Educational Administration: Theory and Practice
2024, 30(4), 9094 - 9097
ISSN: 2148-2403
https://kuey.net/
Research Article

Relevance Of Artificial Intelligence In Healthcare: An Exhaustive Review

K. Srikanth[1*], Sonali Das[2], Mukta Deb[3]

[1*]Assistant Professor, Brainware University, Kolkata
[2]Assistant Professor, Brainware University, Kolkata
[3]Assistant Professor, Brainware University, Kolkata

***Corresponding Author:** K. Srikanth
*Assistant Professor, Brainware University, Kolkata

Citation: K. Srikanth, et al (2024) Relevance Of Artificial Intelligence In Healthcare: An Exhaustive Review. *Educational Administration: Theory and Practice*, *3*(4), 9094 - 9097,
Doi: 10.53555/kuey.v30i4.3048

ARTICLE INFO

ABSTRACT

Artificial Intelligence (AI) has evolved as a transformational power in the healthcare sector, revolutionizing multiple facets of medical practice, starting from the detection of disease to the plan of treatment and care of patients. AI is creating a paradigm shift in healthcare because of the fact of increased accessibility of healthcare information & the swift progress of scientific methods. AI applies to varied healthcare data which includes both structured & unstructured data. Prominent AI applications encompass machine learning techniques for instance, classical support vector machine & neural network for the structured data, and modern deep learning & natural language processing for the unstructured data. AI algorithms have been proven to analyze huge proportions of patient data to detect patterns & forecast the progression of a disease facilitating a customized treatment plan & preventive interventions. Deriving upon the evidence from the secondary data sources which include medical & health sciences articles, the current study provides an extensive review of AI in healthcare. Derived from a qualitative content analysis, various subfields of AI in healthcare are portrayed. This article further uncovers the applications of AI in promoting individual and community health. Lastly, the articles close by concluding the leading AI systems in the context of a hospital setting.

Keywords: Artificial Intelligence, Healthcare, Machine Learning, Natural Language Processing, Neural Network.

INTRODUCTION

Artificial Intelligence (AI) denotes the replication of an individual's intelligence actions by machines, particularly computer systems. Such actions encompass learning (the attainment of information & regulations for using the information), interpretation (making use of rules to arrive at estimated or determined conclusions) & self-correction. AI emulates the human mind to explicate the environment & function consistently. In AI, data ingestion is a very crucial attribute. AI systems need to tackle a large amount of data. Furthermore, an AI system preserves data from diversified sources about diversified individuals & machines. All of this emerges nonsynchronous or concurrently on the system.
AI is mainly of two categories. Firstly, artificial general intelligence which is a hypothetical type of intelligent agent has been the early attention of AI research as well as the central description of AI in the accepted culture. Despite the hurdles and intricacies related to the development of this type of AI, a large number of empiricists have shifted their focus towards artificial narrow intelligence which is the capacity of a device to execute a particular activity exceptionally well. In the practical context, all the recent health applications using AI are treated as artificial narrow intelligence (Pennachin et al., 2007)

AI: Healthcare context

AI is increasingly being applied in various areas of healthcare to analyze and leverage healthcare data. But, even before an AI system is deployed in healthcare operations, they are supposed to be originally 'trained' via the information that is produced through the clinical actions, for instance, screening, detection, and therapy assignment along with others, such that they get an understanding on the related groups of subjects, interrelationships among the subject attributes & outcomes of interest. This particular clinical information frequently subsists nevertheless confined to the demographic patterns, health records, computerized recordings from the health equipment, physical evaluations & clinical laboratory & images. Apart from this, the other types of healthcare datasets which are generated from wearable devices and remote monitoring, genomic data analysis, predictive analytics, risk stratification, and lastly drug discovery and development, will leverage AI innovations in enhancing the care of the patient, improving the clinical decision-making & promoting clinical research across the different domains of healthcare.

OBJECTIVES OF STUDY

i) To demonstrate the various sub-fields of AI in the framework of healthcare.
ii) To identify various applications of AI in enhancing individual and community well-being.
iii) To summarize the leading AI systems that are applicable in the framework of a hospital setting.

METHODOLOGY OF STUDY

Qualitative content analysis was done to analyze the secondary data sources using a conventional research design and the observations synthesized via secondary data sources set the foundation for presenting the state of information on the relevance of AI in healthcare. The sequential flow of the article is constructed along these lines. Section 4 precisely illustrates the subfields of AI which includes machine learning & deep learning. In Section 5, we analyze the specific applications of AI in improving individual & population health. In Section 6, we conclude with the leading AI systems in the context of a hospital setting.

DISCUSSIONS

Machine Learning (ML)

One of the AI applications is ML. In the practical context, the ML technique refers to data analysis automation via formulas that reiterate detected patterns in the data & interpret from the same. ML methods fundamentally examine the structured data which includes imaging, genetic & electrophysiological data.

Classical ML

Classical ML establishes data analytical formulas to extricate attributes out of data & the codes to ML algorithms consist of the subject characteristics & at times medical outcomes of interest. The patients' characteristics normally consist of standard data, for instance, age, sex, history of the disease, etc. as well as disease-specific data, such as electrophysiological tests, results of the clinical examination, medications & so on. Apart from these attributes, medical outcomes of the patients are often gathered in the clinical research which includes disease indicators & quantitative disease levels, for instance, the size of the tumors.
ML algorithms are categorized into two vital groups i.e., Unsupervised Learning (UL) & Supervised Learning (SL) based on whether to include the outcomes. UL is applicable for feature extraction, whereas SL is applicable for predictive modeling via developing a few interrelationships amidst the patient attributes & the outcomes of interest. Amongst the SL methods, Support Vector Machine (SVM) & Neural Networks (NN) are the universally accepted ones, applied particularly when confining to three vital data types (image, genetic & electrophysiological). Contemporarily, semi-supervised learning has been recommended as a blend amidst UL & SL, which is ideal in situations where the outcome is lacking for a specific subject.
SL inspects the subjects' outcomes along with their attributes & subjected to a specific training method to examine the finest outputs linked with the inputs that are nearest to the outcomes on average. Undoubtedly, contrasted with UL, SL offers many clinically accepted findings; henceforth AI technologies in healthcare frequently employ SL. Similar methods embrace linear regression, logistic regression, naïve Bayes, decision tree, nearest neighbor, random forest, discriminant analysis, SVM & NN (Goodfellow et al., 2016)

Support Vector Machine (SVM)

One of the crucial characteristics of an SVM is that the verification of model parameters is a convex optimization problem so the solution is all the times global optimum. Moreover, multiple prevailing convex optimization tools are easily suitable for an SVM execution. Because of this fact, SVM is been significantly employed in clinical research, for example, the application of SVM in diagnosing cancer (Sweilam et al., 2010) , SVM implementation in detecting imaging biomarkers of neurological & psychiatric diseases (Orrù et al., 2012) , the unification of SVM & various analytical tools to attain the early diagnosis of Alzheimer's disease (Khedher et al., 2015), significance of SVM to assess the strength of an offline individual/device connectivity that regulates the upper-limb prostheses (Farina et al., 2017)

Neural Network (NN)

A Neural Network is an expansion of linear regression to represent the composite non-linear associations betwixt the input variables & an outcome. In NN, the relations amidst the outcome & the input variables are

represented via different masked layer combinations of pre-specified functional. The objective is to predict the weights via the input & outcome information so that the average error betwixt the outcome & their estimations is reduced.
NN techniques are employed in medical applications, for instance in diagnosing cancer, wherein the inputs are PCs predicted from 6567 genomes & the end-results are the cancer groups (Khan et al., 2001). Usage of NN to estimate the cancer of mammary glands, where the inputs are the textured data of breast pictures & the outcomes are tumor indicators (Dheeba et al., 2014). Advanced NN prototype to detect Parkinson's condition formed on the inputs of motor, non-motor signs & neuroimages (Hirschauer et al., 2015)

Deep Learning (DL)
DL is a recent branch of the conventional NN technique. DL has gained popularity for two reasons: a rise in the volume & data intricacy and because of viewing DL as an NN amidst many layers as well as exploring multiple composite non-linear patterns in the dataset (Ravi et al., 2017). DL algorithms most frequently used in medical applications are Convolution NN, Recurrent NN, Deep NN & Deep belief network. CNN is advanced given the incompetency of the traditional ML formulas while dealing with a multi-dimensional dataset i.e., data having multiple attributes. Classically, ML formulas are prearranged to investigate the data at times of a minimal number of traits. Nonetheless, data with images are generally multi-dimensional for the reason that every image usually encompasses thousands of picture elements as traits. The initial solution is to run dimension reduction: initially choose a portion of picture elements as features & then run ML algorithms on the subsequent lower dimensional features.

Applications of AI in community health
A huge proportion of data produced via healthcare has resulted in an abundance of the right set of circumstances for implementing AI to enhance the individual & population's well-being. This is especially evident in resource-poor establishments, where there has been an intense cellular phone adaptation, advancements in cloud computing, significant funding for the digitalization of health information & initiating mobile health (m-Health) apps. Various applications of AI in community health are as follows:

Health Informatics (HI)
HI refers to the capture, deposit, and retrieval of healthcare data, which is used to enhance patient care over exchanges with the health system. HI shapes community health programs by making sure that vital information is in place for designing strong policies & program decisions.

Electronic Medical Records (EMR)
EMR, which is an online version of patient & population health information is a vital data source for HI. EMR helps in catering the relevant clinical information and in evaluating the diagnostic process (Li et al., 2021). Eventually, an EMR provides real-time scores that help in transferring intensive care to the patients in hospital mortality check (Escobar et al., 2016), risk of readmission, length of stay for maximum days, and discharge diagnosis (Rajkomar et al., 2018). Furthermore, with the use of EMR, future predictions of diseases could be done efficiently such as acute kidney injury (Tomašev et al., 2019).
One typical case of an EMR platform that is presently being adopted is OpenMRS. Researchers concluded that this particular EMR platform aids in enhancing the extensiveness of the data collected & ceases critical gaps in care (Tomašev et al., 2015). Another typical example of an EMR platform is DHIS2 which is used for assembling, verifying, investigating & presenting accumulated & patient-based statistical data.

Cloud Computing (CC)
The developments in CC have resulted in the extension of AI applications in health. CC deals with the utilization of a network of remote servers to deposit, arrange, retrieve & mine the data. Organizations were fast enough to acquire CC because of the benefits it provides against an in-house IT system, which includes improved reliability & significant cost savings.

Mobile Health
m-Health utilizes mobile & hands-free technologies to attain the determined health objectives. The increased accessibility & penetration of mobile phones in poverty-stricken nations have created multiple possibilities for making use of these innovations to foster health efforts. Cellular phones are employed by public health professionals to advance the opportunities of health care services.

CONCLUSIONS

One of the leading AI systems in the context of hospital settings is Cloud-based CC-Cruiser which is an archetype to link up the AI application with the front-end data input & the back-end clinical actions (Long et al., 2017). During the patient's visit to a hospital setting, with their approval, their demographic & clinical information (images, electro-physiological findings, genetic findings, BP, medical history, etc.) are fed into an AI system & the AI system that instance, gathers the patients' data to arrive at medical advices. These inputs

are then transferred to the medical practitioners to aid in their clinical decision-making. Comments regarding the inputs (right/wrong) are again accumulated & entered within the AI system in such a way that it can constantly increase the accuracy.
To conclude, AI holds immense promise in revolutionizing healthcare delivery and its successful integration requires a multidisciplinary approach involving a collaboration between clinicians, data scientists, policymakers, and ethicists. By handling the issues & harnessing the opportunities offered by AI, the healthcare industry could leverage technology to improve patient outcomes, enhance efficiency, and ultimately transform the way healthcare is delivered and experienced.

REFERENCES

1. Dheeba, J., Singh, N. A., & Selvi, S. T. (2014). Computer-aided detection of breast cancer on mammograms: A swarm intelligence optimized wavelet neural network approach. *Journal of biomedical informatics*, *49*, 45-52. https://doi.org/10.1016/j.jbi.2014.01.010
2. Escobar, G. J., Turk, B. J., Ragins, A., Ha, J., Hoberman, B., LeVine, S. M., ... & Kipnis, P. (2016). Piloting electronic medical record–based early detection of inpatient deterioration in community hospitals. *Journal of hospital medicine*, *11*, S18-S24. https://doi.org/10.1002/jhm.2652
3. Farina, D., Vujaklija, I., Sartori, M., Kapelner, T., Negro, F., Jiang, N., ... & Aszmann, O. C. (2017). Man/machine interface based on the discharge timings of spinal motor neurons after targeted muscle reinnervation. *Nature biomedical engineering*, *1*(2), 0025. https://doi.org/10.1038/s41551-016-0025
4. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT press.
1. 15. Haskew, J., Rø, G., Turner, K., Kimanga, D., Sirengo, M., & Sharif, S. (2015). Implementation of a cloud-based electronic medical record to reduce gaps in the HIV treatment continuum in rural Kenya. *PLoS One*, *10*(8), e0135361. https://doi.org/10.1371/journal.pone.0135361
5. Hirschauer, T. J., Adeli, H., & Buford, J. A. (2015). Computer-aided diagnosis of Parkinson's disease using enhanced probabilistic neural network. *Journal of medical systems*, *39*, 1-12. https://doi.org/10.1007/s10916-015-0353-9
6. Khan, J., Wei, J. S., Ringner, M., Saal, L. H., Ladanyi, M., Westermann, F., ... & Meltzer, P. S. (2001). Classification and diagnostic prediction of cancers using gene expression profiling and artificial neural networks. *Nature medicine*, *7*(6), 673-679. https://doi.org/10.1038/89044
7. Khedher, L., Ramírez, J., Górriz, J. M., Brahim, A., Segovia, F., & Alzheimer′ s Disease Neuroimaging Initiative. (2015). Early diagnosis of Alzheimer′ s disease based on partial least squares, principal component analysis and support vector machine using segmented MRI images. *Neurocomputing*, *151*, 139-150. https://doi.org/10.1016/j.neucom.2014.09.072
8. Li, R., Niu, Y., Scott, S. R., Zhou, C., Lan, L., Liang, Z., & Li, J. (2021). Using electronic medical record data for research in a Healthcare Information and Management Systems Society (HIMSS) Analytics Electronic Medical Record Adoption Model (EMRAM) stage 7 hospital in Beijing: cross-sectional study. *JMIR Medical Informatics*, *9*(8), e24405. https://doi.org/10.2196/24405
9. Long, E., Lin, H., Liu, Z., Wu, X., Wang, L., Jiang, J., ... & Liu, Y. (2017). An artificial intelligence platform for the multihospital collaborative management of congenital cataracts. *Nature biomedical engineering*, *1*(2), 0024. https://doi.org/10.1038/s41551-016-0024
10. Orru, G., Pettersson-Yeo, W., Marquand, A. F., Sartori, G., & Mechelli, A. (2012). Using support vector machine to identify imaging biomarkers of neurological and psychiatric disease: a critical review. *Neuroscience & Biobehavioral Reviews*, *36*(4), 1140-1152. https://doi.org/10.1016/j.neubiorev.2012.01.004
11. Pennachin, C., & Goertzel, B. (2007). Contemporary approaches to artificial general intelligence. In *Artificial general intelligence* (pp. 1-30). Berlin, Heidelberg: Springer Berlin Heidelberg. https://link.springer.com/chapter/10.1007/978-3-540-68677-4_1
12. Rajkomar, A., Oren, E., Chen, K., Dai, A. M., Hajaj, N., Hardt, M., ... & Dean, J. (2018). Scalable and accurate deep learning with electronic health records. *NPJ digital medicine*, *1*(1), 1-10. https://doi.org/10.1038/s41746-018-0029-1
13. Ravì, D., Wong, C., Deligianni, F., Berthelot, M., Andreu-Perez, J., Lo, B., & Yang, G. Z. (2016). Deep learning for health informatics. *IEEE journal of biomedical and health informatics*, *21*(1), 4-21. doi: http://doi.org/10.1109/JBHI.2016.2636665
14. Sweilam, N. H., Tharwat, A. A., & Moniem, N. A. (2010). Support vector machine for diagnosis cancer disease: A comparative study. *Egyptian Informatics Journal*, *11*(2), 81-92. https://doi.org/10.1016/j.eij.2010.10.005
15. Tomašev, N., Glorot, X., Rae, J. W., Zielinski, M., Askham, H., Saraiva, A., ... & Mohamed, S. (2019). Developing Deep Learning Continuous Risk Models for Early Adverse Event Prediction in Electronic Health Records: an AKI Case Study. https://doi.org/10.21203/rs.2.10083/v1