ISSN:0048-2706 E-ISSN:2227-9199

DATA ANALYTICS AND ARTIFICIAL INTELLIGENCE (AI): IOT DATA: DATA ANALYTICS AND AI APPLICATIONS, PROVIDING INSIGHTS INTO PATIENT TRENDS, TREATMENT EFFICACY, AND POPULATION HEALTH

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ABSTRACT
Internet of Things (IoT) systems may now generate data at a dizzying rate, thanks to the proliferation of sensors and smart gadgets. To enable diverse IoT services and functions, IoT systems often process, transform, and analyze huge volumes of data. Data analytics using Machine Learning (ML) techniques have proven effective for the Internet of Things (IoT). There is a huge need for skilled data scientists because there are still numerous obstacles to overcome when applying ML models to data analytics jobs related to the Internet of Things (IoT), such as successful model selection, design/tuning, and updating.In this paper, we extend the potential of AI-enabled IoT healthcare to theorize how AI and IoT can make preventative public health services more accessible and help us move from a reactive to a proactive, continuous, and coordinated system of secondary and tertiary healthcare. The Internet of Things (IoT) and artificial intelligence (AI) also aid in achieving responsibility and satisfaction by encouraging patients to work more closely with their healthcare providers. On top of that, there are a lot of ways in which the Internet of Things (IoT) may improve healthcare delivery, including the ability to better anticipate health problems, diagnose them, treat them, and keep tabs on patients both inside and outside of hospitals. In this research, we use artificial intelligence and the internet of things to survey the healthcare industry's problems and potential solutions in a nutshell. It also gives a general idea of what artificial intelligence and the internet of things are, how they work, what the present trends are, what the future holds, and the difficulties faced by healthcare systems.

1. INTRODUCTION
Health care communities, businesses, governments, and universities are all paying close attention to "smart health care" as a result of developments in cloud computing, things technology, smart multiple sensory media (MulSeMedia) systems, and other related fields. A more realistic vision of a smarter world, complete with numerous services and vast amounts of data, has just emerged thanks to the Internet of Things (IoT) [1]. Machine learning algorithms developed by artificial intelligence (AI) companies have also attracted a lot of interest in the wake of the COVID-19 pandemic as a means to improve healthcare delivery. Nonetheless, as previously mentioned in the literature, new opportunities may arise when AI and IoT meet. Smart health care can greatly benefit from AI-driven IoT because it can improve our understanding of individual patients' health records, which in turn can help us provide high-quality, cost-effective treatment [2]. Even if individual "things" can't offer real-time automated medical decision-making, AI-driven IoT might allow for massive volumes of data streams from the network to be stored and processed. Researchers have made great strides in understanding the potential of AI and the Internet of things (IoT) to improve healthcare, but the privacy and security concerns raised by these technologies have received comparatively less focus. While the AI-driven Internet of Things (IoT) has the potential to transform many areas of the healthcare sector, certain technological hurdles must be cleared before this vision can come to fruition [3].

Security measures for the AI-driven Internet of Things (AIIoT), such as authentication, access control, security models, and privacy concerns, are the focus of this study. There has long been substantial worry about security concerns related to the Internet of Things due to the large amount of data associated with the numerous devices connected to the internet. Security in smart healthcare and medical equipment driven by artificial intelligence (AIIoT) is the topic of this essay. This essay defines Internet of Things (IoT) security, compares AI-driven IoT (AIIoT) security issues to those of network and information or traditional cybersecurity, explains the various approaches to IoT security, and concludes with a list of security measures that should be implemented to address AIIoT security issues. Because AI-driven IoT (AIIoT) is so closely tied to IT and communication, experts say it's wise to think about privacy and security issues that are well-known in the field of information security and see how they apply to AIIoT now and in the future [4]. Despite claims in the literature that AI-driven IoT (AIIoT) presents unique privacy and security concerns, few research have looked at the actual problems with health care IoT security and privacy. The situation necessitates more examination. The present research will be highly beneficial, as this finding explains. In light of the importance of AI-driven Internet of Things (IoT) in smart health care, this article provides a synopsis of the problems and issues surrounding AIIoT as it relates to smart health care systems.

2. LITERATURE REVIEW

In the past, medical professionals treated patients based on their own experiences and the little data at their disposal. These days, it's possible to get a complete picture of a patient's health because to the abundance of data available from many sources. The application of cutting-edge technology over this data also allows for the delivery of correct care by providing access to the right information at the right time and place [5]. Given that one wrong move in healthcare might result in fatal consequences, this is of the highest significance [1]. A considerable portion of healthcare data is unstructured. This includes both static data from sources like patient records and diagnostic images and reports and dynamic data from sources like bedside monitors or remote patient monitoring. Due to the complexity and dynamic nature of the data, it exceeds the capabilities of conventional analytical tools [6]. Processing this data with big data analytics and AI can yield valuable insights that could be life-saving for patients. As an additional benefit, this technology has the ability to analyze illness trends and monitor epidemics, which could greatly enhance public health management [7].

Big data analytics and AI are not only changing the way patients are cared for, but they are also being used in medical research and the life sciences. New avenues for the development of therapeutic interventions become apparent when molecular data analysis is performed [6]. Another chance to progress customized treatment arises when clinical and genetic data is integrated and analyzed. By using predictive analytical models to omics data, we may find genetic disease indicators, create and test new medications, and determine how well they work [8, 9]. As a supplement to Randomized Controlled Trials (RCTs), Big-data Clinical Trials (BCTs) make a huge data sample available to researchers in the field of clinical research [10]. Thus, researchers can now use advanced data analytics and machine learning techniques to formulate hypotheses based on data analysis, plan prospective clinical trials, analyze trial effects, and identify product risks and adverse effects before they are made available for use [7], [12], [13].

Research and practice in healthcare have begun to focus more on these new methods due to their enormous potential for bettering healthcare quality. Big data analytics and AI have made some strides in the healthcare industry, however there is a lack of cohesion in the published literature. A systematic mapping research was conducted to gain a comprehensive grasp of the potential of these technologies in healthcare. There is a wealth of varied and extensive literature in this field, hence a systematic mapping study is considered suitable [14-20]. This work presents the findings of a mapping study by surveying the literature on the topic and offering a visual summary of the key points [21-30].

3. ROLE OF DATA ANALYTICS IN IOT

Data analytics plays a crucial role in the Internet of Things (IoT) since it provides the foundation for making sense of the massive amounts of data produced by IoT devices. In data analytics, the goal is to find useful patterns, trends, and information by gathering, processing, and analyzing data. The term "Internet of Things" (IoT) refers to the network of interconnected computing devices, sensors, and systems that generate vast amounts of data. Some important things to know about data analytics in the internet of things are these:

- **Data Transformation:** Streams of raw data are continuously generated by IoT devices. Data analytics takes all this raw data and makes sense of it in a systematic way. Preparing data for analysis requires cleaning, aggregating, and arranging it. In order to get useful insights, this step is necessary.
- **Real-time Monitoring and Decision-making:** Real-time answers are frequently needed for IoT applications. With data analytics, we can keep an eye on IoT data in real-time, so we can spot any suspicious patterns or outliers that need fixing right away. In cases such as predictive maintenance in industrial IoT for healthcare monitoring, this feature is vital.
- **Predictive and Prescriptive Analytics:** When it comes to the Internet of Things, data analytics don't stop at descriptive statistics. It consists of two parts: predictive analytics and prescriptive analytics. The former examines past data to make predictions about the future, while the latter proposes changes to the data in order to get better results. Predictive analytics in smart agriculture, for instance, can tell farmers when crop diseases are likely to strike, while prescriptive analytics can advise them on how to best water their crops.
- **Cost Reduction and Efficiency:** Organizations can optimize operations by evaluating data from the Internet of Things (IoT). Saving money, making better use of resources, and increasing productivity are all possible outcomes of this. One sector that can benefit from data analytics is logistics, where it can aid in route optimization and fuel consumption reduction.
- **Enhancing User Experience:** When it comes to consumer IoT, data analytics is key for better user experiences. To illustrate how analytics may improve everyday life, consider a smart house. By learning user

preferences, these systems can adapt heating, lighting, and security to suit the user's needs.

3.1 Key Technologies Driving the Intersection

The technology components that are crucial to the convergence of the Internet of Things (IoT) and data analytics are highlighted in the section on "Key Technologies Driving the Intersection" of your blueprint. For a deeper dive into the highlighted technologies, here it is.

Edge Computing

- **Definition and importance in IoT and Data Analytics:** Instead of depending entirely on centralized cloud servers, edge computing moves data processing closer to the source, which in this case is Internet of Things devices. Because it enhances real-time data processing and decreases latency, it is essential in the IoT. Thanks to edge computing, data analytics can process incoming data much more quickly.
- **Examples of edge computing in IoT applications:** Some real-world applications of edge computing include autonomous vehicles making split-second choices based on real-time sensor data processing and industrial sensors in manufacturing plants optimizing operations through local analytics.

Artificial Intelligence (AI) and Machine Learning (ML)

- **Role of AI and ML in analyzing IoT data:** Show how algorithms powered by artificial intelligence and machine learning can sort through mountains of data generated by the internet of things (IoT) to find patterns, insights, and forecasts. They have the ability to detect outliers, base choices on data, and automate processes.
- **Enhancing decision-making through predictive analytics:** Using past data to foretell what's to come, businesses and organizations may optimize their operations and deal with problems ahead of time with the help of AI and ML. Predictive maintenance in the IoT, for instance, can foretell when machines will break down, cutting down on repairs and downtime.

4. MATERIALS AND METHODOLOGY

The interconnection of billions of physical devices that can gather and exchange data via the Internet is what the Internet of Things is all about. To form the Internet of Things (IoT), various sensors and software work together. Devices that are physically located in different locations, as well as mobile devices and others, can communicate with one another through the use of wireless communication mechanisms. When it comes to improving healthcare models, the Internet of Things is king. Numerous sensors, both internal and exterior to the body, are utilized to gather data from patients. Internal data is collected via sensors implanted in the body, while external and ambient data is collected by the everlasting sensor. In order to forecast illness, doctors examine the received data. In order to distinguish between healthy and sick individuals, the created model makes use of a number of machine learning classification techniques. Early and accurate illness prediction is achieved by machine learning classifiers. The proposed model makes use of the Internet of Things to gather three types of patient data:

1. Domestic patient data: In this data set, patients are using inexpensive, widely available Internet of Things (IoT) devices. In order to process the patient's health data, these IoT sensors gather it and transmit it to an IoT agent.
2. Clinical or laboratory patient data: In this scenario, patients visit clinics and laboratories, but there are no available doctors who are concerned, despite the availability of all necessary resources. The patients' data was collected by the medical support staff.

Thirdly, information about patients who are located in remote areas: these patients may be residing in areas that are quite distant from hospitals. In order to provide better care, doctors can use data collected from patients' Internet of Things (IoT) sensors, which are transmitted to them in real-time.

Any Internet of Things (IoT) device can then transmit the collected data to a fog server for additional analysis. Using classification techniques, the fog server examines the data. The data is transmitted to a server in the cloud, where it is stored, and then used by doctors to make an early diagnosis of the patient. Due to the fact that AI applications such as Decision Tree (DT), Support Vector Machine (SVM), Naïve Bayes (NB), Adaboost (AB), Random Forest (RF), Artificial Neural Network (ANN), and K-Nearest Neighbor (K-NN) are being developed for use in healthcare models, their implementation is a matter of concern. Data sets from the UCI machine learning repository system are used to apply these algorithms. The datasets include information about cardiovascular illness, diabetes, hepatitis, dermatology, thyroid, breast cancer, and liver disorders.

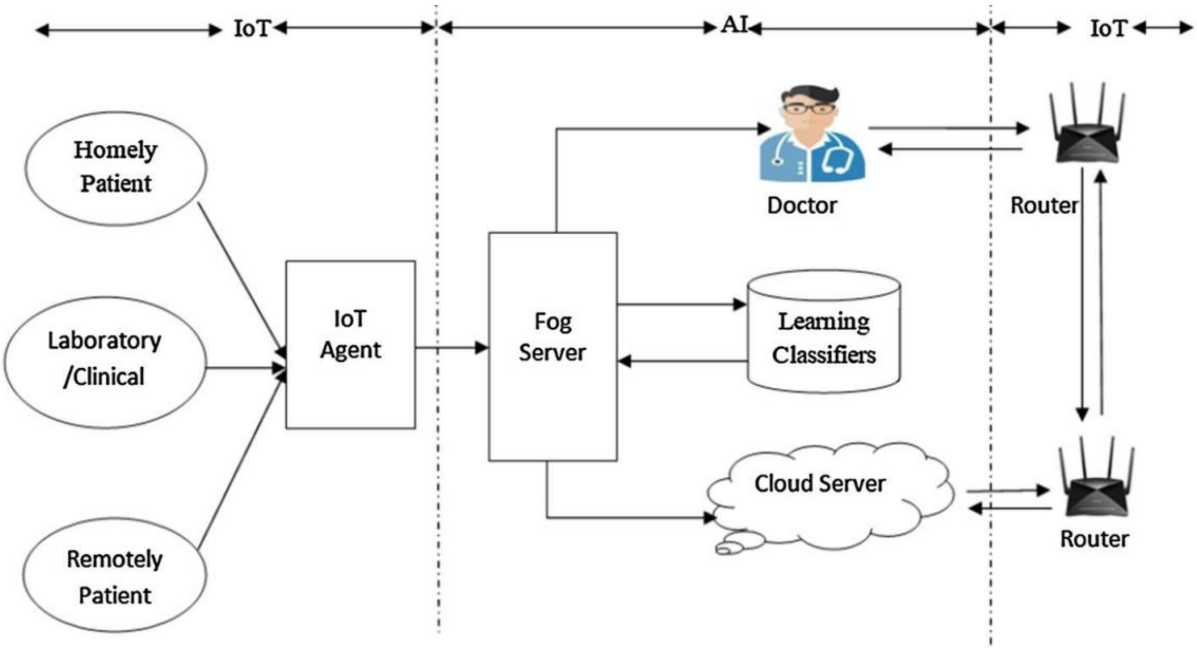

Fig. 1. The architecture of the proposed AI and IoT based healthcare model

The suggested system model's architecture is shown in Figure 1. The proposed model heavily relies on AI and the Internet of Things. As a starting point, the Internet of Things (IoT) is utilized to link all objects to the web. It takes in patient information in real-time, processes it, and sends it on to the care provider immediately. Second, artificial intelligence (AI) processes these data sets to deliver results promptly. AI and the Internet of Things efficiently manage massive amounts of data.

4.1 Working of a proposed system model

There are three distinct stages of the project. Data collection is the first step, followed by pre-processing and computing. The results are then saved in the cloud and made visible to clinicians or end-users in the third phase.

4.2 Collection of data

Here, information about patients is gathered from various places, including their homes, labs, clinics, and even distant databases. In order to gather patient data in real-time, a variety of sensors and Internet of Things devices are utilized. Individuals residing in their homes are outfitted with the necessary sensors. The laboratory technicians are responsible for transmitting clinical and laboratory data to the Internet of Things agent. Patients in distant locations use specialized sensors. These sensors gather information, which is then transmitted to the IoT agent for additional processing.

4.3 Pre-processing and computation of data

Filtering and checking for missing values are part of the pre-processing steps for the supplied data. After the preliminary processing is finished, the data is transmitted to the fog server to be computed. The data is being computed and classified using seven machine learning classifiers in this case, including DT, SVM, NB, AB, RF, ANN, and K-NN.

4.4 Decision Tree (DT)

Data mining (DT) is a method for classifying data using supervised machine learning. Leaf, internal-nodes (branch), and non-leaf are the three types of nodes utilized in a structure-like tree. The conditional probabilities are evaluated using these three nodes, which serve as distinct properties. Class labels are determined by leaf nodes, which are located at the very top of the tree; test decisions are derived from branch nodes, which are further down the tree. The nodes in the DT that are not leaves represent the test. The decision tree method does not necessitate domain knowledge. Not to mention how much easier it is to manage and understand numerical and categorical data. Performance, on the other hand, is dataset dependent and has a single output attribute limit.

5. RESULTS AND DISCUSSION

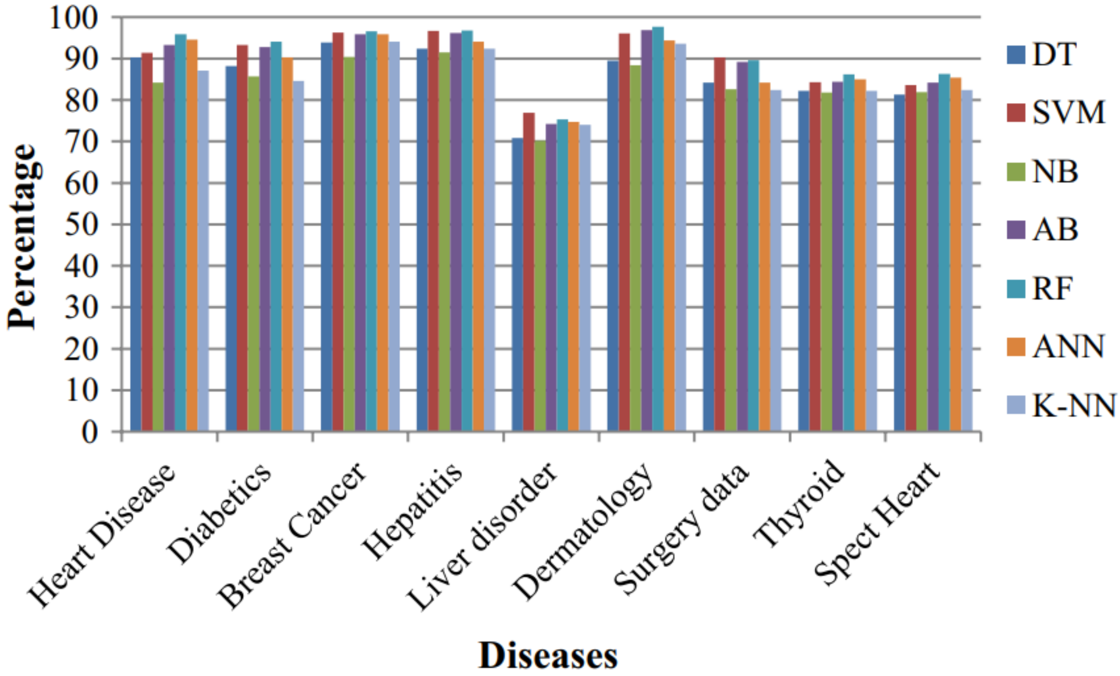

Fig. 2 Accuracy of the seven classifers for diferent disease

The seven classification methods are shown in Figure 2, which provides a visual comparison of their accuracy with respect to a different disease. The RF classifier is the most accurate disease predictor in the majority of instances. A huge number of DTs make up an RF classifier. The voting strategy's results are provided by the RF classifier. This is why, when contrasted with other classification algorithms, the RF classifier consistently produces superior results.

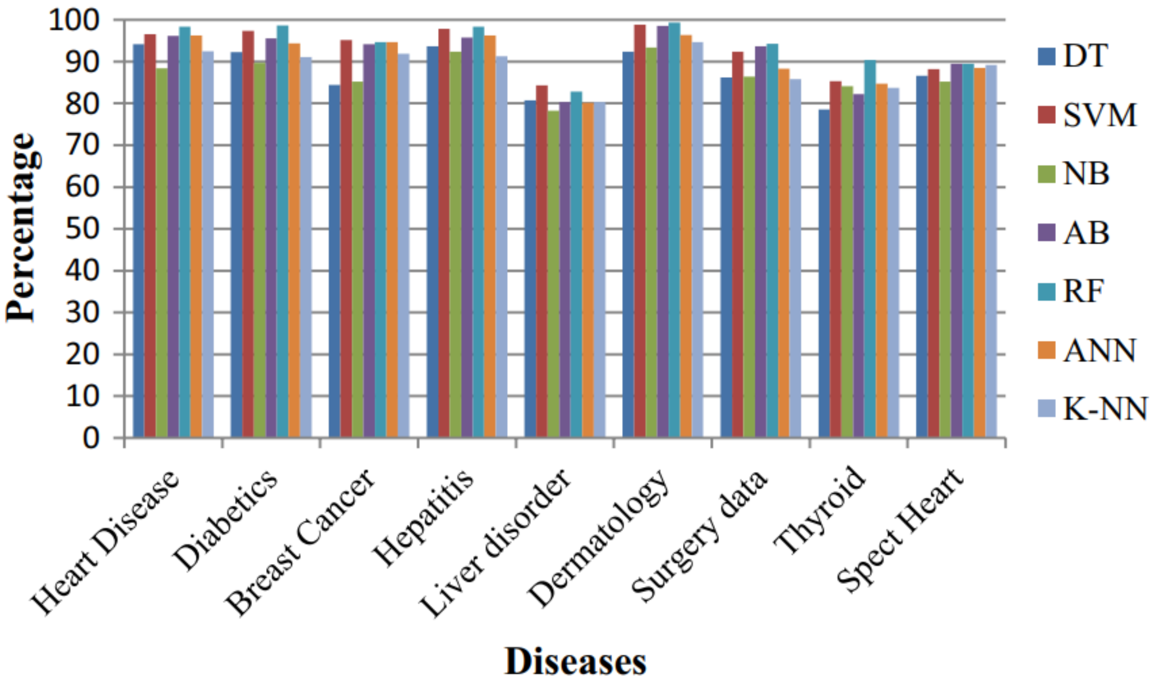

Fig. 3 Sensitivity of the seven classifiers for different disease

As shown in Figure 3, the created model compares the sensitivity of seven classifiers for different diseases.

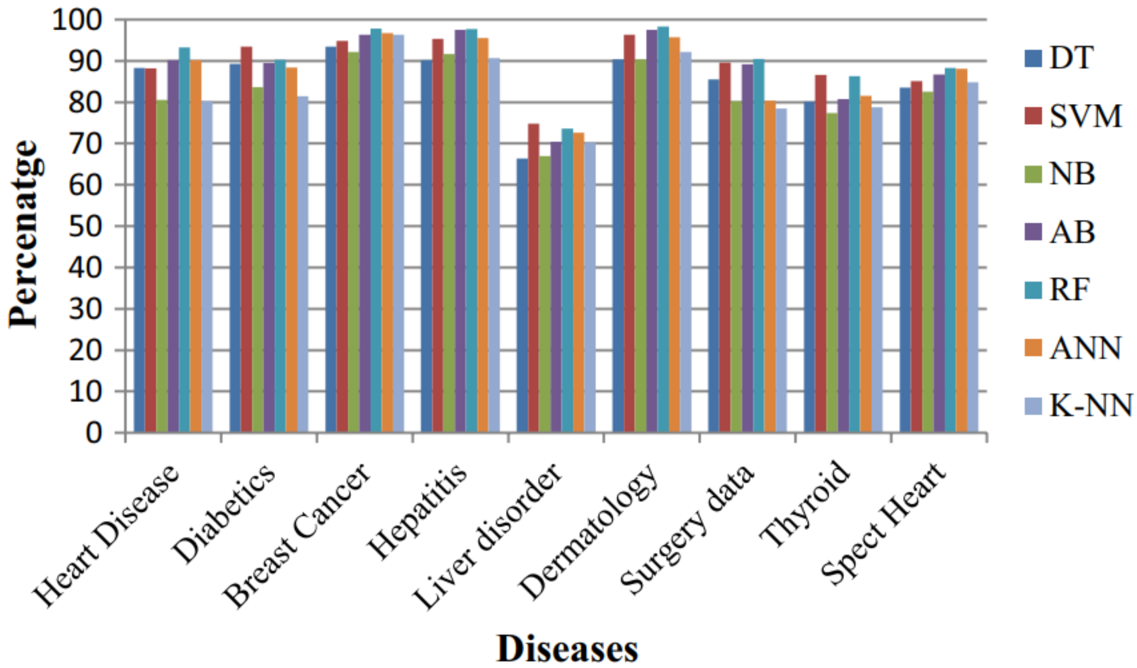

Fig. 4Specificity of the seven classifiers for different disease

Figure 4 shows the generated model's seven classifiers side-by-side in terms of the specificity they acquired for various diseases.

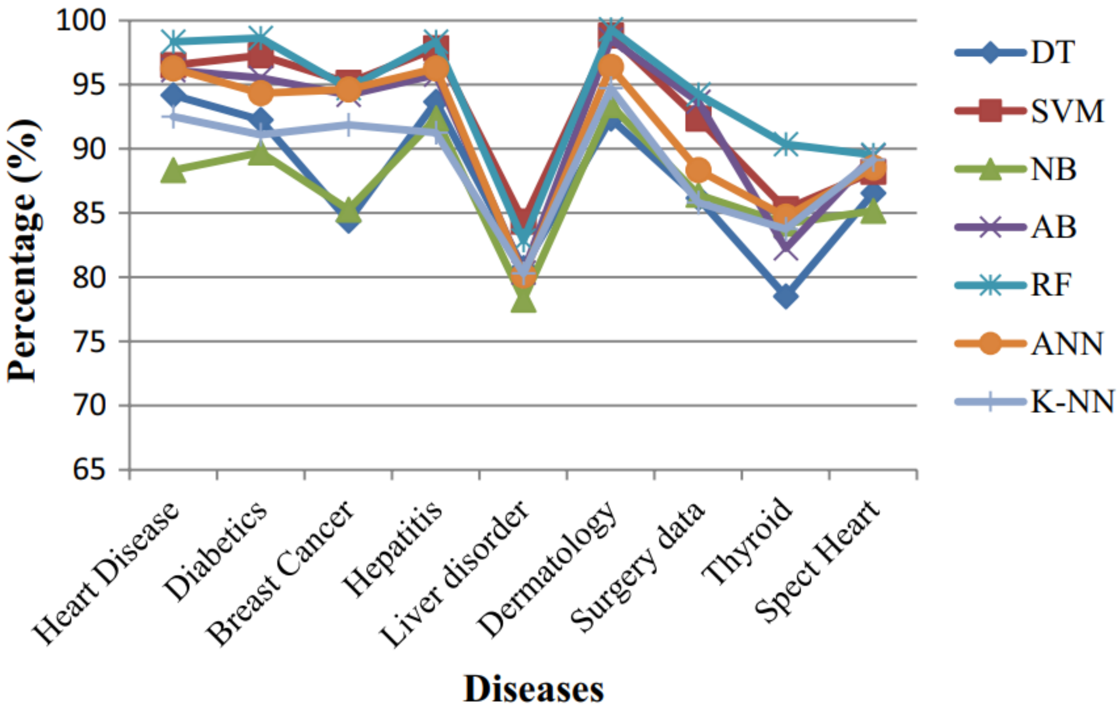

Fig. 5 AUC of the seven classifiers with different disease

Figure 5 is a graphical representation of the seven classifiers' AUC values for various diseases in the created model, showing how they compare to one another.

CONCLUSION

As a result, there are numerous security and privacy issues, in addition to pertinent needs, that must be resolved, as it is clear that the AI-driven IoT frameworks utilized in smart medical devices are extremely vulnerable to various data breaches. While much of the current research on AI-driven IoT has been on authentication and access control protocols, it is crucial to incorporate other new networking protocols as technology advances. An expanding field in the globe is the implementation of machine learning classification algorithms for the prediction of diseases. One healthcare model was built in this suggested study using seven different classification algorithms: DT, SVM, NB, AB, RF, ANN, and K-NN. A variety of disease datasets, including those pertaining to cardiovascular disease, diabetes, breast cancer, hepatitis, liver disorders, dermatology, surgery, thyroid, and spectral heart, are trained using these classifiers. The accuracy, sensitivity, specifcity, and area under the curve (AUC) are the four measures used to assess the classifiers' efficacy. While the NB classifier achieves a minimum accuracy of 70.11 percent, the constructed healthcare model attains a maximum accuracy of 97.62 percent for the condition.

REFERENCES

1. C. Butpheng, K.-H. Yeh, H. XiongSecurity and privacy in IoT-cloud-based e-health systems—a comprehensive reviewSymmetry, 12 (7) (Jul. 2020), p. 1191, 10.3390/sym12071191
2. F. Firouzi, B. Farahani, M. Barzegari, M. Daneshmand AI-driven data monetization: the other face of data in IoT-based smart and connected healthIEEE Internet Things J. (2020), 10.1109/JIOT.2020.3027971
3. M. Wang, T. Zhu, T. Zhang, J. Zhang, S. Yu, W. Zhou Security and privacy in 6G networks: new areas and new challengesDigital CommunNetw, 6 (3) (2020), pp. 281-291
4. H. Kim, J. Ben-Othman, L. Mokdad, J. Son, C. LiResearch challenges and security threats to AI-driven 5G virtual emotion applications using autonomous vehicles, drones, and smart devices6IEEE network, vol. 34 (Nov/Dec 2020), pp. 288-294, 10.1109/MNET.011.2000245
5. B. Kayyali, D. Knott, S. Van Kuiken The big-data revolution in US health care: accelerating value and innovation McKinsey Co. (2013), pp. 1-6, 10.1145/2537052.2537073
6. F.F. Costa Big data in biomedicine Drug Discov. Today., 19 (2014), pp. 433-440, 10.1016/j.drudis.2013.10.012
7. Knowledgent, Big data analytics in life sciences and healthcare : an overview (2016).
8. D. Gutierrez, InsideBIGDATA Guide to Healthcare & Life Sciences, DellEMC and INTEL, 2016. http://en.community.dell.com/cfs-file/__key/telligent-evolution-components-attachments/13-4431-00-00-20-44-33-27/FINAL-White-Paper-insideBIGDATA-Guide-to-Healthcare-and-Life-Sciences.pdf?forcedownload=true.
9. B. Chen, A.J. Butte Leveraging big data to transform target selection and drug discovery Clin. Pharmacol. Ther., 99 (2016), pp. 285-297, 10.1002/cpt.318
10. R. Harpaz, W. DuMochel, N.H. Shah Big data and adverse drug reaction detection Clin. Pharmacol. Ther., 99 (2016), pp. 268-270, 10.1002/cpt.302
11. C.A. Hudis Big data: are large prospective randomized trials obsolete in the future? Breast, 24 (2015), pp. S15-S18, 10.1016/j.breast.2015.07.005
12. D. Alemayehu, M.L. Berger Big Data: transforming drug development and health policy decision making Heal. Serv. Outcomes Res. Methodol., 16 (2016), pp. 92-102, 10.1007/s10742-016-0144-x
13. S.D. Wang Opportunities and challenges of clinical research in the big-data era: from RCT to BCT J. Thorac. Dis., 5 (2013), pp. 721-723, 10.3978/j.issn.2072-1439.2013.06.24
14. B. Kitchenham, S. Charters Guidelines for performing Systematic Literature reviews in Software Engineering Version 2.3 Engineering, 45 (2007), p. 1051, 10.1145/1134285.1134500
15. K. Petersen, R. Feldt, Systematic mapping studies in software engineering, …Conference Eval. …., 2008, http://robertfeldt.net/publications/petersen_ease08_sysmap_studies_in_se.pd
16. Dash, B., Sharma, P., Ansari, M. F., & Swayamsiddha, S. (2022). A review of ONDC's digital warfare in India taking on the e-commerce giants. International Journal of Engineering & Technology, 11(2), 96-99.
17. Dash, B., Ansari, M. F., & Sharma, P. (2022a). FUTURE READY BANKING WITH SMART CONTRACTS-CBDC AND IMPACT ON THE INDIAN ECONOMY.
18. Ansari, M. F., Dash, B., Sharma, P., &Yathiraju, N. (2022a). The Impact and Limitations of Artificial Intelligence in Cybersecurity: A Literature Review. International Journal of Advanced Research in Computer and Communication Engineering, 11(9), 81-90.
19. R Pulimamidi, GP Buddha, AI-Enabled Health Systems: Transforming Personalized Medicine And Wellness, Tuijin Jishu/Journal of Propulsion Technology 44 (3), 4520-4526.
20. GP Buddha, SP Kumar, CMR Reddy, Electronic system for authorization and use of cross-linked resource instruments, US Patent App. 17/203,879.
21. R Pulimamidi, P Ravichandran, Connected Health: Revolutionizing Patient Care Through Artificial Intelligence Innovations, Tuijin Jishu/Journal of Propulsion Technology 44 (3), 3940-3947.
22. R Pulimamidi, P Ravichandran, Enhancing Healthcare Delivery: AI Applications In Remote Patient Monitoring, Tuijin Jishu/Journal of Propulsion Technology 44 (3), 3948-3954.
23. Naga Simhadri, TNVR Swamy, Awareness among teaching on Artificial Intelligence (AI) and Machine learning (ML) applications based on fuzzy in education sector at USA, Soft Computing, Pages 1-9, 2023.
24. N Simhadri Apparao Polireddi, J Kavitha, Effectiveness of automated chatbots for operational support and self-service based on fuzzy classifier for ASD, Soft Computing, Pages 1-8. 2023.
25. Naga Simhadri Apparao Polireddi, K Chaitanya, Web accessibility evaluation of private and government websites for people with disabilities through fuzzy classifier in the USA, Soft Computing, Pages 1-9. 2023.
26. R Thatikonda, SA Vaddadi, PRR Arnepalli, A Padthe, Securing biomedical databases based on fuzzy method through blockchain technology, Soft Computing, 1-9

27. Satyajit Panigrahy, Bibhu Dash, Ramya Thatikonda, From Data Mess to Data Mesh: Solution for Futuristic Self-Serve Platforms, International Journal of Advanced Research in Computer and Communication Engineering, Volume 12, Issue 4.
28. Ramya Thatikonda, Adithya Padthe, Srinivas Aditya Vaddadi, Pandu Ranga Rao Arnepalli, Effective Secure Data Agreement Approach-based cloud storage for a healthcare organization, International Journal of Smart Sensor and Adhoc Network, Pp 60-70.
29. Ramya Manikyam, J. Todd McDonald, William R. Mahoney, Todd R. Andel, and Samuel H. Russ. 2016.Comparing the effectiveness of commercial obfuscators against MATE attacks. In Proceedings of the 6th Workshop on Software Security, Protection, and Reverse Engineering (SSPREW'16)
30. R. Manikyam. 2019.Program protection using software based hardware abstraction.Ph.D. Dissertation.University of South Alabama