



Machine Learning Techniques for Big Data Analysis in Healthcare: A Review

Ahmed Tawfiq Jamil¹, Mohammed R. Al-Qassab², Jameel Al-Naffakh³

¹General Directorate of Education Najaf Iraq, ^{2,3}Mechanical Power Department

¹Iraqi Ministry of Education, ^{2,3}AL-Furat Al-Awsat Technical University

alahmedtawfiq@gmail.com

Abstract

Machine learning (ML) has become a crucial tool in analyzing big data within the healthcare domain, offering predictive capabilities, personalized treatments, and enhanced decision-making processes. This review systematically examines the latest ML techniques applied to big data analysis in healthcare, including supervised and unsupervised learning, deep learning, and ensemble methods. We analyze the advantages and limitations of these approaches and their effectiveness in improving patient outcomes, diagnosing diseases, and optimizing resource allocation. Furthermore, we highlight key challenges such as data privacy, model interpretability, and computational efficiency. This paper provides a comparative assessment of ML-based healthcare solutions, offering insights into future research directions and best practices for integrating ML in real-world medical applications.

Keywords: Machine Learning, Big Data, Healthcare Analytics, Predictive Modeling, Deep Learning and Data Privacy.

Nomenclature	
Abbreviation	Definition
AI	Artificial Intelligence
AEs	Auto-Encoders
BMF	Bayesian Model Fusion
BSA	Battery Smoothing Algorithm
CKD	Chronic Kidney Disease
CNN	Convolutional Neural Network



DL	Deep Learning
EHRs	Electronic Health Records
ECG	Electrocardiogram
E-Ciouds	Electronic Cloud
EDs	Emergency Departments
H-IoT	Healthcare Internet of Things
IoMT	Internet Of Medical Things
IT	Information Technology
IoT	Internet Of Things
LR	Logistic Regression
KNN	K-Nearest Neighbor
ML	Machine Learning
M-QoS	Medical Quality of Service
MRI	Magnetic Resonance Imaging
NB	Naive Bayes
PD	Parkinson's Disease
PMR	Peak Mean Ratio
QoS	High Fault Tolerance
RF	Random Forest
RNN	Recurrent Neural Networks
RPN	Reverse Polish Notation
SDN	Software Defined Networks
SD	Standard Deviation
SVM	Support Vector Machines
W-RCA	Window-based Rate Control Algorithm

1. Introduction

Many healthcare operations have been developed over the past few decades to improve many fields of medicine as a result of recent trends and advancements in information technology [1], which have allowed for novel electronic healthcare and artificial exploration. Connected, perceiving, and communicative gadgets form the IoT (Internet of Things). Insight into past struggles shows how IoT bias has wreaked havoc on biomedical operations [2]. These IoT devices have the potential to play a crucial role in the development of automated medical data



collection systems [3], because of the vast amounts of biomedical data they are capable of creating. When Internet of Things (IoT) detectors are combined with cutting-edge machine learning (ML) algorithms for diagnosis, treatment, and decision-making, big data becomes an essential part of improving these healthcare systems. As the Internet of Things (IoT) has become more integral to biomedical operations, the scope exploration has broadened to include not just signature cures but also case monitoring and surveillance [4]. The advent of miniature detectors in healthcare that can cover cases' vital signs in real time holds great promise for the early opinion and treatment of patients [5]. Wearable widgets, detectors, and other connected gadgets have given medical translators access to a lot of patient health data. However, translators in the healthcare sector cannot fully benefit from this knowledge unless efficient information processing mechanisms are in place. In Healthcare Internet of Things (H-IoT), data generated by IoT bias is gathered, saved, analyzed, and disseminated. Vital signs, including blood pressure, heart rate, and oxygen saturation, may be tracked alongside a patient's activity level, sleep schedule, and medication adherence. Some potential applications for this information include early disease detection, remote case monitoring, and individualized treatment regimens [6]. Data gathering is the initial stage of information recycling for the Internet of Things. Connected gadgets, including detectors and wearables, gather data. The data is then transferred to a remote data repository, such as Pall. The database must be able to hold a huge quantity of data and be available from several places in order for medical practitioners to access it from any location. The data warehouse is followed by analysis in the following step. Judges utilize sophisticated algorithms to discover trends and patterns in the data. Changes in vital signs, unusual patient gestation, and impending health difficulties are all examples. Data may also be anatomized using machine learning and artificial intelligence to discover health hazards. Data dispersion is the last step in information processing for H-IoT [7]. Data must be supplied to medical care providers in an understandable format. Graphs and maps are two examples of data visualizations that may be used to show interesting patterns and trends in data. A major change in a patient's health state may result in warnings and professional medical dispatches. The mind sponge idea was developed in response to the rise of H-IoT bias,

which generates a stream of data that healthcare interpreters may find difficult to use. According to this theory (Mind Sponge), clinicians must be able to "soak up" and interpret data in order to make educated choices and increase the quality of care they deliver to customers. To do this, we may use sophisticated analytics and machine-literate algorithms to interpret the data and determine the data that is most important for croakers [8]. It is important to note that this approach leverages the potential of IoT data to improve healthcare decision-making and patient outcomes, healthcare practitioners may be able to improve patient issues and the general level of treatment [8]. IoT security concerns are expected to gradually worsen as a result of the

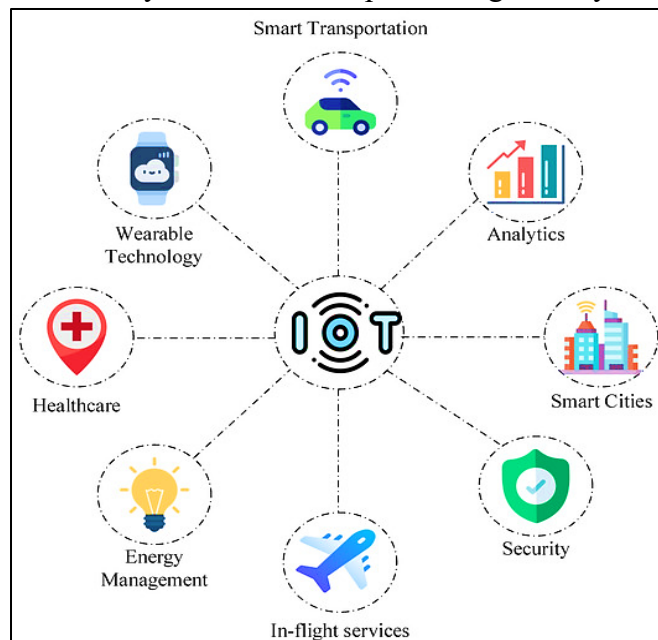


Fig. 1: The innovative capabilities of the Hybrid Internet of Things (H-IoT) technology are examined within the specific context of a healthcare setting [9].

fast deployment and broad use of IoT technologies. The introduction of H-IoT presents serious security issues since data breaches might result in deaths, making it a crucial issue. The specific characteristics of H-IoT in a medical environment are shown in Figure 1. Diabetes patients are given identity cards that may be scanned and linked to a cloud-based network that stores electronic health records (EHRs), medications, notable test results, and records of medical history. With the implementation of this system, nurses, doctors, and other healthcare professionals will have better access to medical records through a variety of electronic devices,



including tablets, laptops, and desktop computers [9]. It has been acknowledged as a big endeavor to strike a balance between comfort and security while exchanging personal health information, which is made more difficult by the presence of many security regulations and access control systems.

It's great to see that there are several cryptographic platforms available, such as blockchain, big data, software-defined networks, edge computing, and artificial intelligence, that are working towards solving this issue. The development of the Internet of Things (IoT) in healthcare is keeping pace with other technological advancements. The integration of blockchain, big data, software-defined networks, edge computing, and artificial intelligence in H-IoT has the potential to bring about positive changes in the industry, including greater data security, efficiency, and accuracy, as well as new and enhanced diagnostic and therapeutic alternatives [9]. Although adopting these technologies may require specialized knowledge and investment, it is possible to overcome these challenges and reap the benefits they offer [10]. It's exciting to see how data ownership and accountability laws and regulations are continually developing. Although dealing with and analyzing large datasets may be challenging, they present an opportunity for growth and innovation. Furthermore, some H-IoT applications may be a great match for edge computing, and with the right hardware and software infrastructure, they can be successfully implemented. While setting up and maintaining the necessary infrastructure for H-IoT can be costly, there are solutions and strategies available to overcome this hurdle and make it a viable option. Although the price of Internet of Things (IoT) devices, sensors, and wearables may seem high, there are many benefits to integrating them with current healthcare systems that make the investment worthwhile. Furthermore, the increasing use of IoT devices in healthcare may create new job opportunities for data analysts and IT specialists. Lastly, it's important to consider the ongoing maintenance costs, but with proper planning and budgeting, you can easily manage expenses like battery replacement, software updates, and new gadget purchases. Although healthcare providers with a tight budget may face challenges, there are still ways to manage costs effectively. Hence, by carefully examining the costs and advantages of H-IoT technology, one can make informed decisions regarding substantial investments.



Vuong et al. explored the issue of "near-suicide," where people face financial difficulties and discontinue lifesaving medical care. Through the use of BMF analytics, researchers analyzed data from 1042 Vietnamese patients and discovered that patients who received treatment were less likely to have severe illnesses that would have a significant impact on their family's finances. Remote patient monitoring, wearables, predictive analytics, and smart hospitals are just a few examples of how the H-IoT sector is revolutionizing healthcare with cutting-edge innovations [11]. There is optimism that health outcomes, diagnostic times, and patient engagement may all be enhanced by combining AI with telemedicine. With the ability to integrate cutting-edge medical devices with IoT technology, use health data for strategic planning, and create individualized treatment plans, the future of H-IoT systems seems promising. For H-IoT to be used effectively and securely, it is essential that users' data be kept private and safe.

High fault tolerance, data security, reliable QoS parameters (such low power consumption), low latency, robust scalability with high data integrity, and interoperability are essential components of a trustworthy IoT system in healthcare. Exciting themes including portability, real-time processing, and easy deployment are discussed in this essay [12]. It's fantastic to see that the explosion of H-IoT systems has only just begun. It's fantastic that there is research that go deeply into this question. Readers may still get a solid grasp of H-IoT from these studies, even if they don't cover every advancement, technology, and application. Having complete data will improve our capacity to draw conclusions, move the field forward, and learn new things. We can improve the breadth and depth of our investigations by drawing attention to these caveats and stimulating more study in this area. The novel and original concepts and viewpoints presented in this article provide a bright future for the field. Future researchers and scholars in the discipline will surely benefit from the information it provides [13-15].

1.1 Systematic Review of Machine Learning Techniques in Healthcare Big Data

1.1.1 Methodology

To ensure a structured review, we followed a systematic approach in analyzing recent studies on machine learning (ML) applications in big data analytics for healthcare. Our inclusion criteria were: -

- 1-Relevance: The study must focus on ML techniques applied to healthcare big data.
- 2-Empirical Evidence: Papers must include results from real-world datasets, model comparisons, or detailed discussions of ML frameworks.
- 3-Recent Publications: We only included articles published in the last five years (2019–2024) to maintain relevance.

1.1.2 Survey of Literature

Based on our review, we categorized existing ML methodologies into four main types:

1. Supervised Learning – Used in predictive analytics and disease classification.
2. Unsupervised Learning – Applied in patient clustering and anomaly detection.
3. Deep Learning – Used in medical image processing and genomic data analysis.
4. Hybrid and Ensemble Learning – Combining multiple models to improve accuracy and robustness. To support our findings, we summarize notable research in the table1 below:

Table 1: Summary of Notable Studies on Machine Learning Applications in Healthcare

Study	ML Methodology	Application	Key Findings
(Yu et al., 2021)[16]	CNN	Medical Image Analysis	Achieved 95% accuracy in cancer detection
(Yang et al., 2020)[17]	Random Forest	Disease Prediction	Improved predictive performance over statistical models
(Paganelli et al., 2022)[18]	LSTM	Patient Monitoring	Effective in real-time health data prediction
(Dubey et al., 2023)[19]	Hybrid Ensemble	COVID-19 Diagnosis	Enhanced classification accuracy using multiple classifiers

1.1.3 Comparative Analysis of ML Techniques

We compared different ML techniques used in healthcare big data analysis to highlight their strengths and limitations as shown in table 2.

Table 2: Comparison of Machine Learning Techniques in Healthcare Big Data Analytics

Technique	Strengths	Weaknesses	Use Case Examples
Supervised Learning	High accuracy, well-understood models	Requires labeled data, risk of overfitting	Disease diagnosis, medical classification
Unsupervised Learning	Identifies hidden patterns, useful for clustering	Hard to evaluate, needs domain expertise	Patient segmentation, anomaly detection
Deep Learning	Excellent for image analysis, feature extraction	Computationally expensive, requires large datasets	Medical imaging, genomic data processing
Ensemble Methods	Boosts predictive accuracy, reduces bias	Computationally intensive	Hybrid diagnostic systems

1.1.4 Research Gaps and Future Directions

Despite the advancements in ML-based healthcare analytics, key challenges remain: -

- 1-Explain ability Issues: Deep learning models lack transparency, making clinical adoption difficult.
- 2-Data Privacy and Security: Handling sensitive healthcare data raises privacy concerns, requiring privacy-preserving ML solutions.
- 3-Generalization Challenges: Many ML models perform well in controlled settings but fail in real-world healthcare applications.

1.1.4 Future Research Recommendations:

- 1-Develop interpretable AI models to enhance trust among medical professionals.
- 2-Explore privacy-preserving ML techniques such as federated learning and homomorphic encryption.
- 3-Improve ML robustness by integrating domain-specific knowledge in training datasets.



3 Power of H-IoT for Personalized and Connected Care

H-IoT is a rapidly evolving domain that amalgamates medical devices, sensors, and software programs enabled by the Internet. The system offers instantaneous data, anticipatory statistical analysis, and distant supervision with the aim of enhancing patient results as well as optimizing productivity and reducing expenses. H-IoT applications encompass a variety of technologies, including wearable devices, remote patient monitoring systems, telemedicine platforms, and intelligent hospital systems, among others [20]. The Healthcare Internet of Things (H-IoT) possesses the capability to revolutionize healthcare provision through the utilization of artificial intelligence (AI) and machine learning (ML), thereby enabling more personalized and efficacious medical interventions [21]. The protection of confidential data poses a potential challenge that necessitates resolution prior to the secure and efficient implementation of H-IoT technologies. The Internet of Things (IoT) has been identified as a significant advancement in medical technology in recent times. Rodrigues and colleagues (2019) conducted a comprehensive examination of the utilization of Internet of Things (IoT) technology in the healthcare sector, commonly referred to as "H-IoT." Furthermore, this study underscores the advantages of H-IoT and the obstacles it encounters. According to Rodrigues et al., additional research is required to address the current challenges faced by H-IoT. The comprehensive examination we conducted will provide a significant asset for academics, technology specialists, medical professionals, and individuals who are keen on improving H-IoT. Tsafack and colleagues (2013) developed a proficient cryptographic system for securely transmitting magnetic resonance imaging (MRI) images in the context of the healthcare internet of things (H-IoT) [22]. The study investigated the characteristics and behavior of a 2-dimensional trigonometric map that is infinitely solvable. The intricate dynamics of the map were demonstrated through the utilization of phase portraits, bifurcation diagrams, and the Lyapunov exponent. The study's performance analysis indicates that the proposed cryptosystem exhibits a high degree of security and is well-suited for integration into the realm of the Health Internet of Things (H-IoT) for the purpose of facilitating secure transmission of medical images. The graphical representation in Figure 2 shows the increasing adoption of Internet of Things (IoT)

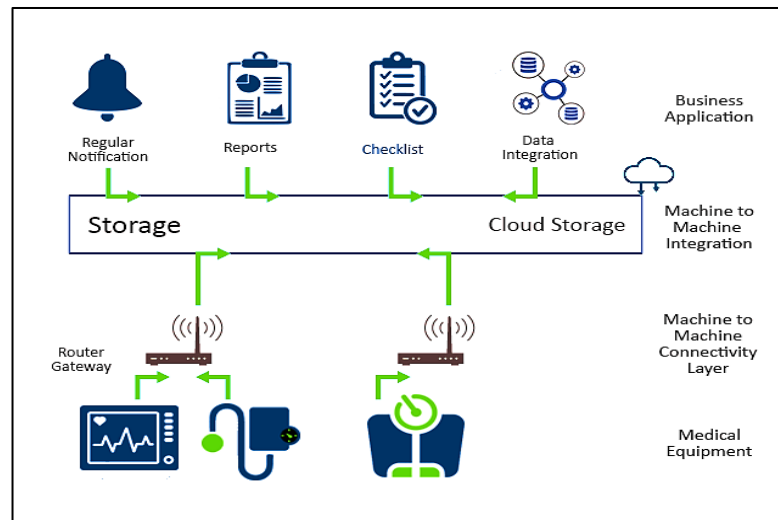


Fig. 2: IoT technology in healthcare industries has become a topic of interest in recent years

technology in the healthcare sector, aimed at improving patient outcomes, enhancing operational efficiency, and reducing expenses.

4 IoT Impact on Big Data in Healthcare

The Internet of Things (IoT) has facilitated the acquisition and examination of extensive medical data through the use of Health Internet of Things (H-IoT) technology, which is heavily reliant on big data. The integration of big data in H-IoT has facilitated the development of predictive models, which have the potential to detect potential health hazards and anticipate the advancement of illnesses [23]. The utilization of machine learning algorithms in healthcare enables medical professionals to analyze vast amounts of data, thereby facilitating the development of personalized treatment strategies. The collective evidence suggests that the utilization of big data analytics in the context of the Health Internet of Things (H-IoT) has the potential to enhance patient outcomes, reduce healthcare expenses, and streamline healthcare delivery through the identification of patterns and trends. E-health services offered by the personalized healthcare system have the potential to address the clinical requirements of older adults. Comprehensive examination of recent advancements in healthcare information technology, encompassing various areas such as big data analytics, mobile applications, the internet of things, fog computing, and cloud computing. Additionally, the present study



evaluated the difficulties associated with establishing a makeshift healthcare infrastructure for prompt illness identification and provided perspectives on feasible approaches to tackle these challenges [24]. It is our contention that the execution of this assessment will establish the foundation for a more efficient healthcare system in the future. have presented an intelligent large data storage system for H-IoT that is equipped with data security features. The proposed system boasts several supplementary attributes, such as adaptive access control, elevated data security, emergency and routine access control, and intelligent de-duplication techniques that optimize storage capacity when handling substantial data volumes [25]. The company H-IoT has created a secure system for sharing medical records among healthcare professionals of varying specializations through the use of encryption technology. Furthermore, these access control techniques facilitate the decoding of a patient's confidential medical data solely by authorized personnel, a critical aspect in the provision of life-saving initial aid. The research findings have led to the proposal of a novel access control system by the researchers. This system is designed to possess enhanced resilience and can adapt to anomalous and exigent situations in an automated manner. In emergency situations, the utilization of a shatter-glass access device has been proposed as a means to obtain patients' medical records [26]. The study's findings suggest that the proposed framework is deemed secure. Big data is being accumulated in significant quantities for various business applications, including H-IoT and robotics. The utilization of IoT-powered systems plays a significant role in the implementation of big data analytics. The process of sensing may introduce complexities when accurately predicting specific outcomes. Suggested an H-IoT system that utilizes artificial intelligence (AI) to address PD and enhance the gait of individuals affected by the condition. A brief overview of the crucial function of robots in the management of Parkinson's disease is also presented. Robotic applications in the treatment of Parkinson's disease include the prediction of walker motion and physical therapy [27]. Robotic technology has the potential to facilitate human interaction with vast quantities of data. The task of forecasting the movement of a walker necessitates the deployment of robots that can ambulate alongside patients while simultaneously monitoring the movements of both the robotic and human legs through the use



of sensors. The study encompassed an evaluation of the effectiveness of the proposed approach in relation to established methodologies.

In the past decade, there has been a proliferation of new discoveries and approaches in the field of healthcare, with a notable increase in the utilization of large datasets. The utilization of big data techniques has proven to be highly advantageous for healthcare researchers and biomedical informaticists [28]. In recent times, the healthcare sector has experienced a significant surge in the quantity of data generated by various sources, such as researchers, hospitals, patients, sensors, and mobile devices. The consistent generation of such data by clinical institutions is of utmost importance in the identification and management of nascent diseases. Scholars globally have developed innovative techniques for gathering data. Patients are increasingly utilizing technological advancements, particularly mobile applications, to independently manage their rehabilitation process. Furthermore, the Internet of Things (IoT) facilitates the increasing utilization and amalgamation of said tools and applications with telehealth and telemedicine. The advantages and disadvantages of utilizing big data in the healthcare sector were discussed by Mishra and colleagues in their publication [29]. The study presented novel approaches for enhancing healthcare systems through the utilization of distributed computing and big data technology. Figure 3 shown that the Internet of Things (IoT) is considered a significant advancement in the era of big data due to its ability to enhance services and facilitate real-time applications. It is generally accepted in the field of IoT that each device will generate a significant amount of data, calling for the development of effective means of processing and storing that data. The development of cloud computing was one answer to this problem. Data from healthcare applications must be processed in real time to maximize efficiency and reduce delays. The healthcare industry is one of the many that might benefit from fog computing's emergence as a viable option. It's a promising technology because of its potential to reduce data connection latency, provide flexible services, and divide up resource demands. The fog-based H-IoT system that Feng et al. [30] proposed aimed to decrease network lag and power consumption. To further analyze medical big data on fog devices, the study presented and highlighted important features of big data architecture. The

communication, transportation, healthcare, surveillance, and business sectors are just a few of the many that make use of smart sensors and IoT devices. Numerous sensors and gadgets

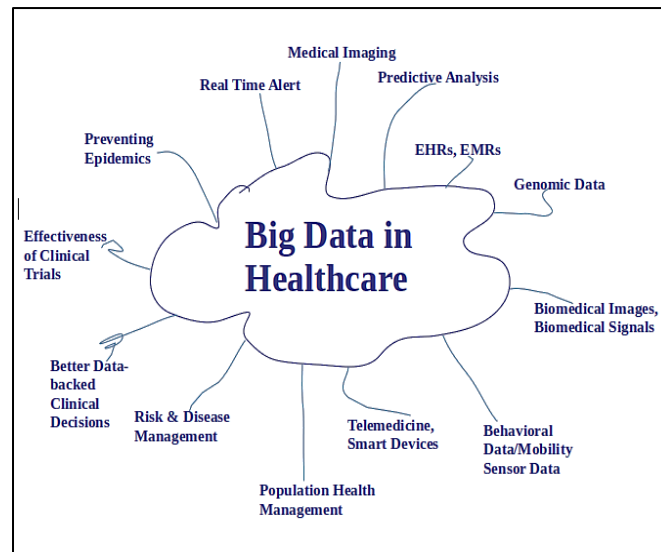


Fig. 3: The use of big data in the medical field [31]

provide copious amounts of data that, with further analysis, might be beneficial and helpful for healthcare facilities [31].

5 Enhancing Healthcare Delivery and Efficiency

The Internet of Things (IoT) commonly entails the linking of numerous intelligent sensing devices through diverse networks, which are subsequently incorporated into diverse applications such as the smart grid, smart home, and smart health [32-35]. In the domain of healthcare systems based on the Internet of Things (IoT), guaranteeing the security of both IoT devices and data holds paramount significance. The utilization of edge computing has been proposed as a viable approach to tackling complex computational obstacles encountered in the context of IoT. The utilization of edge computing has the potential to augment the computational and communicative velocity of Internet of Things (IoT) devices [36,37], thereby leading to a decrease in data latency. The utilization of artificial intelligence and optimized networks can aid in the facilitation of load balancing and resource utilization efficiency within



healthcare systems that are reliant on edge computing, which is enabled by the Internet of Things (IoT). Nevertheless, such devices exhibit reduced power capabilities and heightened susceptibility to security threats. As asserted by sources [38], it is imperative to establish a secure framework for healthcare systems utilizing IoT-enabled edge computing via software-defined networks (SDN). Edge servers utilize a low-weight authentication approach to verify Internet of Things (IoT) devices. Upon completion of the authentication procedure, the Internet of Things (IoT) devices will proceed to accumulate and subsequently dispatch patient data to edge servers. The objective of this communication is to facilitate the retention, manipulation, and evaluation of the information. The utilization of software-defined networking (SDN) controllers in healthcare systems facilitates the connection of edge servers, thereby enabling the optimization of network resources, load balancing, and network performance. The evaluation of the suggested methodology was conducted via computer-generated simulations [38]. The findings of the study indicate that the suggested methodology produced more favorable results for healthcare systems that are dependent on edge computing and IoT, as per the simulation outcomes. The progress in sensing techniques, as demonstrated by [39], has enabled the creation of intelligent systems capable of ongoing monitoring of human behaviors. The utilization of recurrent neural networks (RNN) on personal computers or laptops has led to the increasing popularity of wearable sensor-based frameworks for activity prediction. The dataset comprised a range of wearable healthcare sensors, encompassing gyroscopes, accelerometers, magnetometers, and ECG sensors, which stand for electrocardiography [39]. The efficacy of the proposed methodology was assessed in comparison to traditional methodologies through the utilization of pre-existing datasets. Based on the empirical findings, the investigation deduced that the suggested approach demonstrates exceptional efficacy in contrast to alternative traditional approaches. Emerging trends in edge computing have facilitated the development of effective healthcare applications. An example of an application that has gained prominence is patient remote monitoring, which has been enabled by the utilization of centralized electronic clouds (E-clouds). In order to attain maximum efficiency, it is imperative to guarantee high-caliber service, accurate levels of sensing, and a prioritized



focus on lucid visualization [40] has proposed a window-based rate control algorithm (W-RCA) aimed at optimizing the medical quality of service (M-QoS) in edge computing. The aforementioned factors, namely the peak-to-mean ratio (PMR), delay, standard deviation (SD), and network jitter, are taken into consideration in order to accomplish this. The present study aimed to assess the efficacy of the W-RCA algorithm in improving M-QoS by comparing it with other established algorithms, such as the Battery Smoothing Algorithm (BSA). The experimental investigation revealed that the proposed methodology demonstrated better performance in comparison to other pre-existing methodologies by optimizing applications such as telesurgery. The widespread availability and utilization of information technology and the Internet of Things (IoT) have enabled the incorporation of intelligent systems. The integration of cloud and edge computing is of paramount importance in the advancement of intelligent healthcare systems within sophisticated and intelligent urban locales. The utilization of real-time systems and tailored methodologies is imperative for the purpose of modeling, simulating, and optimizing service flow and system resources within emergency departments (EDs). A model for non-consumable resources was proposed by the author [41]. The system was devised with the purpose of providing a description and theoretical validation of the resources. The Reverse Polish Notation (RPN) was employed in real-time scenarios, considering performance metrics such as the average waiting time of patients, rate of resource utilization, and duration of the patient's stay. The study involved simulation of the proposed system, with the primary objective of improving the quality-of-service delivery by enhancing the length of stay, minimizing patient waiting time, and optimizing resource allocation.

6 Healthcare Analytics Integration with ML and DL

The following section provides an explanation of how H-IoT utilizes machine learning and deep learning. A novel deep learning (DL) architecture utilizing H-IoT was created [38] for the purpose of detecting and categorizing cervical cancer. The utilization of transfer learning techniques played a pivotal role in achieving this outcome. The conventional machine learning techniques, namely Support Vector Machines (SVM), Random Forest (RF), Logistic Regression (LR), Naive Bayes (NB), and K-Nearest Neighbor (KNN), were enhanced with the



assistance of a Convolutional Neural Network (CNN), as reported in references [42-44]. This study utilized pre-trained convolutional neural network models such as ResNet50, SqueezeNet, VGG19, and Inception V3 for the purpose of feature extraction. The study assessed the H-IoT framework and found that the suggested model achieved a classification rate of 97.89%, indicating its effectiveness. Reference [45] suggests that an effective technique for classifying and predicting CKD is to utilize a Soft max classifier in conjunction with stacked auto-encoders (AEs) within a deep learning framework. The proposed method utilized autoencoders to perform feature extraction and recognize multi-modal patterns in the linked dataset. Furthermore, it facilitated the attainment of improved categorization accuracy. Feature reduction can facilitate the classification of individual adverse events. A Soft max classifier has been utilized to achieve the classification of multiple classes based on common characteristics. The diagnostic outcomes of the deep-stacked AE model for chronic kidney disease (CKD) can be observed and assessed. The model exhibits remarkable performance in classifying CKD, as evidenced by its exceptional accuracy, specificity, recall, and precision. As such, it represents a valuable asset in the medical domain. The aforementioned work [46] presented and evaluated a deep learning approach for predicting chronic kidney disease using retinal images. Several published papers have addressed the diagnosis of P. vivax. The researchers proposed a distinctive architecture for stacked convolutional neural networks (CNN) in their aforementioned paper. This architecture enhances the automated detection of malaria without the need for time-consuming manual feature engineering. The accuracy of identifying parasites has been improved by implementing the five-fold cross-validation method. The results indicate that the convolutional layers possess the ability to extract diverse features for classification objectives, as evidenced by their reaction to modifications in filter size and depth.

7 Technical Challenges

Problems with H-IoT's performance in areas like security, latency, dependability, and efficiency are a major barrier to the technology's advancement. Low latency, great dependability, low power consumption, and good security are all desirable in a future iteration



of the H-IoT. The difficulties experienced by various writers with IoT systems are then elaborated upon.

8 Enhanced Productivity

Because of the H-IoT's low latency, these technologies may be used effectively in emergency response systems, remote patient monitoring, and telemedicine to process and analyze data in real time. Low latency allows providers to make rapid decisions and respond effectively to circumstances. Although reducing latency is difficult, it is not impossible with well-designed networks and the right hardware and software. H-IoT presents difficulties in real-time transmission and analysis, but with technological developments, healthcare professionals may still make informed decisions. We work to reduce delays in data transmission and processing across all nodes in an H-IoT network. We might possibly lessen the effects of latency by lowering transmission time by investigating communication systems with high availability and huge capacity. It's wonderful news because channel access and routing can make use of ML algorithms, which have the potential to drastically cut end-to-end latency. There are several advantages to using fog and edge computing frameworks. AI's efficacy when combined with these edge and fog computing frameworks has also been proven [47]. The use of deep learning methods has been a huge help to the big data analytical system, and while there are still challenges to be met, progress is being made in making the most of the data we have. The possibility of creating powerful algorithms that can use and finish the dataset's accumulation of information is, thus, quite fascinating. This increases the usage of computing resources at the network's periphery and reduces transmission and processing delays. In time-critical H-IoT systems, using fog computing platforms has been recommended to guarantee low latency [48]. There may be a way to lessen the impact of cloud latency on ERS systems by incorporating fog computing with H-IoT. The problems with latency, energy consumption, and response time can be addressed, however.

9 Threats to Security

These threats can manifest in different forms and compromise the integrity, confidentiality, and availability of Ensuring security is of paramount importance in the healthcare IoT industry



due to the sensitive nature of patient information. The likelihood of security vulnerabilities and cyberattacks is on the rise with the increasing interconnectivity and accessibility of H-IoT devices and systems. Medical records possess the potential to serve as a valuable resource for individuals seeking to engage in identity theft and fraudulent activities. Furthermore, the revelation of confidential medical data and/or the tampering of medical devices due to a security breach in a Health Internet of Things (H-IoT) system can result in significant harm to patients. The implementation of stringent security protocols is imperative for ensuring the safety and dependability of medical equipment as well as the confidentiality, accuracy, and accessibility of patient data in the context of Health Internet of Things (H-IoT) systems. The limited resources of H-IoT pose a challenge in the development of algorithms that are optimized for efficiency. Maintaining a high level of energy efficiency poses a significant challenge. The incorporation of security risk mitigation features requires the utilization of a machine learning or deep learning algorithm that has low power consumption and can operate with lightweight encryption, as indicated by sources [49-53]. Nevertheless, the system mentioned above exhibits computational complexity. Hence, it may be feasible to implement a fog computing paradigm that employs a federal system in proximity to the devices to ensure their safety. The Internet of Medical Things (IoMT) holds promise for delivering efficient healthcare services; however, it is susceptible to intermediary attacks and exhibits low levels of security awareness among inexperienced users.

10 Platforms for Real-Time Operations

In general, the data acquired from the sensors might lead to a more in-depth understanding of the user's health situation. It's important to recognize that the volume of data being produced is rather large, necessitating the development of novel processing techniques for data mining. However, many already-existing algorithms have proved unable to handle all of the data, thus real-time data handling methods must be used instead. The extraction of numerous and redundant characteristics from the dataset is essential [54], despite the fact that deep learning algorithms can manage huge real-time data.



11 H-IoT's Potential Uses

Healthcare Internet of Things (H-IoT) has revolutionized the healthcare industry with its diverse applications. One significant application is remote patient monitoring, wherein H-IoT allows healthcare providers to continuously monitor patients' health conditions from a distance. Through the use of connected devices and wearables, vital signs, activity levels, and medication adherence can be collected and transmitted in real-time. This capability enables healthcare professionals to track patients' well-being, detect any deviations from normal health parameters, and intervene promptly when necessary. Telehealth services have also benefited from H-IoT, providing patients with the opportunity to access healthcare remotely. Through video consultations and digital communication platforms, patients can connect with healthcare providers, receive medical advice, and even undergo virtual examinations. The integration of H-IoT in telehealth services has enhanced access to healthcare, particularly for individuals in remote or underserved areas. Overall, the applications of H-IoT in healthcare have brought about transformative changes, improving patient care, facilitating early interventions, and enhancing access to healthcare services. Such intelligent strategies aid healthcare professionals and physicians in making informed decisions based on accessible datasets, resulting in enhanced patient care and treatment. In cases where a patient presents with a complex medical history and concomitant critical health disorders, these strategies may prove to be more efficacious. Additionally, novel technologies have been developed that are capable of forecasting the likelihood of cardiovascular disease, hypertension, and diabetes. Individuals afflicted with these ailments may be recommended to engage in routine medical check-ups, seek frequent medical consultation, and utilize dietary regimens or weight control initiatives [55-61]. The findings of the analysis demonstrate a notable level of precision when utilizing

IoT techniques, indicating its prospective application within the healthcare industry, as illustrated in Figure 4.

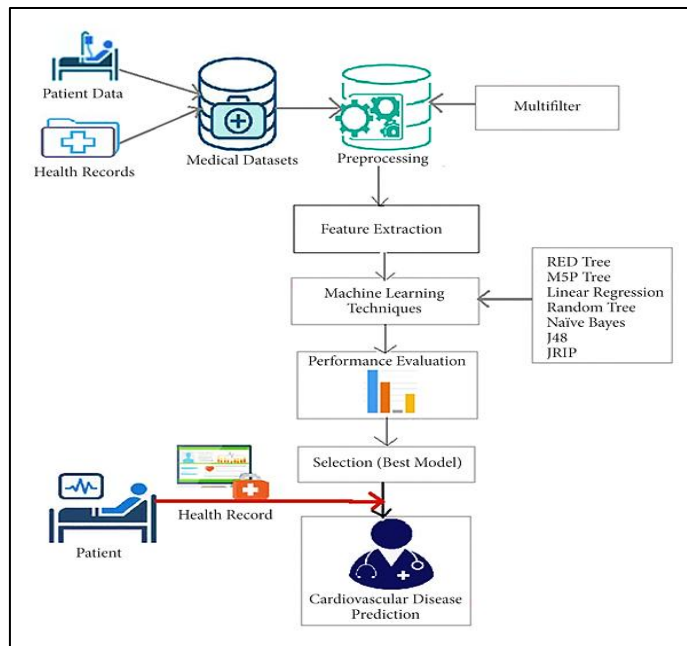


Fig. 4: Accuracy of cardiovascular disease prediction systems [59]

12 Conclusions

The main impediment to using IoT devices in healthcare is patient privacy and security. Many ingenious security measures were restricted. Cryptographic frameworks were used to secure data access in big data, blockchain, ML/DL, edge computing, and SDN IoT settings. We covered H-IoT challenges and uses. H-IoT trends and future potential enable cutting-edge applications and solutions that improve patient care and healthcare outcomes. Thus, this article's techniques may solve the challenges and enable widespread adoption of strong H-IoT devices and infrastructure. The paper recommends legislation and regulations to facilitate collaboration between government agencies and H-IoT researchers. For healthcare systems to leverage the Internet of Things, user security and privacy must be ensured. This paper recommends H-IoT cryptography technologies to accomplish this purpose. This paper investigates H-IoT difficulties and applications, presents solutions for building a reliable infrastructure, and emphasizes the necessity for legal and regulatory frameworks. This paper



might start your H-IoT research. Data collecting starts Internet of Things recycling. Network technology collects data like sensors and mobile devices. Data is transferred to a remote data storage like the Pall. Medical professionals must be able to remotely access the database, which must contain vast amounts of data. Analysis usually follows data warehousing. The judiciary analyzes data and recognizes patterns. Examples include changes in vital physiological indicators, aberrant pregnancies, and impending medical difficulties. Machine learning and artificial intelligence may identify health hazards. The Hybrid Internet of Things (H-IoT) data pipeline ends with data dissemination. Medical providers need clear information. Graphs and maps may highlight intriguing data linkages. If a patient's health worsens, medical personnel may be called in. to manage H-IoT devices' huge data output. This idea holds that healthcare personnel need data assimilation and analytical abilities to provide best care. Complex analytics and algorithms may analyze data and extract the most important information for croaking stakeholders.

13 References

- 1- Ndurukia, Z., Njeru, A. W., & Waiganjo, E. (2017). Factors Influencing Demand for Micro Insurance Services in the Insurance Industry in Kenya. *International Journal of Academic Research in Business and Social Sciences*, 7(7), 232-259.
- 2- World Industry Outlook, Healthcare, and Pharmaceuticals, The Economic Intelligence Unit, June 2017.
- 3- Roughley, S. D. (2019). Five Years of the KNIME Vernalis Cheminformatics Community Contribution. *Current medicinal chemistry*.
- 4- Hildebrandt, H. (2014). Crossing the boundaries from individual medical care to regional public health outcomes: The triple aim of “Gesundes Kinzigtal”—better health+ improved care+ affordable costs. *International journal of integrated care*.



- 5- Kathpalia, S. K. (2015). WITHDRAWN: Disabilities found during services selection board medical examination–An overview.
- 6- Dam, L. (2017). Comparative Analysis of Life Insurance Sector in India with BRIC Nations.
- 7- World Industry Outlook, Healthcare and Pharmaceuticals, The Economic Intelligence Unit, June 2017.
- 8- Lim, Y., & Yoo, Y. (2010). Study on Green Building Certification Criteria for Healthcare Facilities. Journal of the Architectural Institute of Korea Planning & Design, Planning and Design Section, 26(08), 153-162.13
- 9- FRIEDEN, J. (2008). Techno-Smart systems Can Make Life Easier for Diabetes Patients. Pediatric News, 42(8), 40-40.
- 10- De - loyde, K. J., Harrison, J. D., Durcinoska, I., Shepherd, H. L., Solomon, M. J., & Young, J. M. (2015). Which information source is best? Concordance between patient report, clinician report and medical records of patient co - morbidity and adjuvant therapy health information. Journal of evaluation in clinical practice, 21(2), 339-346.
- 11- Hodson, H. (2012). Wearable smart systems enhance symbiosis of man and machine.
- 12- Beck, C., & Georgiou, J. (2016, May). A wearable, multimodal, vitals acquisition unit for intelligent field triage. In 2016 IEEE International Symposium on Circuits and Systems (ISCAS)(pp. 1530-1533).
- 13- Wang, J., Qiu, M., & Guo, B. (2017). Enabling real-time information service on telehealth system over cloud-based big data platform. Journal of Systems Architecture, 72, 69-79.
- 14- World Industry Outlook, Healthcare and Pharmaceuticals, The Economic Intelligence Unit, June 2017.
- 15- Hill, J., Nielsen, M., & Fox, M. H. (2013). Understanding the social factors that contribute to diabetes: a means to informing health care and social policies for the chronically ill. The Permanente Journal, 17(2), 67.
- 16- Dubey, A. K., Chabert, G. L., Carriero, A., Pasche, A., Danna, P. S. C., Agarwal, S., Mohanty, L., Nillmani, Sharma, N., & Yadav, S. (2023).



- 17- Ensemble deep learning derived from transfer learning for classification of COVID-19 patients on hybrid deep-learning-based lung segmentation: a data augmentation and balancing framework. *Diagnostics*, 13(11), 1954. <https://doi.org/10.3390/diagnostics13111954>
- 18- Paganelli, A. I., Mondéjar, A. G., da Silva, A. C., Silva-Calpa, G., Teixeira, M. F., Carvalho, F., Raposo, A., & Endler, M. (2022). Real-time data analysis in health monitoring systems: A comprehensive systematic literature review. *Journal of Biomedical Informatics*, 127, 104009. <https://doi.org/10.1016/j.jbi.2022.104009>
- 19- Yang, L., Wu, H., Jin, X., Zheng, P., Hu, S., Xu, X., Yu, W., & Yan, J. (2020). Study of cardiovascular disease prediction model based on random forest in eastern China. *Scientific Reports*, 10(1), 5245. <https://doi.org/10.1038/s41598-020-62133-5>
- 20- Yu, H., Yang, L. T., Zhang, Q., Armstrong, D., & Deen, M. J. (2021). Convolutional neural networks for medical image analysis: state-of-the-art, comparisons, improvement and perspectives. *Neurocomputing*, 444, 92–110. <https://doi.org/10.1016/j.neucom.2020.04.157>
- 21- Goodwin, N. (2015). How should integrated care address the challenge of people with complex health and social care needs? Emerging lessons from international case studies. *International journal of integrated care*, 15(3).
- 22- Marmot, M., Friel, S., Bell, R., Houweling, T. A., Taylor, S., & Commission on Social Determinants of Health. (2008). Closing the gap in a generation: health equity through action on the social determinants of health. *The lancet*, 372(9650), 1661-1669.
- 23- Cohen, A. J., Brauer, M., Burnett, R., Anderson, H. R., Frostad, J., Estep, K., & Feigin, V. (2017). Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: an analysis of data from the Global Burden of Diseases Study 2015. *The Lancet*, 389(10082), 1907-1918.
- 24- BEF. Healthcare industry in India. <http://www.ibef.org/industry/healthcareindia.aspx,2015>.



- 25- Tripathi, V. V. R., Tripathi, A., & Jaiswal, S. (2019). Health welfare system in modern India revitalizing Indian Healthcare-Its potential and challenges. *ZENITH International Journal of Multidisciplinary Research*, 9(2), 178-193.
- 26- Prinja, S., Bahuguna, P., Gupta, I., Chowdhury, S., & Trivedi, M. (2019). Role of insurance in determining utilization of healthcare and financial risk protection in India. *PloS one*, 14(2), e0211793.
- 27- Jones, R. (2015). Links between bed occupancy, deaths and costs. *British Journal of Healthcare Management*, 21(11), 544-545.
- 28- World Health Organization. (2016). Guidelines on core components of infection prevention and control programmes at the national and acute health care facility level. World Health Organization.
- 29- Earnest, A., Chen, M. I., Ng, D., & Sin, L. Y. (2005). Using autoregressive integrated moving average (ARIMA) models to predict and monitor the number of beds occupied during a SARS outbreak in a tertiary hospital in Singapore. *BMC Health Services Research*, 5(1), 36.
- 30- Kutafina, E., Bechtold, I., Kabino, K., & Jonas, S. M. (2019). Recursive neural networks in hospital bed occupancy forecasting. *BMC medical informatics and decision making*, 19(1), 39.14
- 31- Butt, S. A., Jamal, T., Azad, M. A., Ali, A., & Safa, N. S. (2019). A multivariant secure framework for smart mobile health application. *Transactions on Emerging Telecommunications Technologies*, e3684.
- 32- Zhecheng, Z. (2014). An online short-term bed occupancy rate prediction procedure based on discrete event simulation. *Journal of Hospital Administration*, 3(4), 37-41.
- 33- Jamal, T., & Butt, S. A. (2018). Malicious node analysis in MANETS. *International Journal of Information Technology*, 1-9.
- 34- Paranjape, K., Schinkel, M., Panday, R. N., Car, J., & Nanayakkara, P. (2019). Introducing Artificial Intelligence Training in Medical Education. *JMIR Medical Education*, 5(2), e16048.
- 35- Butt, S. A., Diaz-Martinez, J. L., Jamal, T., Ali, A., De-La-Hoz-Franco, E., & Shoaib, M. (2019, July). IoT Smart Health Security Threats. In 2019 19th



- International Conference on Computational Science and Its Applications (ICCSA) (pp. 26-31). IEEE.
- 36- Asam, M., & Ajaz, A. (2019). Challenges in Wireless Body Area Network. Proc. of International Journal of Advanced Computer Science and Applications, 10(11).
- 37- Li, C., Xu, X., Zhou, G., He, K., Qi, T., Zhang, W., ... & Hu, J. (2019). Implementation of National Health Informatization in China: Survey About the Status Quo. JMIR medical informatics, 7(1),12238.
- 38- Simblett, S., Matcham, F., Siddi, S., Bulgari, V., di San Pietro, C. B., López, J. H., ... & Gamble, P. (2019). Barriers to and facilitators of engagement with mHealth technology for remote measurement and management of depression: Qualitative analysis. JMIR mHealth and uHealth, 7(1), e11325.
- 39- Shetty, A. L., Teh, C., Vukasovic, M., Joyce, S., Vaghasiya, M. R., & Forero, R. (2017). Impact of emergency department discharge stream short stay unit performance and hospital bed occupancy rates on access and patient flowmeasures: a single site study. Emergency Medicine Australasia, 29(4), 407-414.
- 40- Wang, W., Chen, J., & Hong, T. (2018). Occupancy prediction through machine learning and data fusion of environmental sensing and Wi-Fi sensing in buildings. Automation in Construction, 94, 233-243.
- 41- Stewart, R., Urban, M., Duchscherer, S., Kaufman, J., Morton, A., Thakur, G., ... & Moehl, J. (2016). A Bayesian machine learning model for estimating building occupancy from open source data. Natural Hazards, 81(3), 1929-1956.
- 42- Mtonga, K.; Kumaran, S.; Mikeka, C.; Jayavel, K.; Nsenga, J. Machine Learning-Based Patient Load Prediction and IoT Integrated Intelligent Patient Transfer Systems. Future Internet 2019, 11, 236. 2. Mosenia, A.; Sur-Kolay, S.; Raghunathan, A.; Jha, N.K. Wearable Medical Sensor-Based System Design: A Survey. IEEE Trans. Multi-Scale Comput. Syst. 2017, 3, 124–138.
- 43- Iqbal, N.; Jamil, F.; Ahmad, S.; Kim, D. A Novel Blockchain-Based Integrity and Reliable Veterinary Clinic Information Management System Using



- Predictive Analytics for Provisioning of Quality Health Services. IEEE Access 2021, 9, 8069–8098.
- 44- Wu, T.; Wu, F.; Redoute, J.-M.; Yuce, M.R. An Autonomous Wireless Body Area Network Implementation towards IoT Connected Healthcare Applications. IEEE Access 2017, 5, 11413–11422.
- 45- Birje, M.N.; Hanji, S.S. Internet of things based distributed healthcare systems: A review. J. Data Inf. Manag. 2020, 2, 149–165.
- 46- Shahbazi, Z.; Byun, Y.-C. Towards a Secure Thermal-Energy Aware Routing Protocol in Wireless Body Area Network Based on Blockchain Technology. Sensors 2020, 20, 3604.
- 47- Kumar, P.M.; Gandhi, U.D. A novel three-tier Internet of Things architecture with machine learning algorithm for early detection of heart diseases. Comput. Electr. Eng. 2018, 65, 222–235.
- 48- Yuvaraj, N.; SriPreethaa, K.R. Diabetes prediction in healthcare systems using machine learning algorithms on Hadoop cluster. Clust. Comput. 2017, 22, 1–9.
- 49- Miotto, R.; Wang, F.; Wang, S.; Jiang, X.; Dudley, J.T. Deep learning for healthcare: Review, opportunities and challenges. Brief. Bioinform. 2018, 19, 1236–1246.
- 50- Shahbazi, Z.; Byun, Y.-C. Improving Transactional Data System Based on an Edge Computing–Blockchain–Machine Learning Integrated Framework. Processes 2021, 9, 92.
- 51- Sohaib, O.; Lu, H.; Hussain, W. Internet of Things (IoT) in E-commerce: For people with disabilities. In Proceedings of the 2017 12th IEEE Conference on Industrial Electronics and Applications (ICIEA), Siem Reap, Cambodia, 18–20 June 2017; pp. 419–423.
- 52- Gao, H.; Qin, X.; Barroso, R.J.D.; Hussain, W.; Xu, Y.; Yin, Y. Collaborative Learning-Based Industrial IoT API Recommendation for Software-Defined Devices: The Implicit Knowledge Discovery Perspective. IEEE Trans. Emerg. Top. Comput. Intell. 2020, 1–11.



- 53- Rajkomar, A.; Hardt, M.; Howell, M.D.; Corrado, G.; Chin, M.H. Ensuring Fairness in Machine Learning to Advance Health Equity. *Ann. Intern. Med.* 2018, 169, 866–872. *Forecasting* 2021, 3 204
- 54- S. Oueida, Y. Kotb, M. Aloqaily, Y. Jararweh, and T. Baker, "An Edge Computing Based Smart Healthcare Framework for Resource Management," *Sensors*, vol. 18, no. 12, p. 4307, 2018. DOI: 10.3390/s18124307.
- 55- G. Abhishek, M. Kumar, A. Rangra, V. K. Tiwari, and P. Saxena, "Network Intrusion Detection Types and Analysis of Their Tools," Department of Computer Science and Information Technology, Jaypee University of Information Technology, Waknaghat, India, 2012.
- 56- N. Mani, M. Moh, and T. S. Moh, "Defending deep learning models against adversarial attacks," *Int. J. Softw. Sci. Comput. Intell.*, vol. 13, pp. 72-89, 2021. DOI: 10.1080/19427867.2021.1931904.
- 57- M. Kumar, P. Mukherjee, K. Verma, S. Verma, and D. B. Rawat, "Improved Deep Convolutional Neural Network Based Malicious Node Detection and Energy-Efficient Data Transmission in Wireless Sensor Networks," *IEEE Trans. Netw. Sci. Eng.*, vol. 9, no. 5, pp. 3272-3281, 2021. DOI: 10.1109/TNSE.2021.3090858.
- 58- R. Gupta, E. S. Verma, and E. Kavita, "Solving ipv4 (32 bits) address shortage problem using ipv6 (128 bits)," *IJREISS*, vol. 2, 2012.
- 59- S. Dash, S. Verma, Kavita, M. S. Khan, M. Wozniak, J. Shafi, and M. F. Ijaz, "A Hybrid Method to Enhance Thick and Thin Vessels for Blood Vessel Segmentation," *Diagnostics*, vol. 11, no. 11, p. 2017, 2021. DOI: 10.3390/diagnostics11112017.
- 60- C. Sabanayagam, D. Xu, D. S. W. Ting, S. Nusinovici, R. Banu, H. Hamzah, C. Lim, Y.-C. Tham, C. Y. Cheung, E. S. Tai, et al., "A deep learning algorithm to detect chronic kidney disease from retinal photographs in community-based populations," *Lancet Digit. Health*, vol. 2, no. 4, pp. e295-e302, 2020. DOI: 10.1016/S2589-7500(20)30089-2.



- 61- M. Umer, S. Sadiq, M. Ahmad, S. Ullah, G. S. Choi, and A. Mehmood, "A Novel Stacked CNN for Malarial Parasite Detection in Thin Blood Smear Images," IEEE Access, vol. 8, pp. 93782-93792, 2020. DOI: 10.1109/ACCESS.2020.2996814.