AN EFFICIENT MACHINE LEARNING ALGORITHM IS BEING USED IN A RAPIDLY EXPANDING HEALTH CARE MONITORING SYSTEM.

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Abstract
The application of machine learning in healthcare also benefits patients by improving their care. Deep learning algorithms might be used to create systems that proactively monitor patients and notify medical equipment or electronic health records to changes in their status. Modern industry and daily life are increasingly adopting artificial intelligence (AI) technology, and these technologies are already making their way into the medical sector. AI has the potential to help practitioners in a variety of healthcare contexts, from front-line patient care to back-end administrative duties, where it may be utilized to improve practice and hasten the creation of novel solutions to urgent issues. Although AI and healthcare technology are widely used, there may still be significant heterogeneity in approach between different healthcare facilities. And while some publications on AI in healthcare claim that AI can perform as well as or better than humans at specific operations like disease diagnosis, it will be many years before AI in healthcare is able to fully replace people in the medical field.
Keywords: Healthcare system, AI, SVM, Machine Learning

Introduction
The use of digital technology in the healthcare sector has been hampered by persistent practical and application issues. Slow progress has been made in integrating various healthcare systems, and the majority of nations throughout the world still do not have fully integrated healthcare systems. The distinctiveness and complexity of human biology, as well as patient variability, have repeatedly shown the importance of the human component in illness diagnosis and therapy. However, developments in digital technology are undeniably becoming essential tools for healthcare professionals to provide patients with the best care possible. The advancement of data technologies, such as storage size, processing power, and data transport speeds, has enabled the broad application of machine learning in a variety of disciplines, including healthcare. Because providing effective healthcare to an individual ismultifaceted, recent medical developments have emphasized the necessity for a customized medicine or "precision medicine" approach to healthcare. The purpose of personalized medicine is to use enormous volumes of healthcare data to uncover, forecast, and analyse diagnostic decisions for each unique patient, which physicians can then execute. Genetic or family information, medical imaging data, drug combinations, population-wide patient health outcomes, and natural language processing of existing medical paperwork are examples of such data.
We will concentrate on three of the most significant uses of machine learning (ML) in the medical and biomedical areas. As a constantly expanding area, machine learning has a wide range of possible applications in healthcare, which may include auxiliary parts of the profession such as staff management, insurance policies, regulatory affairs, and much more. As a result, the concepts discussed in this chapter have been condensed down to three common machine learningapplications. The first is the use of machine learning to medical images such as MRIs, computerized axial tomography (CAT) scans, ultrasound (US) imaging, and positron emission tomography (PET) scans. These imaging techniques produce a set or series of images that must be interpreted and diagnosed by a radiologist. ML approaches are quickly improving in their ability to

anticipate and locate images that may signal a disease condition or major concern. The second is medical document natural language processing. Many healthcare professionals agree that the push toward electronic medical records (EMR) in many countries is slow, cumbersome, and, in many cases, entirely mishandled. This can occasionally result in patients receiving poorer overall healthcare. The volume of physical medical data and documentation that already exists in many hospitals and clinics is one of the biggest issues. Different formats, handwritten notes, and a multitude of incomplete or no centralized data have made the transition to electronic medical records less than efficient. The third machine learning application involves the use of human genetics to predict disease and identify disease causes. With the introduction of next-generation sequencing (NGS) tools and the explosion of genetic data, particularly massive databases of population-wide genetic information, the attempt to decipher significant information about how genetics may affect human health has risen to the top of many research agendas. Understanding how complicated diseases appear and how genetics might raise or decrease a person's risk can help with preventative healthcare. This could provide doctors more information about how to adjust a patient's care plan to lessen the likelihood of developing more complex diseases. The unifying difficulty in all three of these subjects is determining how to transfer health data obtained from the Internet of Things into understandable, relevant, and trustworthy information for patients and clinicians. How can we evaluate data with hundreds of thousands of inputs and parameters? How can we do this effectively? What is the current status of resolving this issue?

Related works

It has been proposed by Zupic and ater [15] that bibliometric methods can be used to objectively and impartially assess a line of study. Due to its reputation as a trustworthy and objective method of study analysis [16, 17], bibliometric techniques are gaining popularity among academics. In order to analyse and anticipate shifts in the field of study, bibliometrics has become increasingly important in recent years [18]. There have been more studies along these lines in the research stream examined, and they are listed in Table 1. There are notable variations in the reported scientific articles' use of keywords and examined research areas. Huang et al[19] .'s bibliometric analysis describes the use of VR in rehabilitation medicine. Patients with physical impairmentsor disabilities have their quality of life and capacity for daily activities improved via rehabilitation, as stated by the authors. Over the past few years, numerous areas of medicine have had increasing access to cutting-edge technological developments that have facilitated advances in both research and clinical practise.

Hao et al. [20] highlight the use of text mining in the field of medicine. According to the reports, text mining uncovers fresh, unforeseen information by automatically extracting data from various text resources using a computer. Essentially, text mining techniques are just data mining applied to text. The role of text mining in the healthcare industry is expanding. Data mining and machine learning (ML) are used to public health issues in the studies by dos Santos et al. [21]. This study suggests that public health can be thought of as "the science and art of keeping peoplewell and alive for as long as possible." Discovering previously unknown knowledge is one of themain goals of data mining and other machine learning approaches. Both of these papers are connected to the field of "medical big data." Big data, as defined by Liao et al. [22], is a common "buzzword" in the business and research communities and refers to a large quantity of digital data gathered from multiple sources. The medical area is a gold mine of information, and we can learn a great deal (i.e., medical big data). As a result, data mining and ML approaches can be used to process this data and yield useful insights for both patients and doctors. Recent research by Choudhury et al. [23] provides a comprehensive evaluation of ML's application to geriatric care, highlighting studies that are eligible for inclusion due to their focus on mental health and vision impairments.

The work of Tran et al. [2] examines how the field of artificial intelligence (AI) in medicine has developed around the world. Their bibliometric research sheds light on emerging themes and methods in the field of artificial intelligence. According to research by Connelly et al. [24], the number of operations performed with

robotic assistance has risen sharply in recent years. Their bibliometric research shows the widespread use of robotic surgery in domains as varied as urology, colon and rectal surgery, cardiothoracic procedures, orthopaedics, oral and maxillofacialsurgery, and neurosurgery. Additionally, the bibliometric analysis of Guo et al. [25] provides an in-depth review of AI papers through December 2019. This study explores real-world uses of AI in healthcare, providing insight into the ways in which algorithms might aid clinicians. There's a new school of thought exploring AI, too. Therefore, Choudhury and Asan's [26] research contribution provides a comprehensive analysis of the artificial intelligence literature to pinpoint potential dangers to patients' health. The authors summarise the findings of 53 research projects on the use of technology in clinical warnings, clinical reports, and drug safety. Given the significant interest in this area of study, this analysis departs in several key ways from the existing literature. Its goal is to provide in-depth analysis, with a focus on business, management,and accounting rather than just medical and health articles.
Similar studies have been conducted for several publications in various research streams [15, 16, 27], and ours intends to give a bibliometric analysis of characteristics such as authors, countries, citations, and keywords to guide future research perspectives for academics and practitioners. To do this, we turn to Scopus, a database more commonly used in the social sciences. Finally, we will suggest and talk about a dominant framework of variables in this topic; our analysis will extend beyond only descriptions of AI applications.

Artificial intelligence applications in healthcare
Medical use cases for artificial intelligence It is widely held that AI tools will serve to supplement and improve human efforts rather than displacing them. AI is prepared to help healthcare workers with a wide range of duties, including general office work, clinical documentation, patient outreach, and more specialist areas like image analysis, medical device automation, and patient monitoring. When it comes to healthcare, there is a wide range of views regarding the most fruitful uses of AI. The most significant developments in 2018 will be in administrative workflows, image analysis, robotic surgery, virtual assistants, and clinical decision support, according to Forbes [8]. Similar themes and associated data were also discussed in a 2018 research by Accenture. Recent years have seen an increase in the use of AI in healthcare, particularly with regard to 27 machines, the decrease of dosage errors, and cybersecurity [9]. McKinsey's 2019 study [10] highlights the importance of connected and cognitive devices, targeted and personalised medicine, robotics-assisted surgery, and electroceuticals. We will address some of the most important uses of artificial intelligence in healthcare in the following sections, including both clinical and nonclinical uses, such as drug discovery and ambient assisted living (AAL)

Methodology
This section describes the proposed Pima diabetes patient classification model using Decision tree and SVM. Figure 1 presents an overview of the suggested model.
Architecture diagram

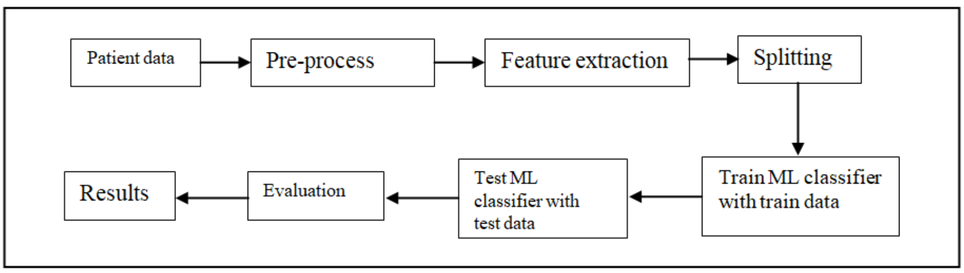

Figure 1:Methodology:

Patient data is used in the above proposed architecture for training and testing the proposed ML algorithms, which in turn improves the performance of those algorithms. The proposed algorithms in the figure above are more sensitive than some more conventional ones. Machine learning methods will be used to pre-process the input data and divide it into training and testing data using an 80:20 split, with the former serving as training data and the latter as test data. The machine learning algorithms that are developed will be trained on 80% of the available train dataand then tested on the remaining 20%. As soon as the results of the model evaluations and categorizations are shown. Only the most precise model can make reliable predictions.

Proposed Algorithm

Algorithm: Artificial medical care using machine learningInputs: medical dataset as S, prediction models M
Output: Fraud detection Results as R

a. Start
b. Input dataset(S)
c. Pre-processing (S)
d. Extract features from training set()
e. For each model m in M
f. Train the model m
g. End For
h. For each model m in M
i. Use model for testing
j. Evaluate
k. Display results
l. End For
m. End
n. Return R

As input, the suggested algorithm accepts a dataset and uses it to create a pipeline of prediction models. It uses an 80:20 split to separate the dataset into a training and testing set. After then, a series of iterations employs alternate ML models to make predictions. Various indicators are used to compare the effectiveness of the various models. Precision, recall, F1-score, and accuracy are all calculated using a model's unique confusion matrix. Fraud detection outcomes and metrics are generated by the algorithm.

Performance Evaluation Metrics

In many ML-based issues, the confusion matrix is used to derive metrics for assessing performance. Confusion matrix is commonly utilised as studied in [2], [3], [7] and [10]. Both TP and TN are right forecasts, whereas FP and FN are wrong.

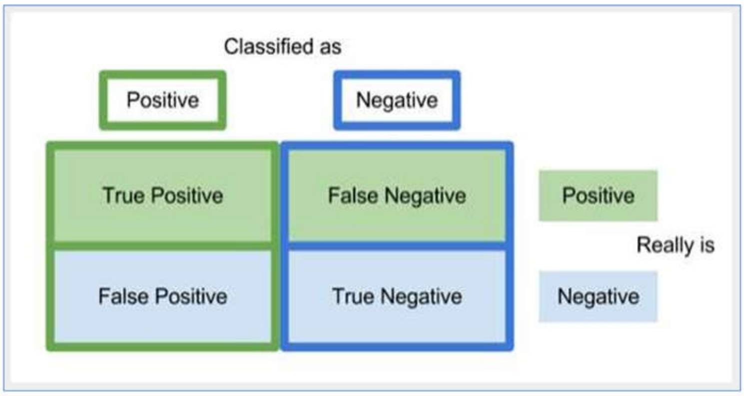

Figure 2: Confusion matrix model

Figure 3 shows how the performance metrics are calculated using various confusion matrixinstances. Performance indicators are given in Eq. (4) through Eq (7).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (5)$$

$$\text{F1-measure} = 2 * \frac{(precision * recall)}{(precision + recall)} \quad (6)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

The values of these indicators range from 0 to 1, with 0 indicating the worst potentialperformance and 1 the best. Gains in efficiency translate to greater value.

RESULTS

Model classification tables and graphs

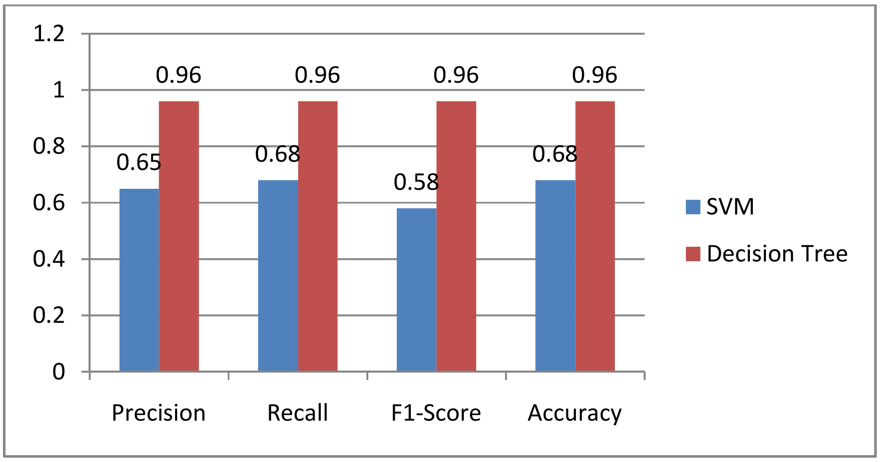

Figure.3. Performance Comparison

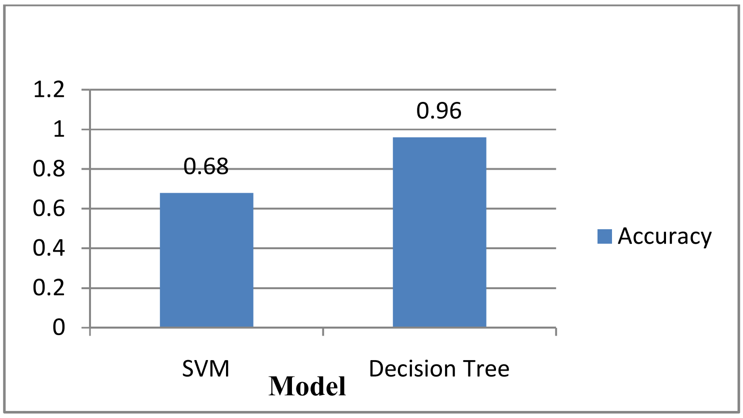

Table 4: Accuracy

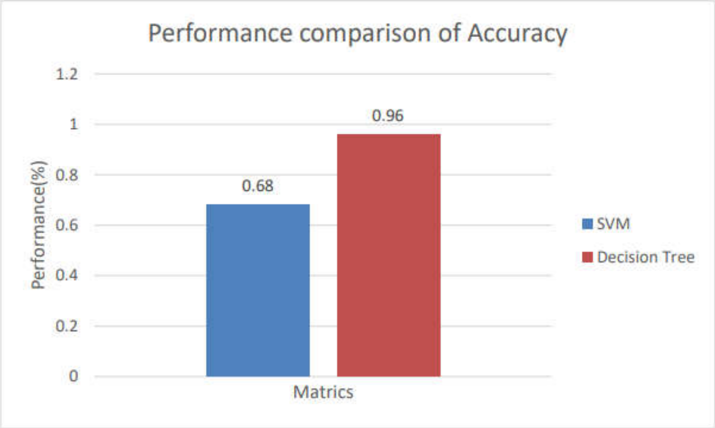

Figure 5: Accuracy

Conclusions

The use of artificial intelligence in the health services, particularly in the administration of health services, aids in medical decision-making, particularly predictive analysis in the diagnosis and treatment of patients. Although not effectively used, technology is necessary for the deployment of AI in the public health sector. The issues include not respecting the viewpoint of the user and promoting early adoption as well as sustainable implementation in the health system. The ethical issues that AI clinical applications face include those related to safety, effectiveness, privacy, information and consent, the freedom to choose, "the right to try," costs, and access, to name just a few.

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