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Automation of Healthcare services using Machine learning

Parul Chhabra [1], Pradeep Kumar Bhatia [2]

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Abstract: Machine learning has changed healthcare and other industries. Healthcare automation using machine learning has improved efficiency, accuracy, and patient outcomes. This groundbreaking technology might simplify diagnosis, treatment planning, and patient care. Machine learning affects diagnostics. Complex algorithms may identify early diseases using imaging scans, pathology reports, and patient data. Machine learning algorithms find patterns and anomalies quicker and more accurately, enhancing prognosis and treatment. Personalized medicine uses machine learning for diagnosis and more. Examining genetic and therapeutic data using algorithms may help physicians tailor treatment. This customized approach enhances medication efficacy and negative effects, improving healthcare. Machine learning is used in predictive analytics in healthcare automation. Previous patient data may help machine learning algorithms forecast sickness patterns, admission rates, and resource allocation.

Purpose: The main purpose of research is to consider issues of performance and accuracy related to automated health care services with machine learning and reducing training and testing time along with accuracy enhancement.

Methods: In order to perform data classification Machine learning methods such as Decision trees, SVMs, neural networks are used.
Results: Accuracy in case of proposed work is 99.24% where as it is 98.94% in case of conventional research. Average time consumption of proposed work is below 50 minutes where as in case of conventional work it was above 50 minutes.

Conclusion: It is concluded that proposed work is providing solution with better performance and accuracy

***Keywords:** Healthcare, Machine learning, Diagnostics, Accuracy, Performance*

1. Introduction

Machine learning has modified several sectors, including healthcare. Recently, machine learning has emerged as a potentially game-changing tool for improving efficiency, accuracy, and patient outcomes. To improve patient outcomes, healthcare services are automated. In the healthcare ecosystem, new technologies may simplify difficult operations. Clinical diagnosis, therapeutic planning, and patient care are some examples. Machine learning is transforming the healthcare business, introducing new opportunities and breakthroughs. Machine learning algorithms may transform healthcare delivery, administration, and customization in a setting with massive volumes of complicated data. Due to sophisticated computer models, these algorithms can analyse massive datasets with incredible speed and accuracy, providing insights that were previously unachievable. The complicated computer models that drive these algorithms allow this. Machine learning is transforming healthcare with applications in enhanced diagnostic imaging, predictive analytics, tailored treatment, and administrative automation. Technology and healthcare may increase care quality and change how we diagnose, treat, and provide healthcare. Machine learning in healthcare is expected to lead to major advances that will shape the medical industry in the future. Machine learning is continually growing.

Machine learning is having a major influence on diagnostics, a well-recognized topic. Advanced algorithms can assess imaging images, pathology reports, and patient information. These algorithms examine enormous data sets to spot illnesses early. Machine learning models may spot trends and abnormalities, enabling faster and more accurate diagnosis. This allows for early treatment, which improves prognosis. In addition to diagnostics, machine learning is important in customized medicine. Algorithms may help doctors tailor therapy to particular patients. Individual patient data, including genetics and drug reactions, may help. This personalized strategy improves therapeutic effectiveness and reduces side effects. Healthcare quality improves as a consequence. Predictive analytics is another healthcare automation use of machine learning. Machine learning algorithms can anticipate illness patterns, patient admission rates, and resource allocation using patient data. This proactive method helps healthcare providers distribute resources more efficiently, lowering costs and improving patient care. Telemedicine and remote monitoring are easier to deploy due to machine learning automation. Real-time data analysis lets doctors remotely watch patients. This allows them to treat quickly and reduces needless hospital visits. This makes healthcare systems more efficient and

1 Research Scholar, Department of Computer Science and Engineering, Guru Jambheshwar University of Science and Technology Hisar Haryana, India Email: parul15march@gmail.com (Corresponding Authpr)
2Professor, Department of Computer Science and Engineering, Guru Jambheshwar University of Science and Technology Hisar Haryana, India Email: pkbhatia.gju@gmail.com
ORCID ID : 0000-3343-7165-777X
3 Computer Eng., Selcuk University, Konya – 42002, TURKEY
ORCID ID : 0000-3343-7165-777X
** Corresponding Author Email: author@email.com*

patient treatment more pleasant. These concerns must be solved to guarantee the proper and successful deployment of machine learning in healthcare. Despite many advances, this is true. Data security, ethics, and regulations are among the numerous challenges. Machine learning can automate healthcare services, which might revolutionize the business. This may lead to more efficient, patient-centred healthcare in the future.

1.1. Role of Machine Learning in Automation Healthcare System

Machine learning transforms healthcare automation, improving efficiency, accuracy, and patient care. Machine learning algorithms analyse big data sets to predict sickness risks and identify potential health issues, enabling early interventions and personalized therapy. Machine learning speeds up and enhances medical image interpretation and diagnosis. Machine learning personalizes medicine by tailoring treatment strategies to patient data. Machine learning streamlines appointment scheduling and billing, easing healthcare workers and improving efficiency. Real-time remote patient monitoring using machine learning allows for rapid interventions and proactive care management. Healthcare automation solutions using machine learning improve efficiency, customization, and simplicity. Automation in healthcare services relies on machine learning, transforming the sector. In healthcare automation, machine learning performs several roles:

- To forecast disease risk and prospective health difficulties, machine learning algorithms evaluate large datasets such as patient records, genetic information, and lifestyle variables. Early illness identification allows proactive therapies, improving outcomes and lowering healthcare expenditures.
- Machine learning improves medical imaging accuracy by detecting patterns and anomalies in X-rays, MRIs, CT scans, and other imaging modalities. Automated image analysis speeds diagnosis and lets radiologists concentrate on challenging patients.
- Machine learning allows for personalized treatment regimens based on patient traits, genetics, and health history. Tailored therapies improve results and decrease side effects, making them more patient-centred.
- ML models find medication candidates, forecast interactions, and improve formulations using biological data. Automation speeds medication development and lowers market entry costs.
- Machine learning algorithms may identify billing and claims abnormalities, identifying healthcare fraud. ML improves cyber security to secure patient data.
- ML aids healthcare practitioners make decisions by evaluating patient data and suggesting therapy choices. CDS improves diagnostic accuracy and evidence-based decision-making.
- Machine learning aids in assessing population health data for trend identification, resource allocation, and targeted treatments. Proactive healthcare planning and management use population-level information.

1.2. Need of Research

Machine learning is becoming increasingly accepted as a crucial necessity for healthcare system automation to tackle the complex issues confronting the healthcare industry. Machine learning may help extract meaningful insights and patterns from patient data, which includes electronic health records and medical imaging, as it grows. Machine learning is becoming increasingly significant in healthcare due to the need for more efficient and reliable diagnostic methods, predictive analytics for early sickness diagnosis, and tailored treatment regimens. As the demand for simpler, cost-effective administrative processes and solutions grows, machine learning's capacity to automate appointment scheduling, billing, and claims processing becomes crucial. Machine learning algorithms can stay up with healthcare developments and adapt to patient needs. Their ability to learn and adapt makes this possible. In summary, machine learning in healthcare automation can improve patient care, reduce operational burdens, and drive innovations that benefit the entire healthcare ecosystem by addressing the growing complexity of healthcare data.

2. Literature review

In 2022, Jaun et al. conducted a study examining biomarkers derived from the brain, which might potentially aid in the diagnosis and prediction of outcomes related to mental illness. Machine learning has been instructed to use EEG signals for the classification of mental disorders. However, the tedious process of (FE) and sub sampling over raw EEG data is necessary and contingent upon the specific condition. (DL) is considered a crucial area of research for interpreting EEG data due to its capacity to be trained on large volumes of data generated by EEG and its use of automated (FE) techniques that leverage raw EEG signals to enhance discoveries. [1].

Ahmed et al. (2019) discussed the (EEG) as a major approach for diagnosing neurological issues, specifically for identifying seizures. The EEG measures and records the electrical activity of the brain. This letter presents a novel approach for diagnosing epileptic seizures by classifying raw EEG data, hence removing the need for predefined feature extraction. The system employs a one-dimensional convolution variation autopen coder to integrate both supervised and unsupervised deep learning techniques. They use k-fold cross-validation to evaluate the performance of the recommended system in classifying unknown data [2].

Acharya (2012) presented a (CAD) technique that utilizes nonlinear features to automatically differentiate between normal and intoxicated (EEG) data. In order to train a (SVM) classifier using various kernel functions, the first step involves extracting nonlinear features such as (ApEn),(LLE),(SampEn), and other (HOS) features. The input features consist of polynomials of orders 1, 2, and 3, as well as an RBF kernel. According to their results [3], these nonlinear measures are able to successfully distinguish between EEG signals that are connected to alcohol and those that are not.

Tan et al. (2018) introduced the diagnosis of epilepsy, in which (EEG) is often used as an adjunctive examination. The EEG signal supplied specific information about the brain's electrical activity. Neurologists have typically depended on direct visual examination to identify irregularities in the form of epilepsy. Several drawbacks were associated with this technique, such as its potential labor-intensiveness, vulnerability to technical artefacts, reliance on the reader's level of expertise for drawing conclusions, and lack of reliable anomaly detection capability. Therefore, it is essential to have a CAD system that can automatically categorize this EEG data using machine learning. Prior to this, there has been no instance where EEG signals were examined using a (CNN) [4].

Aydin and colleagues (2019) examined the effects of depression on a substantial proportion of the global population. The identification of this mood illness may be achieved by the use of EEG data. An arduous and time-consuming task, the manual examination of EEG data for depression detection requires a significant level of competence. Medical professionals will get advantages from a fully automated depression diagnosis system that is constructed using EEG data. Therefore, in order to detect depressive episodes from EEG data, they propose using a sophisticated hybrid model that is trained using (CNN) and (LSTM) architectures. [5].

The main challenge addressed by Wang et al. (2017) is the extraction of valuable insights from complex, multi-dimensional, and heterogeneous biological data, which hinders the transformation of healthcare. Electronic health records, pictures, omissions, sensor data, and text are among the novel data formats that have lately appeared in modern scientific research. These data kinds are intricate, varied, inadequately documented, and sometimes unorganized. Prior to developing prediction or clustering models, traditional data mining and statistical learning approaches often need feature engineering to extract more precise and dependable properties from the information. [6].

Fathi et al. (2021) examined the use of deep learning techniques in healthcare systems, specifically investigating the sophisticated network structures, practical applications, and prevailing industry patterns. The primary goal is to provide a thorough comprehension of how deep learning models may be used in healthcare solutions to address the disparity between deep learning techniques and the interpretability of healthcare by humans. Lastly, let us address the current challenges and future prospects [8]

P.E.Y. and L (2021) conducted a study to examine the latest advancements in the specialized field of deep learning image analysis. The purpose of these advancements is to eliminate barriers to implementation and enable those with less expertise in software to effectively use these methods. The subsequent surge of innovation is facilitated by the combination of expertise in certain fields and the creative use of this technology to tackle unaddressed challenges in low- and middle-income nations. In addition, the study examines the important role that (NGOs) play in identifying issues, gathering and organizing data, and integrating new technologies into healthcare systems [9].

The objective of this article by Nancy et al. (2023) is to provide a comprehensive evaluation of the use of the Meta verse in healthcare. The article specifically examines the current advancements in the field, the technological infrastructure required for implementing the Meta verse in healthcare, potential applications, and associated initiatives. Furthermore, this study highlights the challenges encountered when adapting the Meta verse for healthcare applications, and presents possible solutions that will be explored in future research [10]

In their 2023 research, Rakesh et al. demonstrated that the integration of traditional hospital infrastructure with the (IoT) has led to enhanced service quality. Regrettably, the HS depends on wearable sensors and gadgets to continuously monitor and transmit data to nearby devices or servers across an unsecured open channel. The enhanced connectivity between servers and IoT devices enhances operational efficiency, but also exposes patients under critical surveillance to potential risks since hackers might use this vulnerability to launch various attacks. The paper titled "Secure Data Transmission in IoT-enabled Healthcare Systems: A Block chain-orchestrated Deep Learning Approach" is referenced as [11].

The paper by Joseph et al. in 2023 provides a thorough study of the existing research on enhancing deep neural networks for healthcare prediction tasks. The authors specifically focus on the use of structured time series data from patients. From November 4, 2021, they thoroughly searched MEDLINE, IEEE, Scopus, and the ACM Digital Library to identify works that satisfied their specific requirements. The literature on deep time series prediction has been enriched by ten distinct areas of research, namely deep learning models, missing value handling, temporal irregularity management, patient representation, incorporation of static data, attention mechanisms, interpretation, integration of medical ontology's, learning strategies, and scalability [12].

3. Problem statement

Healthcare data complexity and sensitivity are important problems. Machine learning algorithms need large, diverse datasets to be accurate. Healthcare data is sensitive and hard to transmit and combine for model training without compromising patient privacy. Machine learning model interpretability is another issue. Healthcare providers and policymakers must understand how models make decisions in critical situations. Interpretability issues may impede healthcare ML implementation. Healthcare machine learning must be vetted and evaluated to safeguard patients. Algorithm biases may cause erroneous diagnostic and therapy recommendations, impacting patient outcomes. Thus, rigorous and consistent validation procedures are essential to decrease risks and boost healthcare practitioner trust. Healthcare environments are dynamic, therefore machine learning algorithms may fail to adapt to patient demographics, treatment regimens, and medical knowledge. Models must be updated and calibrated to work. Healthcare machine learning involves ethical issues including algorithmic bias and fairness. Machine learning may automate and enhance healthcare, but data privacy, model interpretability, validation, adaptability, and ethics must be addressed for responsible adoption.

4. Proposed Work

Machine learning in healthcare automation improves patient outcomes and streamlines processes. To ensure data quality, healthcare data including electronic health records and medical imaging are collected and prepared. Integrating many data sources yields a full dataset. Feature engineering discovers important variables, and healthcare challenges need the correct machine learning methods. Model training educates the algorithm using old data, whereas validation tests it on new data. This model is optimized and confirmed before being used in healthcare. Real-time healthcare data and process adaptation demands ongoing monitoring and maintenance. Interpreting the model's decisions promotes healthcare transparency and trust. Everyday practice integration requires healthcare workflow integration. This holistic process flow highlights how machine learning improves healthcare automation accuracy, efficiency, and innovation. Machine learning in healthcare automation requires many critical phases.

1. Collect and pre-process healthcare data from numerous sources, such as EHRs, medical imaging, patient questionnaires, and wearable devices. Clean and pre-process raw data for missing values, outliers, and inconsistencies. This phase is essential for machine learning model input data quality.
2. Create a complete dataset from many sources to provide a holistic perspective of patient health and medical history. Select dataset variables needed for model training and predictive analytics.
3. Select machine learning methods depending on the healthcare issue. Decision trees, SVMs, neural networks, and ensemble approaches are common algorithms.
4. Train, validate, and test the chosen machine learning

model using historical data. Data patterns and correlations are learned by the model to predict or classify. Use a dataset not utilized for training to evaluate the developed model. This phase guarantees the model generalizes to new data.

5. Optimize and deploy model parameters and features for better performance. This may need hyper parameter adjustment and model architecture changes. Use the verified machine learning model in healthcare. This may require integration with EHRs, medical imaging equipment, or other platforms.
6. Track model performance in real-world circumstances. Update the model regularly to reflect healthcare data and medical practices.
7. Make sure the machine learning model is interpretable and explainable, particularly in healthcare where transparency and understanding of choices are essential for building confidence with experts.
8. Improve decision-making and patient care by smoothly integrating machine learning into healthcare processes.
9. Use healthcare professionals' insights, patient outcomes, and data updates to enhance model performance over time.

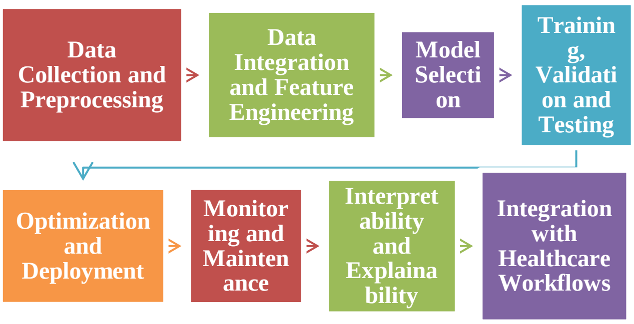

Fig. 1. Process flow of Research work

Figure 1 is showing overall process flow of data collection, data integration, model selection, training, testing, optimization, monitoring maintenance and interpretability.

5. Results

This section delves into several machine learning methods used in healthcare, with a focus on deep learning techniques for disease categorization tasks. Kaggle is where we got the training dataset. However same dataset is also available at https://9nftmania.com/technical.html. These pictures are part of the required dataset for determining if person is healthy or not. After the traditional model's training is complete, the datasets go through a testing process to determine the model's accuracy. For the purpose of testing, a total of 10,000 datasets were used, which include both healthy and not healthy reports. The confusion matrix may be shown in Table 1. To demonstrate how accurate it is, Table 2 is based on the data in Table 1.

Table 1. Confusion matrix in case of conventional approach

	Detected	*Not Detected*
Detected	9889	101
Not Detected	111	9899

TP: 19788
Overall Accuracy: 98.94%

Table 2. Accuracy table for conventional approach

Class	*n (truth)*	*n (classified)*	*Accuracy*	*Precision*	*Recall*	*F1 Score*
1	10000	9990	98.94%	0.99	0.99	0.99
2	10000	10010	98.94%	0.99	0.99	0.99

Table 3 displays the confusion matrix, and the 10,000 dataset includes normal reports and illness diagnosed disturbances. In order to display the accuracy parameter throughout the suggested task, table 4 was developed by considering table 3.

Table 3. Confusion matrix in case of proposed work

	Detected	*Not Detected*
Detected	9916	69
Not Detected	84	9931

TP: 19847
Overall Accuracy: 99.24%

Table 4. Accuracy table for proposed work

Class	*n (truth)*	*n (classified)*	*Accuracy*	*Precision*	*Recall*	*F1 Score*
1	10000	9985	99.24%	0.99	0.99	0.99
2	10000	10015	99.24%	0.99	0.99	0.99

Table 5 displays a comparative examination of the overall correctness between the conventional and suggested work.

Table 5. Overall Accuracy in case of conventional and proposed work

Conventional Approach	*Proposed Work*
98.94%	99.24%

Comparative analysis of overall accuracy in case of conventional and proposed work have been shown in following figure 2.

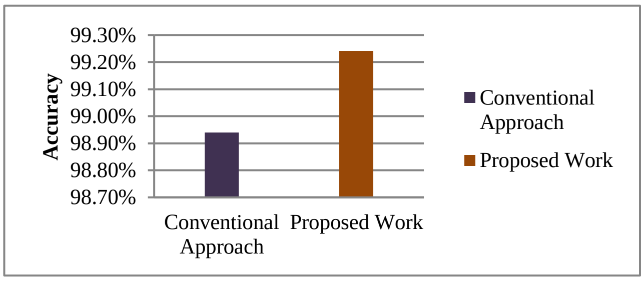

Fig. 2. Comparison of accuracy in case of different applications

Table 6 shows an analysis of time consumption for conventional and proposed work.

Table 6. Time Consumption for Conventional and Proposed Work

Epoch	Conventional Approach	Proposed Work
10	12.08	6.28
20	21.74	17.91
30	33.68	28.16

40	43.96	36.09
50	51.51	47.46
60	61.79	55.86
70	74.19	69.90
80	81.64	75.28
90	94.60	86.50
100	104.49	99.57

Comparative analysis of time consumption in case of conventional and proposed work has been shown in following figure 3.

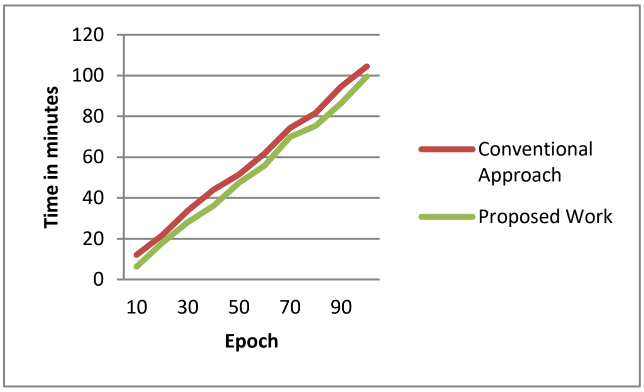

Fig. 3. Performance comparison in case of training and testing of different models

6. Conclusion

Healthcare has been substantially affected by machine learning. Machine learning-powered healthcare automation has improved efficiency, accuracy, and patient outcomes. Machine Complex algorithms that evaluate imaging scans, pathology reports, and patient data may diagnose illness early. Machine learning algorithms identify patterns and anomalies to enhance diagnosis and treatment. Machine learning is essential for diagnostics and tailored medication. Algorithms may help physicians create tailored treatment regimens by examining genetic and therapeutic data. This personalized strategy improves healthcare quality, side effects, and therapeutic effectiveness. Machine learning excels in predictive analytics for healthcare automation. Automation and machine learning enable telemedicine and remote monitoring. By evaluating data in real time, doctors may monitor patients' vitals remotely, reducing clinic visits. This improves healthcare efficiency and patient comfort. Despite these advances, data security, ethics, and regulatory compliance must be addressed before machine learning may be utilized ethically in healthcare. As machine learning advances, healthcare may become more automated, tailored, and patient-centred. This research focuses on automating healthcare services, including illness detection and classification using patient data.

7. Future Scope

Healthcare services using machine learning for automation will improve. As technology progresses, machine learning will change healthcare. Individualized medicine, where machine learning algorithms analyse big datasets to tailor therapy to patient features, genetics, and health history, sounds promising. This approach may enhance therapy and lessen negative effects. Machine learning's predictive capability will assist preventive healthcare. These tools can analyse patient data to predict health risks and enable early treatment, becoming healthcare proactive. Machine learning-enabled remote patient monitoring will allow doctors to monitor patients in real time and react swiftly, reducing hospital admissions and improving patient outcomes. Additionally, machine learning in diagnostics is promising. Advanced algorithms can analyse medical images, diagnose tests, and detect diseases early. This accelerates diagnosis and increases accuracy, boosting therapeutic success. Machine learning-based healthcare will include intelligent EHRs.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. M. J. Rivera, M. A. Teruel, A. Maté, and J. Trujillo, "Diagnosis and prognosis of mental disorders by means of EEG and deep learning: a systematic mapping study," Artificial Intelligence Review, vol. 55, no. 2. Springer Science and Business Media LLC, pp. 1209–1251, Mar. 27, 2021. doi: 10.1007/s10462-021-09986-y.
2. A. M. Abdelhameed and M. Bayoumi, "Semi-Supervised EEG Signals Classification System for Epileptic Seizure Detection," IEEE Signal Processing Letters, vol. 26, no. 12. Institute of Electrical and Electronics Engineers (IEEE), pp. 1922–1926, Dec. 2019. doi: 10.1109/lsp.2019.2953870.
3. U. R. ACHARYA, S. V. SREE, S. CHATTOPADHYAY, and J. S. SURI, "Automated Diagnosis Of Normal And Alcoholic Eeg Signals," International Journal of Neural Systems, vol. 22, no. 03. World Scientific Pub Co Pte Lt, p. 1250011, May 16, 2012. doi: 10.1142/s0129065712500116.
4. U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals," Computers in Biology and Medicine, vol. 100. Elsevier BV, pp. 270–278, Sep. 2018. doi: 10.1016/j.compbiomed.2017.09.017.
5. B. Ay et al., "Automated Depression Detection Using Deep Representation and Sequence Learning with EEG Signals," Journal of Medical Systems, vol. 43, no. 7. Springer Science and Business Media LLC, May 28, 2019. doi: 10.1007/s10916-019-1345-y.
6. Miotto, R., Wang, F., Wang, S., Jiang, X., & Dudley, J. T. (2017). Deep learning for healthcare: review, opportunities and challenges. In Briefings in Bioinformatics (Vol. 19, Issue 6, pp. 1236–1246). Oxford University Press (OUP).
7. S. Yang, F. Zhu, X. Ling, Q. Liu, and P. Zhao, "Intelligent Health Care: Applications of Deep Learning in Computational Medicine," Frontiers in Genetics, vol. 12. Frontiers Media SA, Apr. 12, 2021. doi: 10.3389/fgene.2021.607471.
8. S. Yang, F. Zhu, X. Ling, Q. Liu, and P. Zhao, "Intelligent Health Care: Applications of Deep Learning in Computational Medicine," Frontiers in Genetics, vol. 12. Frontiers Media SA, Apr. 12, 2021. doi: 10.3389/fgene.2021.607471.
9. S. Shamshirband, M. Fathi, A. Dehzangi, A. T. Chronopoulos, and H. Alinejad-Rokny, "A review on deep learning approaches in healthcare systems: Taxonomies, challenges, and open issues," Journal of Biomedical Informatics, vol. 113. Elsevier BV, p. 103627, Jan. 2021. doi: 10.1016/j.jbi.2020.103627.

10. D. Williams, H. Hornung, A. Nadimpalli, and A. Peery, "Deep Learning and its Application for Healthcare Delivery in Low and Middle Income Countries," Frontiers in Artificial Intelligence, vol. 4. Frontiers Media SA, Apr. 29, 2021. doi: 10.3389/frai.2021.553987.
11. R. Chengoden et al., "Metaverse for Healthcare: A Survey on Potential Applications, Challenges and Future Directions," IEEE Access, vol. 11. Institute of Electrical and Electronics Engineers (IEEE), pp. 12765–12795, 2023. doi: 10.1109/access.2023.3241628.
12. P. Kumar, R. Kumar, G. P. Gupta, R. Tripathi, A. Jolfaei, and A. K. M. Najmul Islam, "A blockchain-orchestrated deep learning approach for secure data transmission in IoT-enabled healthcare system," Journal of Parallel and Distributed Computing, vol. 172. Elsevier BV, pp. 69–83, Feb. 2023. doi: 10.1016/j.jpdc.2022.10.002.
13. M. A. Morid, O. R. L. Sheng, and J. Dunbar, "Time Series Prediction Using Deep Learning Methods in Healthcare," ACM Transactions on Management Information Systems, vol. 14, no. 1. Association for Computing Machinery (ACM), pp. 1–29, Jan. 16, 2023. doi: 10.1145/3531326.
14. Z. Ali, M. S. Hossain, G. Muhammad, and A. K. Sangaiah, "An intelligent healthcare system for detection and classification to discriminate vocal fold disorders," Future Generation Computer Systems, vol. 85, pp. 19-28, 2018.
15. G. Yang, L. Xie, M. Mantysalo et al., "A health-IoT platform based on the integration of intelligent packaging, unobtrusive bio-sensor, and intelligent medicine box," IEEE Transactions on Industrial Informatics, vol. 10, no. 4, pp. 2180–2191, 2014
16. Y. Yan, "A home-based health information acquisition system," Health Information Science and Systems, vol. 1, p. 12, 2013.
17. M. Khan, K. Han, and S. Karthik, "Designing smart control systems based on internet of things and big data analytics," Wireless Personal Communications, vol. 99, no. 4, pp. 1683–1697, 2018.
18. P. J. Nachankar, "IOT in agriculture," Decision Making, vol. 1, no. 3, 2018.
19. V. G. Menon, "An IoT-enabled intelligent automobile system for smart cities," Internet of @ings, p. 100213, 2020.
20. E. Qin, "Cloud computing and the internet of things: technology innovation in automobile service," in Proceedings of the International Conference on Human Interface and the Management of Information, pp. 173– 180, Las Vegas, NV, USA, July 2013.
21. B. Alhasnawi, B. Jasim, B. Issa "Internet of Things (IoT) for Smart Precision Agriculture" Iraqi Journal for Electrical and Electronic Engineering, vol. 18, no. 8, p. 1- 11, 2020.
22. P. S. Mathew, "Applications of IoT in healthcare," in Cognitive Computing for Big Data Systems over IoT, pp. 263–288, Springer, Berlin, Germany, 2018.
23. V.Jagadeeswari, "A study on medical Internet of things and Big Data in personalized healthcare system," Health Information Science and Systems, vol. 6, p. 14, 2018.
24. H. Peng, Y. Tian, J. Kurths, L. Li, Y. Yang, and D. Wang, "Secure and energy-efficient data transmission system based on chaotic compressive sensing in body-to-body networks," IEEE Transactions on Biomedical Circuits and Systems, vol. 11, no. 3, pp. 558–573, 2017.
25. A. Gatouillat, Y. Badr, B. Massot, and E. Sejdic, "Internet of medical things: a review of recent contributions dealing with cyber-physical systems in medicine," IEEE Internet of @ings Journal, vol. 5, no. 5, pp. 3810–3822, 2018.