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LUNG CANCER FORECASTING USING HYBRID OPTIMIZATION TECHNIQUE

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Abstract: Lungs are body's oxygen delivery system, controlling the in and out of breath. They also act as air filters, decreasing the potential for dust or germs to enter the lungs. The lungs have natural defences to keep them safe. Nonetheless, they are insufficient to wholly avert the development of a number of lung illnesses. The lungs are vulnerable to infection, inflammation, and possibly the development of a malignant tumor. In this study, we used ML methods to create accurate models for forecasting lung cancer occurrence and progression, so that those at high risk may receive treatment sooner rather than later. In this paper, we propose a hybrid LSTM that outperforms the state-of-the-art models using standard metrics as precision, F-Measure, recall, & accuracy. In particular, experimental assessment demonstrated that the suggested model was superior with a 98.3% accuracy, F-Measure, precision, recall.

Keywords: healthcare; prediction; lung cancer; data analysis; machine learning.

I. INTRODUCTION

Lungs play a key role in the process of breathing. Lungs are found on both sides of the human chest. Because of the heart's need for more space, reduced size of left lung. The lungs' job is to bring oxygen into bloodstream. The heart pumps O_2-poor, CO_2-rich blood to the lungs. CO_2 is exhaled as we breathe out, and O_2 is taken in when we inhale [1,2]. In addition, when we inhale, air travels via the nasal cavity, and bronchi in that sequence to finally reach the lungs. The alveoli are the tiny air sacs that may be found at the end of the bronchial tree within the lungs. The alveoli have an abnormally high concentration of capillaries that exchange carbon dioxide for oxygen. Since oxygen in the blood is what keeps us alive, we can't stop breathing until we die [2].

In addition, bronchi & bronchioles are permanently damaged by asthma. Due to airway constriction, the most prominent symptoms of asthma are shortness of breath wheezing [3]. Tuberculosis is a bacterial illness that mostly manifests in the lungs. Inflammation and subsequent tissue destruction in the lungs are caused by these bacteria [4]. Last but not least, pneumonia is a broad term for group of disorders that result from infections of the lungs by a wide variety of microorganisms, bacteria, & fungi [5].

The use of ML and AI techniques is rapidly expanding in the medical industry. Given the widespread use of AI/ML in risk prediction for many health diseases, as stated in [6,7], it is crucial to evaluate and support practical development of software tools based on AI/ML for early prediction and diagnosis of sickness. Illnesses such as diabetes hypertension [10], COVID-19 [11], hypercholesterolemia [12], COPD [13], systemic lupus erythematosus [17], chronic kidney disease. Lung cancer is of interest for the purposes of this investigation. Many research investigations on this illness have been conducted using an ML approach. Here, we offer a way for developing accurate ML classification models that use prevalent behaviors and symptoms/signs as input characteristics to predict lung cancer incidence. Our contribution is a comprehensive evaluation of several classifiers, allowing us to create a model with optimal sensitivity and discrimination for detecting high-risk individuals. F-Measure, recall, Precision, & accuracy were taken into account as performance criteria for assessing the models. Figure 1 depicts the health care ecosystem.

1.1 Applications of technology in healthcare

There are a variety of ways through which technology may be used to improve healthcare.

- Electronic medical records storage and retrieval
- Fears regarding the safety of medical records have been allayed.
- health information handling
- Genome management in the clinic
- Monitoring the Information Contained Within
- Electronic health records

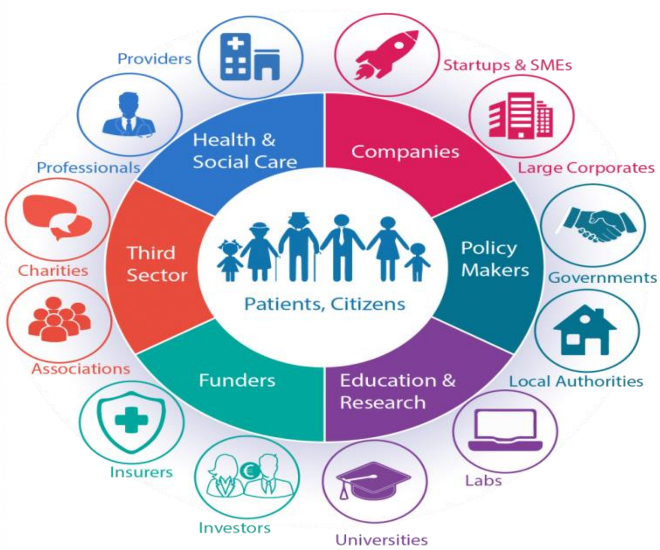

Fig. 1: Healthcare Ecosystem

At the moment, electronic health records are restricted to the use of a single company or network, which prevents the owners of those EHRs from upgrading them or sharing them with anybody else. It's possible that the information will be arranged in this fashion, with non-PHI or PII data being stored in the blockchain's initial few blocks (PII). It's possible that in the future, researchers and corporations may have access to populations numbering in the millions. Modern health care systems are dealing with potentially severe ramifications for the reporting of public health data, data on safety, and data on clinical research. These systems also allow switching of patients between providers without any disruption to their care. It is possible, in theory, for people and institutions to share a private key in order to decrypt blockchain-stored medical information and then transmit those records to one another. Because of this, there is a possibility that the capability of HIT to collaborate and interoperate will rise.

Such systems are required for better, more affordable and more efficient treatment for patients. The medical records of patients might be stored in a centralized database that is regularly updated by personnel with the appropriate permissions. Errors may be prevented in many situations if various physicians who were working on the same patient did not communicate information with one another. Because of this, patients could get more customized treatment as a result.

Electronic medical records that are compatible with one another are managed in health care system. As long as the blockchain continues to utilize the same data set and maintains safe encrypted linkages to supplemental data, it will be possible to make a single layer of transactions accessible. Keeping devices connected to networks could be easier if smart contracts and consistent permission procedures are used.

1.2 Machine learning

"Learning" approaches, or procedures that use data to improve performance on a set of tasks, are the primary focus of ML research. Common agreement exists that this is a component of AI. ML algorithms need training data to construct a model from which they may draw conclusions or make predictions. Computer vision, speech recognition, email filtering, and other fields all use machine learning algorithms when it is impractical or impossible to develop custom algorithms to do necessary tasks. Statistical learning is just one subset of ML, but the discipline is nevertheless strongly tied to CS, which is all about using computers to make predictions. The field of machine learning may benefit from the theoretical frameworks, practical applications, and analytical tools developed via study of mathematical optimization. Data mining is an interrelated field that employs unsupervised learning for exploratory study of large datasets. Some machine learning programmes use information and NN in ways that are quite similar to the way the human brain operates. Predictive analytics is another name for machine learning, and it is increasingly being used to solve problems in business.

1.3 Role of Machine learning for health care

ML, a subfield of AI technology, aspires to improve healthcare processes by improving efficiency and accuracy. This study is evaluating the need for ML in healthcare. The work highlights and explores the key ML for Healthcare applications. Research is looking into the use of ML-based technologies to provide different treatment options, individualized care and boost the efficiency of healthcare systems as a whole. Clinical DSS, disease diagnosis, and other applications of ML in healthcare will be more important in the future, and establishing individualized treatment plans to achieve the best results.

1.4 Optimization

Quantitative issues in physics, biology, & business are all amenable to the optimization framework of mathematical concepts and methodologies that is also known as mathematical programming. Finding the best possible answer to a design challenge is what optimization is all about, and this often means balancing competing needs. Just a few of the many possible and desirable targets for improvement include productivity, strength, reliability, lifetime, efficiency, and utilization.Proposed model would make use of optimization mechanism in order to get best or prioritized data from health care data before training and testing operations.

The remainder of this paper is organized as follows: Section IIcovers the related work, Section III introduces the proposed methodology, Section IV presents the performance evaluation of the proposed system and section V discusses the conclusion.

II. RELATED WORK

Machine learning techniques are being utilized to improve the lives of patients, as discussed by Toh *et al*. (2021), who focused on the massive volumes of data made accessible by the IoT in the area of healthcare. The application of these techniques presents both novel and challenging possibilities. The medical industry makes extensive use of machine learning, particularly in the fields of GI, MI, and NLP of medical literature. Many of these disciplines depend critically on our capacity to diagnose, detect, & predict consequences. In the present day, a vast network of medical devices creates data, but the necessary infrastructure is frequently lacking to make good use of this data. Medical data comes in a wide variety of formats, which may make it difficult to format and analyze, and can also lead to an increase in background noise. In this article, we take a look at the present status of ML in healthcare, as well as its short history and certain fundamentals. [21]

Ozaydin *et al*. (2021) introduced use of ML (a branch of AI) in healthcare has been expanding rapidly in recent years, it was important to utilize the technology responsibly. This article delves into some of the most common objections to ML methods and provides solutions for dealing with issues including bias including but not limited to "black box" systems, & model performance tracking. ML techniques may be applicable to some of these issues. In order to reap the benefits of ML while minimizing its risks, they advocate for more physician engagement in the development, evaluation, and continuous monitoring of ML applications in healthcare.[22]

Ghassemi *et al*. (2020) presented reviews on the barriers and potential in medical ML at the Microsoft Research Toronto Lab. In order to answer questions with clinical significance, modern EHRs collect data that may be analyzed in a variety of ways. With more and more information stored in EHRs, healthcare is an ideal setting to use machine learning. The adoption of standard machine learning techniques, however, is made more difficult by the specific problems of clinical learning. Diseases in EHRs, for instance, are often mislabeled; illnesses may have more than one underlying endotype;

healthy people are underrepresented. This essay is meant as a primer, shedding light on these difficulties and pointing out ways in which the machine learning community might make important contributions to the medical field [23].

Char *et al.* (2018) developed clinically useful models for ML. health care and the use of ML If we want to reap the advantages of machine learning in healthcare, they must first address the ethical concerns that arise from its use [24].

Nisar *et al*. (2021) introduced deep learning in healthcare: prospects, pitfalls, and emerging solutions. In this paper, we'll look at how deep learning is being put to use in various areas of medicine, such as the diagnosis of mental health issues, lymph node metastases from breast cancer, and more. Conditions affecting the brain, heart, or lungs are classified here. After summarizing the studies in each group, comparison tables are drawn up using key criteria. Models for DL draw on a broad range of resources, including software, hardware, techniques, and data. Finally, we discuss future research directions and current obstacles for deep learning models [25].

Seneviratne *et al*. (2020) provided filled up the gaps in healthcare machine learning application. The performance of machine learning applications on clinical data has recently surpassed that of human doctors. 1–3 Since convolutional neural networks are so effective, standard data formats are in place, and there are large data repositories, This trend has been spearheaded by experts in the departments of radiography, pathology, and dermatology. Highly accurate diagnostic and prediction algorithms have been developed with the use of EHR, -omics, and patient-generated data. 4 Editorials with titles like "The AI Doctor Will See You Now" demonstrate how much the public is concerned about the impending extinction of doctors. 5 The consensus among academics is more nuanced: AI-using physicians will eventually replace their human counterparts.[26]

Wiring *et al*. (2020) looked the role of AI in medical care. Many people believe that AI and ML-based technologies have the ability to radically alter the healthcare system by extracting previously unknown information from the mountains of data created by the everyday provision of medical treatment. The use of these innovations is anticipated to vastly enhance the standard of care provided to patients. The legal and regulatory environment is crucial to the expansion of AI and ML-based technologies. In this chapter, they will discuss what artificial intelligence (AI) is, how it functions, and the potential advantages it may offer to the fields of life sciences and healthcare. Different applications of AI in healthcare, such as diagnostics, clinical trials, and surgical robots, are discussed. In addition to a comprehensive overview of the main legal challenges associated with use of AI in healthcare, this chapter offers solutions to these problems. These problems include the overall regulatory framework, product liability issues, intellectual property rights protection, and reimbursement issues [27].

The authors carried on their studies on the benefits of health data sharing and AI applications [28, 29]. In healthcare and clinical note analysis [30, 31], several researchers thought about using automated ML and DL for predictive analysis [32-34].

III. PROPOSED METHODOLOGY

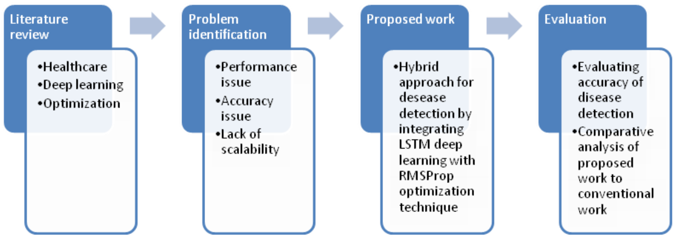

Fig. 2: Proposed Methodology

Proposed work is focused on investigating role of optimization in machine learning for health Care application. Initially existing research related to proposed work would be considered such as Healthcare, deep learning, optimization. Then issues with existing research are considered. Figure 2 depicts these steps. Problem in conventional work related to health care is slow performance and lack of accuracy. Moreover there is need to introduce scalable mechanism. Then optimization mechanism is used to get optimized data in order to eliminate the less significant health care data. Such elimination would resolve the performance and accuracy issues of disease detection. Finally accuracy of proposed work is evaluated and compared to convention mechanism in order assure the reliability of model.

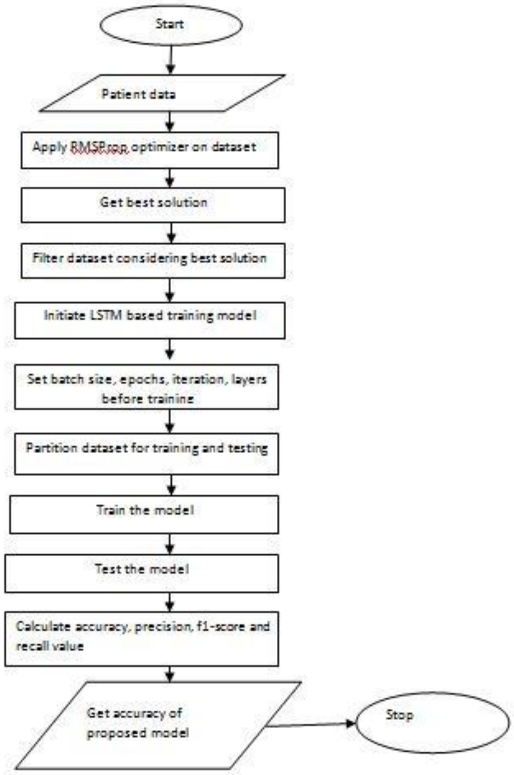

Fig. 3: Proposed work Flow Chart

Above process flow of proposed work flow chart (in Figure 3) shows patient's data is collected, then we apply RMSProp optimization technique on the collected dataset. We get the best optimized solution through this optimization technique. Then, we filter the dataset by eliminating unused columns. Here, we used hybrid LSTM based model for the training. Then also we set various parameters like batch size, epochs, iteration, layers before training. Then we partition the dataset into 80:20 for training and testing. After the prediction it calculates, accuracy, precision, f1-score and recall value. Through this we get overall accuracy of the proposed model.

IV. RESULTS AND DISCUSSION

Several ML models, including NB, BayesNet, LR, KNN,RF, RT, SGD, SVM, J48, RepTree, ANN, LMT, RotF, and AdaBoostM1, are compared in this study to determine which provides the best prediction performance. In particular, Table 1 displays our evaluation of models' efficacy in light of SMOTE and 10-fold cross-validation. With an accuracy of 98.3 percent, LSTM model provides the best performance. In Table 2, we have compared the results with our reference paper table [35] and we got the accuracy equal to 98.3%. This model makes LSTM is the best proposed approach.

Table 1: Performance evaluation after SMOTE with 10-fold cross validation.

	Accuracy	Precision	Recall	F-Measure
NB	0.949	0.949	0.949	0.949
BayesNet	0.949	0.949	0.949	0.949
SGD	0.959	0.959	0.959	0.959
SVM	0.953	0.953	0.953	0.953
LR	0.962	0.962	0.962	0.962
ANN	0.945	0.945	0.945	0.945
3NN	0.959	0.958	0.958	0.958
J48	0.947	0.947	0.947	0.947
LMT	0.958	0.958	0.958	0.958
RF	0.951	0.951	0.951	0.951
RT	0.932	0.932	0.932	0.932
DT(Rep Tree)	0.936	0.936	0.936	0.936
RotF	0.970	0.970	0.970	0.970
AdaBoostM1	0.953	0.953	0.953	0.953
LSTM	**0.982**	**0.982**	**0.982**	**0.982**

Data set

Knowing one's cancer risk at minimal cost and being able to make informed decisions based on one's cancer risk status are both made possible by an effective cancer prediction system. The information comes from an online lung cancer prediction system hosted on a website.

Total attributes:16

Instances:284

Attribute information:

1. Gender: M(male), F(female)
2. Age: Age of the patient
3. Smoking: YES=2 , NO=1.
4. Yellow fingers: YES=2 , NO=1.
5. Anxiety: YES=2 , NO=1.
6. Peer_pressure: YES=2 , NO=1.
7. Chronic Disease: YES=2 , NO=1.
8. Fatigue: YES=2 , NO=1.
9. Allergy: YES=2 , NO=1.
10. Wheezing: YES=2 , NO=1.
11. Alcohol: YES=2 , NO=1.
12. Coughing: YES=2 , NO=1.
13. Shortness of Breath: YES=2 , NO=1.
14. Swallowing Difficulty: YES=2 , NO=1.
15. Chest pain: YES=2 , NO=1.
16. Lung Cancer: YES , NO.

Simulation results

There l= loss, a= accuracy

Epoch 1/20

8/8 [==] - 9s 337ms/st - l: 0.5443 - a: 0.8016 - v_l: 0.2361 - v_a: 0.9677

Epoch 2/20

8/8 [==] - 2s 200ms/st - l: 0.4089 - a: 0.8502 - v_l: 0.1624 - v_a: 0.9677

Epoch 3/20

8/8 [==] - 1s 115ms/st - l: 0.3908 - a: 0.8502 - v_l: 0.2690 - v_a: 0.9677

Epoch 4/20

8/8 [==] - 1s 101ms/st - l: 0.3853 - a: 0.8502 - v_l: 0.2744 - v_l: 0.9677

Epoch 5/20

8/8 [==] - 1s 102ms/st - l: 0.3582 - l: 0.8502 - v_l: 0.1566 - v_a: 0.9677

Epoch 6/20

8/8 [==] - 1s 99ms/st - l: 0.3494 - a: 0.8502 - v_l: 0.1721 - v_a: 0.9677

Epoch 7/20

8/8 [==] - 1s 102ms/st - l: 0.3245 - a: 0.8502 - v_l: 0.3240 - v_a: 0.9677

Epoch 8/20

8/8 [==] - 1s 99ms/st - l: 0.3138 - a: 0.8623 - v_l: 0.1246 - v_a: 0.9677

Epoch 9/20

8/8 [==] - 1s 102ms/st - l: 0.3048 - a: 0.8462 - v_l: 0.1339 - v_a: 0.9677

Epoch 10/20

8/8 [==] - 1s 101ms/st - l: 0.3038 - a: 0.8623 - v_l: 0.1133 - v_a: 0.9677

Epoch 11/20

8/8 [==] - 1s 102ms/st - l: 0.2820 - a: 0.8664 - v_l: 0.1801 - v_a: 0.9839

Epoch 12/20

8/8 [==] - 1s 101ms/st - l: 0.2736 - a: 0.9028 - v_l: 0.1234 - v_a: 0.9839

Epoch 13/20

8/8 [==] - 1s 107ms/st - l: 0.2641 - a: 0.8988 - v_l: 0.1069 - v_a: 0.9677

Epoch 14/20

8/8 [==] - 1s 105ms/st - l: 0.2627 - a: 0.8907 - v_l: 0.1065 - v_a: 0.9839

Epoch 15/20

8/8 [==] - 1s 136ms/st - l: 0.2301 - a: 0.8947 - v_l: 0.1002 - v_a: 0.9839

Epoch 16/20

8/8 [==] - 1s 188ms/st - l: 0.2562 - a: 0.9150 - v_l: 0.1007 - v_a: 0.9839

Epoch 17/20

8/8 [==] - 1s 139ms/st - l: 0.2526 - a: 0.9028 - v_l: 0.1158 - v_a: 0.9839

Epoch 18/20

8/8 [==] - 1s 100ms/st - l: 0.2390 - a: 0.9069 - v_l: 0.1005 - v_a: 0.9839

Epoch 19/20

8/8 [==] - 1s 104ms/st - l: 0.2397 - a: 0.8988 - v_l: 0.2808 - v_a: 0.8065
Epoch 20/20
8/8 [==] - 1s 102ms/st - l: 0.2545 - a: 0.8907 - v_l: 0.1397 - v_a: 0.9839
2/2 [==] - 0s 28ms/st - l: 0.1397 - a: 0.9839
a: 0.9838709831237793
2/2 [==] - 1s 30ms/step

Confusion matrix:
[[1 1]
[0 60]]

Table 2: Classification report

Parameter	Precision	Recall	f1-score	support
0	1.00	0.50	0.67	2
1	0.98	1.00	0.99	60
Accuracy			0.98	62
Macro avg.	0.99	0.75	0.83	62
Weighted avg.	0.98	0.98	0.98	62

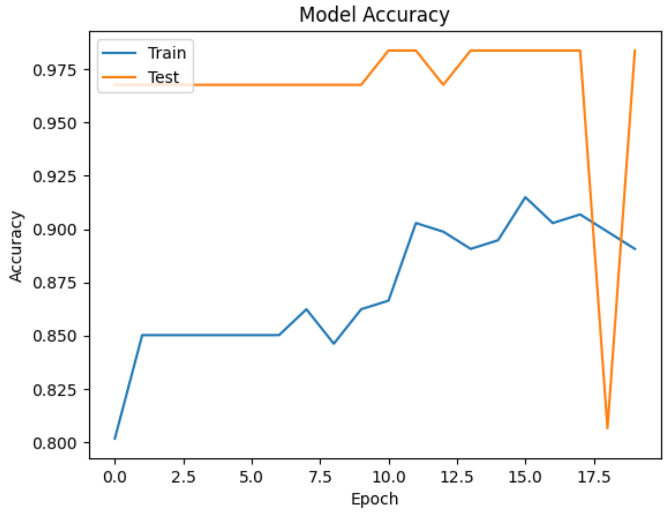

Fig. 4: Model accuracy

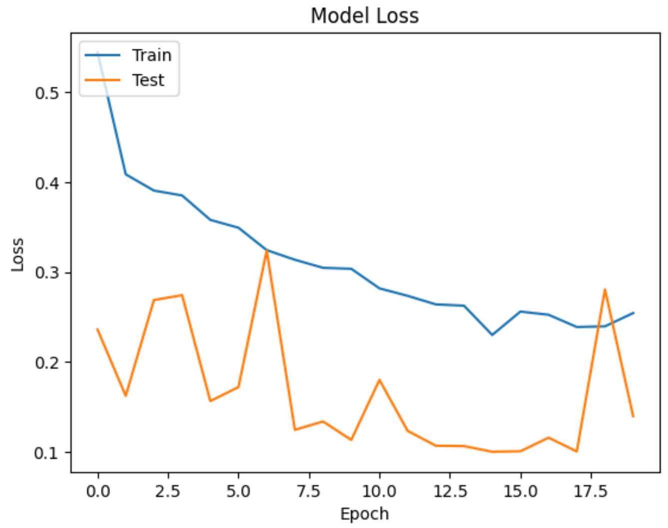

Fig. 5: Model loss

Figure 4 depicts the proposed model accuracy is above 97% and Figure 5 shows proposed model has the less loss.

V. CONCLUSION

ML applications are having a profound effect on the medical field. ML, a subfield of AI, aspires to improve healthcare by enhancing both its speed and accuracy. Countries that are currently experiencing difficulties with overcrowding in their healthcare systems and a lack of physicians will benefit greatly from AI. Ideal research sample may be selected with the use of healthcare data, which can also be utilized for further data collection, reviewing existing data from trial participants, and correcting mistakes. The early warning symptoms of an epidemic or pandemic may be detected with the use of ML-based approaches. This technology examines satellite data, news & SMR, and EVS to determine whether the disease might potentially spiral out of control. The application of ML to the healthcare sector has the potential to bring about a sea change. As a result, medical staff may spend more time caring for patients and less time entering data or searching for it. This paper explores the use of ML in healthcare and then goes on to describe its characteristics and how it would best serve a healthcare institution's foundational tenets. Finally, it summarized the most important medical uses of machine learning. This technology's potential use in healthcare operations may provide significant benefits for the organization. Treatment options & healthcare expenses are all areas where ML-based solutions are being applied to enhance outcomes. Hospitals and other medical facilities will soon experience ML's impact. Optimal results will need the development of clinical DSS, illness diagnosis tools, and individualized treatment approaches.

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