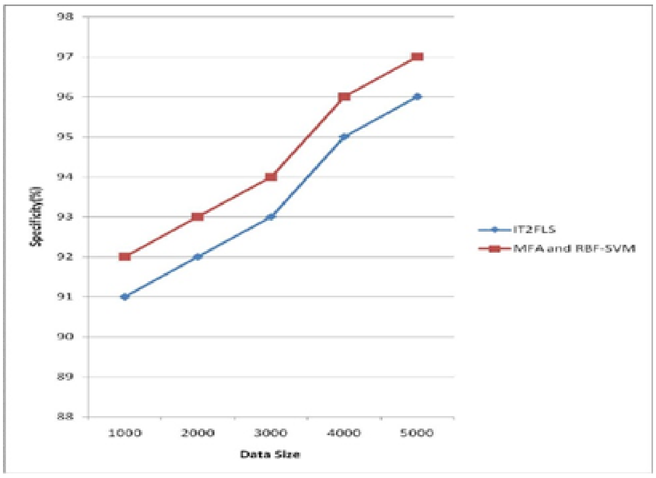

Figure 3: Examining Specificity

In terms of specificity, the following figure compares the existing IT2FLS based classification methodology to the recommended MFA and RBF-SVM based method. The x-axis shows the amount of the dataset, while the y-axis shows the specificity. On all dataset sizes, the proposed MFA and based RBF-SVM classification method outperforms the current system in terms of specificity.

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

Data Size (Bytes)	Accuracy (MFA + IT2FLS)	Accuracy (MFA + RBF-SVM)	Sensitivity (MFA + IT2FLS)	Sensitivity (MFA + RBF-SVM)	Specificity (MFA + IT2FLS)	Specificity (MFA + 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

Table 2: Comparing MFA-RBF-SVM to IT2FLS and Showing Percentage Improvement

Data Size	Accuracy	Sensitivity	Specificity
1000	0.54	2.24	1.08
2000	1.07	2.19	1.07
3000	1.05	2.15	1.06
4000	1.04	1.05	1.04
5000	1.03	2.06	1.03

These datasets were retrieved from the UCI Repository's Cleveland Heart Disease Dataset (CHDD). The thirteen characteristics that are taken into account include age, sex, type of chest pain, resting circulatory strain, serum cholesterol, fasting glucose, resting electrocardiographic results, thalach, exang, old pinnacle, slant, number of significant vessels shaded by fluoroscopy, and ST depression caused by exercise relative to rest. The database contains the information of 303 patients. In our study, we utilise these datasets.

In this work, we evaluate the sensitivity, specificity, and accuracy of the proposed PSO and RBF-TSVM technique compared to the existing system IT2FLS and modified FA and RBF-SVM.

False Positive Rate (FPR)

The fraction of instances where a cancer went undetected in a targeted picture.

$$FPR = \frac{FP}{FP+TN}$$

False Negative Rate (FNR)

Please tell me what percentage of cases the photo segmentation missed the cancer even though it was quite obvious.

$$FNR = \frac{FN}{FN + TP}$$

(i) Accuracy

By using precise measurements, it is able to correctly segment the weighted proportion of tumour components in images. The end product looks like

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

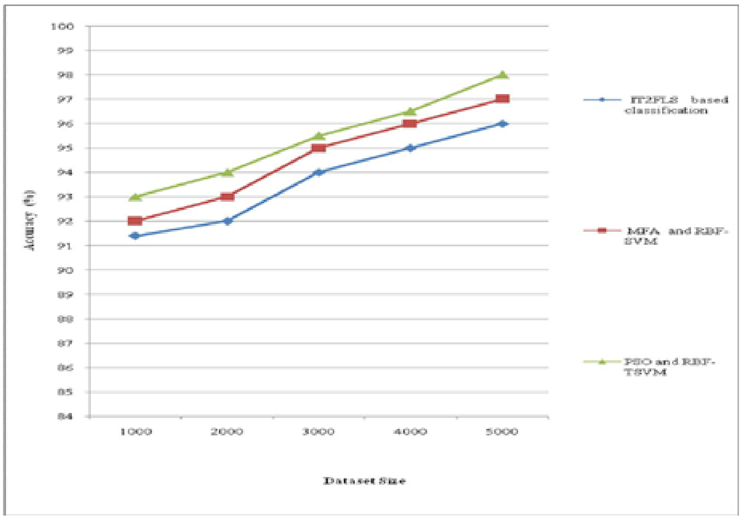

Figure 4: Accuracy Results

Shown in Figure 4.4 is a comparison of the accuracy of the current IT2FLS, MFA, and RBF-SVM based classification techniques with that of the given PSO-RBF-TSVM based methodology. Accuracy is shown on the Y-axis, while the size of the dataset is shown on the X-axis. The suggested approach employs PSO for attribute reduction to get high accuracy. Regardless of the size of the dataset, the PSO and based RBF-TSVM classification algorithms achieved far higher accuracy than the current method.

(ii) Sensitivity

Affectability is the capacity to effectively experience positive emotions. It must identify with the test's border in order to perceive positive findings.

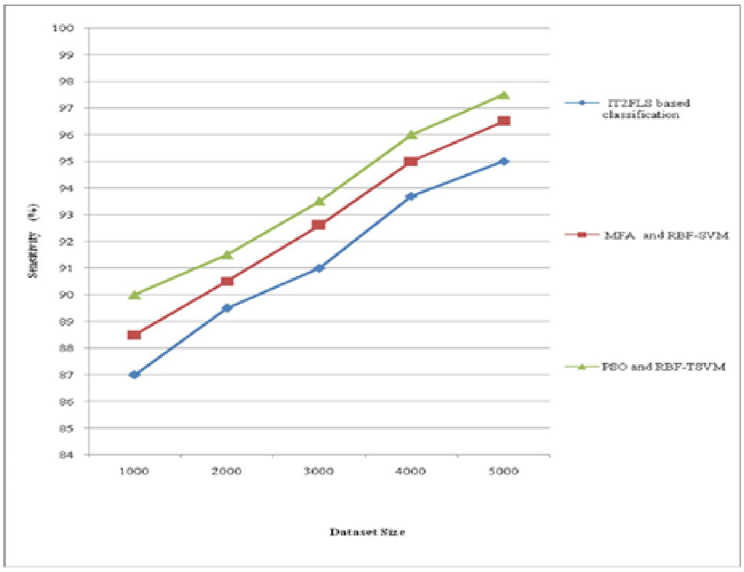

Figure 5: Results for Sensitivity

Figure 5 shows the IT2FLS, RBF-SVM, and PSO-RBF-TSVM based techniques, as well as the suggested PSO-RBF-TSVM classification method. It also shows their sensitivity findings. The sensitivity is displayed on the Y-axis and the dataset size is plotted on the X-axis. The suggested strategy improves the system's performance by applying the Z-Score normalisation procedure. In addition, RBF-TSVM is used to accomplish efficient categorisation. It raises the rate of true positives. When comparing the current system to the suggested PSO and based RBF-TSVM classification method, all dataset sizes demonstrated good sensitivity results.

CONCLUSION

Early detection, individualised treatment, and resource efficiency are three ways in which healthcare prediction systems could be transformed by using artificial intelligence (AI). Artificial intelligence systems can help detect cancer, diabetes, and cardiovascular issues in their early stages by evaluating massive volumes of patient data and discovering trends and patterns that human practitioners could miss. In addition to improving patient outcomes while decreasing healthcare costs, AI-driven solutions assist with clinical decision-making, risk assessment, and real-time monitoring. Additionally, AI has the potential to enhance diagnostic precision, personalise treatments to each patient's unique needs, and simplify administrative tasks. Nevertheless, there are still important obstacles to overcome, including data protection, ethical considerations, and the necessity of governmental supervision. To conclude, predictive healthcare systems that use AI have the potential to revolutionise the industry. However, for this technology to truly improve care delivery, patient safety, and trust in digital healthcare solutions, its responsible implementation is crucial, guided by ethical and legal frameworks.

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