Hypertension Journal

REVIEW ARTICLE

Artificial Intelligence in Hypertension: A Futuristic Approach in Blood Pressure Management

Anjali Singh*, Narsingh Verma

Department of Physiology, King George's Medical University, Lucknow, UP, India.

Abstract

Hypertension is not only the most prevalent disease but also poses a global burden as well as a national burden on the health system. Coping the disease with physical means is quite common but now in emerging India the transformation in management of the disease via technology is getting popular. In the same array, Artificial Intelligence is seeking its way for newer innovations in the field of medicine. AI brings a multitude of benefits to the field of medicine, transforming various aspects of healthcare delivery and improving patient outcomes. AI systems continuously learn from new data, adapting and improving over time to provide more accurate diagnostics and treatment recommendations. Evidently, this review article highlights the role of AI in management of hypertension, taking into account its diagnosis, treatment as well as its limitations. AI-based systems are now replacing conventional BP monitors. Not only measurement but AI could play critical role in diagnosing, treating and managing hypertension. Moreover, prediction of undiagnosed hypertension is also possible through AI. Though there are still technical glitches and biases in AI, but it could be worked on in future. Thus, AI based health care systems will indeed make the clinical practice more precise and will ensure personalized medicine.

Keywords: Artificial intelligence, Blood pressure, Hypertension

INTRODUCTION

Hypertension affects more than 30 percent of the adult population globally, i.e., more than 1 billion people around the world. It is the primary contributor to risk for cardiovascular disorders (CVDs), predominantly coronary heart disease & stroke, but also for heart failure, chronic renal disease, dysrhythmia & dementia.[1] Worldwide, hypertension is a leading cause of mortality. An estimated 46% of individuals with hypertension are unaware of their BP condition.[2] Globally, almost 1 billion people suffer from uncontrolled hypertension,[3] with developed and developing nations accounting for 66.8% and 61.6%, respectively.[4] Alarmingly, less than one-fifth of individuals globally have hypertension under control.[5] Uncontrolled hypertension is more frequent in Asian countries, with the exception of South Korea and Taiwan.[6,7]

According to recent Indian research, the prevalence of hypertension (HTN) is 25% in urban areas and 10% in rural areas.[8-11] According to WHO estimations from 2008, the prevalence of high blood pressure among Indians was 32.5% (31.7% in women and 33.2% in men).[12] Hypertension is a developing disease that has been exacerbated by population increase, lifestyle changes, and ageing, posing a worldwide and national burden on the health-care system. Thus, transformation in its management strategies is urgently required to cope-up with this enormous burden. [13-15]

In the techno world, things are getting digitalized. Health care system is also on the same track. Manual vital measurements are transformed to automatic measuring systems, physical appointments are changed to virtual appointments. Technological advancements like online appointments, telemedicine, electronic health record system, Software as a Medical Device (SaMD), and AI-powered medical devices are some of the most remarkable examples of digital health care system.[16] Apart from these technologies, use of artificial intelligence (AI) is also emerging in medicine world providing numerous opportunities to improve clinical results, automate processes, creation of new treatments, identify precise medicines for complicated diseases, improve the course of care for patients with chronic diseases, lower medical mistakes and enhance overall efficiency.[17-19]

Corresponding author

Anjali Singh, Department of Physiology, King George's Medical University, Lucknow, UP, India.

AI refers to a digital computer or computer-controlled robot's capacity to do activities often associated with intelligent beings. In other words, AI may mimic human thinking and intellectual activity.[20] Therefore, application of AI in hypertension management is an important research area of interest, from both technical as well as clinical viewpoint.

This review aims to discuss the potential role of AI in the measurement, diagnosis, treatment, prediction & management of hypertension.

Artificial Intelligence

Artificial intelligence is a broad term that refers to the process of putting human intellect into computers, which was first proposed in 1956.[21] AI is a form of algorithm-based software that enables robots to solve issues using information. Therefore, AI is multidisciplinary field with numerous perspectives that include reasoning (employing knowledge, data, facts & beliefs to draw logical conclusions), speech recognition (the ability to interpret words spoken and translate it into text), planning (the ability to work independently and fluidly to generate sequential steps to be taken to accomplish the ultimate objective), and machine learning (ML) (approach that learns on its own from experience) (Figure 1).[22] The key areas of AI medical applications include physiological signal recognition, imaging processing, and neurological health issues.[23-26]

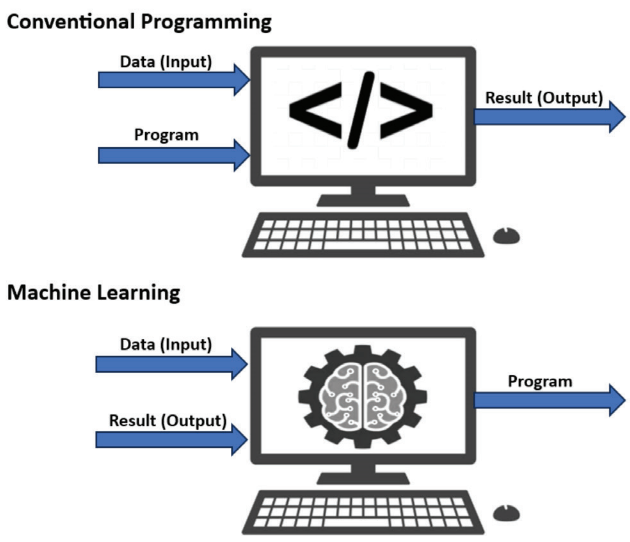

Figure 1: Conventional Programming vs Machine Learning[27]

Types of AI used in Hypertension

Artificial intelligence (AI), machine learning (ML) & deep learning (DL) are the 3 interchangeably used common terms to denote the software or intelligent system. The relationship of ML, DL and AI is depicted in Figure 2. In general, artificial intelligence (AI) integrates human behaviour and intellect into robots or other systems.[28]

ML is a subfield of AI algorithms. It is an approach to automate the process of developing analytical models by learning from data or experience.[29] ML compiles data using mathematical algorithms and generates conclusions based on predefined criteria. It is used in managing medical data, helping in the diagnosis as well as early detection of infectious and degenerative diseases, identification of brain disorders (Alzheimer's, schizophrenia, dementia), personalized medicine, precisely spot abnormal growth of tissue, making surgical plan, analyzing postoperative effects, radio/chemotherapy and analysis of errors in prescriptions, and analysis of the data of multiomics, and wearable devices.[30,31]

A subfield of ML (i.e., a subfield of artificial intelligence) is DL. An upgraded version of ML, i.e., DL is capable of solving problems that ML is unable to. Deep learning is the process of learning concepts on the top of other concepts[28] that calculate using neural networks in multi-layer & processing. The word "Deep" in the DL approach, means an idea of several layers of data processing in order to construct a data-driven model for disease predictions and diagnosis. It is utilized for medical imaging, data analysis, and unfavourable outcome prediction.

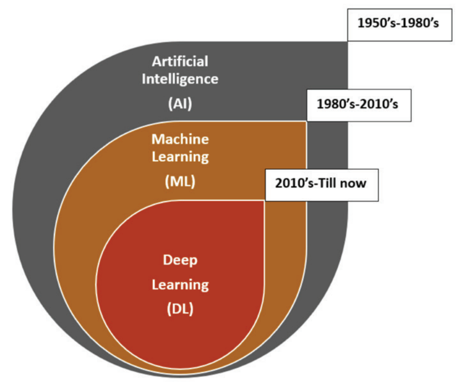

Figure 2: The relationship of ML, DL and AI[29,32]

AI in the Measurement of Blood Pressure

Cuff-based BP monitors (volume-clamps or inflated wrist cuffs) and cuffless systems (tonometry,[33] photoplethysmography (PPG)[34] & capacitance[35]), which employ mechanical and optical sensors to identify characteristics of the blood pulse waveform shape, are available for use in blood pressure monitoring. Studies have reported that the ML uses vital signs and PPG signal to predict BP[36] while Artificial neural network (ANN) uses PPG signal to estimate BP.[37] Another one stated that ML uses electrocardiogram and PPG signal for estimating blood pressure[38] while ANN estimates BP without the use of electrocardiogram.[39]

BP measured at home or clinic is measured using a cuff (a medical device). To measure BP, the BP cuff is wrapped around the arm of patient and then inflated. BP classification typically adheres to the ISH 2020 guidelines and requires a single measurement of BP with a validated upper arm-cuff.[40] Many patients find the cuff-based application to be troublesome and uneasy. The photoplethysmography (PPG) technology in conjunction with AI algorithms is a promising solution, as it is a cuffless BP measurement which is simple, easy to use, and convenient method.[41] The use of PPG signals may increase the number of measures made during the day, increasing the possibility of hypertension detection early.[42] AI blood pressure assessment is beneficial because it improves precision, accuracy & consistency in diagnosing & managing HTN with new wearable technology.

The fastest growing and likely most accurate use of AI for diagnosing Arterial Hypertension (AH) is undoubtedly 24-hour ambulatory blood pressure monitoring (ABPM) i.e., gold standard for out-of-office BP measurement.[43-46] ABPM software can identify and classify AH using BP readings by a fairly simple algorithm. ABPM is very beneficial for analyzing white coats and masked AH.[45,46] Apart from ABPM, there are number of AI-supported gadgets that allow patient to know more about their BP conditions (Table 1).

Table 1: AI-supported gadgets for BP measurement

Gadget	Function	Technology	References
Smart watch	Heart-rate sensor and step counter to predict atrial fibrillation	ML model	**47**
Smart-phone	Cameras, microphones, light emitters & force sensors to detect cardiovascular signals	PPG	**48**
Tablets and smart phones.	The camera on the tablet detects colour changes (microblushes), in a patient's face, which occur every time their heart beats to take BP reading from their face in 40 seconds.	Contact-less technology	**49**
Wi-Fi-Arm Band	Remotely monitor vital signs, like blood pressure, respiratory rate, pulse rate (PR), oxygen levels & body temperature.	AI programs	**50**

AI in Diagnosis of Hypertension

Guidelines for hypertension recommend utilizing home blood pressure monitoring or out-of-office blood pressure measures with ABPM for the diagnosis and categorization of hypertension.[51] One benefit of ABPM is that it may be used to diagnose hypertension and categorize individuals' ABPM status into three groups: true HTN, white-coat HTN, and masked HTN.[52]

When BP, demographic data, co-morbidities & some regular laboratory results are included, AI may reliably diagnose HTN. For example, Samant *et al.*[53] reported that ANN could diagnose hypertension with 92.85% accuracy from the sample size of 981 subjects by means of age, BP, PR & routine blood chemistry. Similarly, LaFreniere *et al.*[54] demonstrated that to diagnose HTN, ML require inputs of age, BMI, BP, PR, lipid profile, smoking history & physical exercise in 379,027 individuals with 82% accuracy. On the top of that, AI can also estimate BP from other variables with little efficacy. Wu *et al.*[55] tried to utilise an ANN to estimate SBP in 498 healthy persons based on their age, BMI, amount of alcohol consumed, level of smoking, and level of activity. Notably, 50% of predicted blood pressure varied by more than 10 mm Hg from observed blood pressure.[55] It's interesting to note that Poplin *et al.*[56] showed DL may predict SBP in 284,335 patients within mean absolute error of 11.23 mmHg with the help of retinal fundus photography. Evidently, BP difference of 10 mm Hg are imprecise to claim that AI can be used to predict BP; yet the validation of AI's ability of diagnosing HTN and predicting BP requires future researches. In the future, if research shows more accuracy, AI might possibly help doctors in their clinical work and even make it easier early identification of HTN.

Primary care physicians would be able to diagnose and treat patients more effectively if they could predict blood pressure status accurately without using ABPM. This would minimize the risk of side effects from antihypertensive drugs, undertreatment of hypertension & the ABPM. This could be possible using machine learning through the use of big data sets and people who had their clinic blood pressure and ABPM monitored.[57]

AI in treatment of Hypertension

New AI program could assist in the treatment of hypertension. Its data-driven model not only anticipate result but also suggests the most suitable medication for hypertensive patients. The Boston University-developed new model could generate a customized prescription of hypertensive patient using his profile, giving physicians a list of suggestive medicines accompanied with their respective success probability. Thus, AI is on the pursuit of effective treatment for controlling systolic blood pressure for each BP patient or for a group of homogenous patients imparting personalized therapeutics for hypertension based on ML algorithms.[58]

For instance, Dawes *et al.*[58] described how an AI-supported cardiac motion algorithm based on magnetic resonance imaging (MRI) may be used to treat patients with high blood pressure and lung illness with more precise data. It also could give prognosis result of pulmonary hypertension accurately among the patients. In patients with recently diagnosed pulmonary hypertension, the ML model "improved the survival prediction that is independent of the disease common risk factors.[55] These professional analytics for prediction have the potential to improve the quality of current treatment provided, by supporting clinician's in making decisions.

In addition to the disease-specific diagnosis, the advances made by Google Health and other research teams demonstrate the prognostication potential and hidden association-finding capabilities of deep learning models. For example, an AI based system could predict gender, smoking status, SBP & risk of MACE (*Major adverse* cardiac *events*) that is solely based on retinal image analysis.[59]

AI for the Prediction of Undiagnosed Hypertension

ML is getting applied widely in genomics to predict the pathogenic potential of coding variants,[60] the functional effects of noncoding variants[61] and to predict certain widespread complex phenotypes as well as disease risk.[62,63] In relation to HTN, Huan et al[63] and Li et al[64] employed ML and network analysis to identify the genes associated with HTN by evaluating the interactions in gene's neighbourhood. The researchers have begun to employ ML in order to categorize CVDs based on a range of genetic markers, including transcriptome and even microbiome.[65,66]

AI approaches are also making their way into gene expression analysis; more particular, by combining data from next-generation sequencing with gene expression in ML analysis, it is feasible to enhance AH prediction models.[67] Furthermore, ML algorithms, enables to find new HTN genes; accordingly, Li *et al*.,[64] examined gene expression in patients with hypertension and were able to identify 177 new genes associated with hypertension as a result of the development of ML algorithms. These genes were then combined with environmental factors to assess the risk of AH.[68,69]

Furthermore, Maxwell *et al.*'s[70] research suggests that health risk prediction utilizing a DL architecture is appropriate for large, complicated datasets. Through an analysis of 110,300 patient physical examination data, every risk factor associated with chronic illnesses like AH, diabetes, and liver steatosis was identified, categorized and examined.[71]

The main takeaway from these examples is that ML techniques may be widely applied to create clinical prediction models based mostly on observational data sets. This is not limited to research on hypertension.

Managing Hypertension

Once hypertension is diagnosed, patients are ought to be counseled on the most effective goals for hypertension treatment, potential repercussions of poorly managed HTN, initiatives that can lower BP, and ultimately the related risk factors for CVD. Among these approaches include pharmacological interventions, out-of-office blood pressure monitoring, and modifications in diet as well as lifestyle.[46]

Emerging technologies have revolutionized healthcare and clinical practice; thus, AI plays a critical role in enhancing the effectiveness of innovative digital treatments by detecting parameters linked to treatment, its adherence & predicting the treatment success.[71] In order to provide behavioural therapy to hypertensive patients, Guthrie *et al.*[72] created a smartphone application that included skill-learning, goal-setting, self-monitoring of biometrics & personalized feedback. This application was able to significantly lower blood pressure in 172 patients. They showed that, with an AUC of 0.78, ML could predict the completion of the intervention on day seven. Predictive factors were biometric self-monitoring, completing app interactions, increasing exercise frequency, and smartphone brand. In order to promote patients' awareness, self-monitoring, and adherence to medication, da Silva *et al.*[73] recently created a complete digital intervention that uses ML to assess adherence to antihypertensive drugs by analyzing data gathered via a smartphone application. Numerous clinical trials are now being conducted to evaluate the impact of AI-integrated hypertension therapy on the treatment, patient compliance & overall efficacy.

Soon AI will grow into a tool for designing accurate and thorough risk prediction models that include behavioural, environmental, and conventional CV risk variables with further research and application. AI may also be used to anticipate the treatment failure and pinpoint the causes of each patient's uncontrolled blood pressure and poor treatment compliance. AI has the potential to create intelligent systems of healthcare that offer individualized advice and course of treatment.

Limitations of AI

As AI has gained significant attention in recent years, it is important to highlight that biases and technical problems still exist in this system. The quality of algorithms that support AI may be impacted by a number of limitations which include erratic level of research that makes up the databases underlying the core of AI.[74]

In case of ML models, overfitting is a significant issue, this results when a model has become unduly fitted to the training set of data.[75] Particularly, supervised learning algorithms need manually labeled data since they are restricted in their ability to anticipate only predetermined outcomes. This suggests that the usual application for supervised models is typically limited to the emulation, automation, and standardization of manual tasks. There are still boundaries between definition, assessment, and judgment when it comes to human intellect and insight.[75]

However, one of the main problems with unsupervised models is validation. To get the unsupervised model externally validated, the true clusters must be known to compare the ML-generated clusters with the unsupervised model.[76] However, it is difficult to find such information often. If such is the case, internal validation techniques are the only means of validating models. Nevertheless, the current techniques are not always credible since they are sensitive to different types of data, such as noise, fluctuations in cluster densities, the existence of subclusters, and uneven cluster sizes.[77] Determining the ideal number of hidden nodes for neural networks continues to be one of the trickiest parts of network constructing.[78]

Without any patients' input, the study of the problem is mostly from the perspective of the doctors. However, patients should be satisfied with the new AI-based cardiovascular technology. Future and further study on the issue should consider the perspectives of the physician and the patient.

CONCLUSION

Hypertension is a major public health problem that has a substantial effect on the burden of disease worldwide. A comprehensive global effort to treat the burden of hypertension and diseases connected to hypertension is necessary to improve health outcomes globally. Accurate monitoring of blood pressure is essential for the proper diagnosis and management of hypertension. The field of hypertension needs transformation. Although there are still obstacles to overcome, the use of digital treatments and approaches, the push for personalized medicine, collaborative decision-making, and advancements in treatment are all important factors in improving the outcomes of patients. Its future hinges on the successful fusion of biotechnological and biological sciences with digital data, as well as their use in the provision of healthcare through innovative delivery methods and population health strategies.

Furthermore, Artificial Intelligence is gaining momentum in today's world. AI brings numerous benefits to the field of medicine. AI could suggest personalized treatment plans based on each individual's unique attributes. AI speeds up the drug development process using large datasets by identifying the disease, suggesting a suitable drug and predicting its effectiveness. Moreover, an AI-based system supports hypertension care by encouraging patient awareness, self

BP monitoring, good lifestyle choices and medical compliance, along with advancing digital technology. Also, AI has technical flaws and challenges such as data privacy, ethical considerations, ongoing validation requirements, and regulation to ensure the responsible and effective deployment of AI in healthcare.

Thus, future research must concentrate on AI-based precision AH therapy to reduce AH's worldwide burden while acknowledging the substantial shortcomings that this approach still has.

REFERENCES:

1. Pan American Health Organization-PAHO/WHO. World Hypertension Day 2020. https://www.paho.org/en/campaigns/world-hypertension-day-2020#:~:text=Hypertension%20affects%20more%20than%2030,heart%20failure%2C%20arrhythmia%20and%20dementia. Accessed November 17, 2023.
2. World Health Organization (WHO). Hypertension 2023. https://www.who.int/news-room/fact-sheets/detail/hypertension. Accessed November 17, 2023.
3. Mendis S, Puska P, Norrving BE, World Health Organization. Global atlas on cardiovascular disease prevention and control. World Health Organization; 2011.
4. Pereira M, Lunet N, Azevedo A, Barros H. Differences in prevalence, awareness, treatment and control of hypertension between developing and developed countries. Journal of hypertension. 2009 May 1;27(5):963-75.
5. Egan BM, Kjeldsen SE, Grassi G, Esler M, Mancia G. The global burden of hypertension exceeds 1.4 billion people: should a systolic blood pressure target below 130 become the universal standard?. Journal of hypertension. 2019 Jun 1;37(6):1148-53.
6. Zhou B, Carrillo-Larco RM, Danaei G, Riley LM, Paciorek CJ, Stevens GA, Gregg EW, Bennett JE, Solomon B, Singleton RK, Sophiea MK. Worldwide trends in hypertension prevalence and progress in treatment and control from 1990 to 2019: a pooled analysis of 1201 population-representative studies with 104 million participants. The Lancet. 2021 Sep 11;398(10304):957-80.
7. Kario K, Mogi M, Hoshide S. Latest hypertension research to inform clinical practice in Asia. Hypertension Research. 2022 Apr;45(4):555-72.
8. Gupta R. Trends in hypertension epidemiology in India. Journal of human hypertension. 2004 Feb;18(2):73-8.
9. Thankappan KR, Sivasankaran S, Khader SA, Padmanabhan PG, Sarma PS, Mini GK, Vasan RS. Prevalence, correlates, awareness, treatment, and control of hypertension in Kumarakom, Kerala: baseline results of community-based intervention program. Indian heart journal. 2006 Jan 1;58(1):28.
10. Gupta R. Meta-analysis of prevalence of hypertension in India. Indian heart journal. 1997 Jan 1;49(1):43-8.
11. Das SK, Sanyal K, Basu A. Study of urban community survey in India: growing trend of high prevalence of hypertension in a developing country. International journal of medical sciences. 2005;2(2):70.
12. World Health Organization. Noncommunicable diseases. World Health Organization. Regional Office for Europe; 2011.
13. Jose AP, Prabhakaran D. World hypertension day: contemporary issues faced in India. The Indian journal of medical research. 2019 May;149(5):567.
14. Lewington S. Prospective studies collaboration. Age-specific relevance of usual blood pressure to vascular mortality: a meta-analysis of individual data for one million adults in 61 prospective studies. Lancet. 2002;360:1903-13.
15. Dzau VJ, Balatbat CA. Future of hypertension: The need for transformation. Hypertension. 2019 Sep;74(3):450-7.
16. Stoumpos AI, Kitsios F, Talias MA. Digital Transformation in Healthcare: Technology Acceptance and Its Applications. International journal of environmental research and public health. 2023 Feb 15;20(4):3407.
17. Miller DD, Brown EW. Artificial intelligence in medical practice: the question to the answer?. The American journal of medicine. 2018 Feb 1;131(2):129-33.
18. Umapathy VR, Raj RD, Yadav S, Munavarah SA, Anandapandian PA, Mary AV, Padmavathy K, Akshay R, Rajkumar DS, Anandapandian IV PA, Mary V. Perspective of Artificial Intelligence in Disease Diagnosis: A Review of Current and Future Endeavours in the Medical Field. Cureus. 2023 Sep 21;15(9).
19. Bitkina OV, Park J, Kim HK. Application of artificial intelligence in medical technologies: A systematic review of main trends. Digital Health. 2023 Jul;9:20552076231189331.
20. https://www.britannica.com/technology/artificial-intelligence
21. Moor J. The Dartmouth College artificial intelligence conference: The next fifty years. Ai Magazine. 2006 Dec 15;27(4):87-.
22. Padmanabhan S, Tran TQ, Dominiczak AF. Artificial intelligence in hypertension: seeing through a glass darkly. Circulation Research. 2021 Apr 2;128(7):1100-18.
23. Howard J. Artificial intelligence: Implications for the future of work. American journal of industrial medicine. 2019 Nov;62(11):917-26.
24. Letzen B, Wang CJ, Chapiro J. The role of artificial intelligence in interventional oncology: a primer. Journal of vascular and interventional radiology: JVIR. 2019 Jan;30(1):38-41.
25. Alexander G, Staggers N. A systematic review of the designs of clinical technology: findings and recommendations for future research. Advances in nursing science. 2009 Jul 1;32(3):252-79.
26. Matias I, Garcia N, Pirbhulal S, Felizardo V, Pombo N, Zacarias H, Sousa M, Zdravevski E. Prediction of Atrial Fibrillation using artificial intelligence on Electrocardiograms: A systematic review. Computer Science Review. 2021 Feb 1;39:100334.
27. Mehra S, Hasanuzzaman M. Detection of Offensive Language in Social Media Posts (Doctoral dissertation, Ph. D. thesis). 2020 May
28. Sarker IH, Furhad MH, Nowrozy R. Ai-driven cybersecurity: an overview, security intelligence modeling and research directions. SN Computer Science. 2021 May;2:1-8.
29. Sarker IH. Machine learning: Algorithms, real-world applications and research directions. SN computer science. 2021 May;2(3):160.
30. Balafar MA, Ramli AR, Saripan MI, Mashohor S. Review of brain MRI image segmentation methods. Artificial Intelligence Review. 2010 Mar;33:261-74.
31. Gudigar A, Raghavendra U, Hegde A, Kalyani M, Ciaccio EJ, Acharya UR. Brain pathology identification using computer aided diagnostic tool: A systematic review. Computer Methods and Programs in Biomedicine. 2020 Apr 1;187:105205.
32. Lee D, Yoon SN. Application of artificial intelligence-based technologies in the healthcare industry: Opportunities and challenges. International Journal of Environmental Research and Public Health. 2021 Jan;18(1):271.
33. Huang KH, Tan F, Wang TD, Yang YJ. A highly sensitive pressure-sensing array for blood pressure estimation assisted by machine-learning techniques. Sensors. 2019 Feb 19;19(4):848.

34. Chowdhury MH, Shuzan MN, Chowdhury ME, Mahbub ZB, Uddin MM, Khandakar A, Reaz MB. Estimating blood pressure from the photoplethysmogram signal and demographic features using machine learning techniques. Sensors. 2020 Jan;20(11):3127.

35. Quan X, Liu J, Roxlo T, Siddharth S, Leong W, Muir A, Cheong SM, Rao A. Advances in non-invasive blood pressure monitoring. Sensors. 2021 Jun 22;21(13):4273.

36. Monte-Moreno E. Non-invasive estimate of blood glucose and blood pressure from a photoplethysmograph by means of machine learning techniques. Artificial intelligence in medicine. 2011 Oct 1;53(2):127-38.

37. Solà J, Proença M, Braun F, Pierrel N, Degiorgis Y, Verjus C, Lemay M, Bertschi M, Schoettker P. Continuous non-invasive monitoring of blood pressure in the operating room: a cuffless optical technology at the fingertip. Current Directions in Biomedical Engineering. 2016 Sep 1;2(1):267-71.

38. Miao F, Fu N, Zhang YT, Ding XR, Hong X, He Q, Li Y. A novel continuous blood pressure estimation approach based on data mining techniques. IEEE journal of biomedical and health informatics. 2017 Apr 28;21(6):1730-40.

39. Wang L, Zhou W, Xing Y, Zhou X. A novel neural network model for blood pressure estimation using photoplethesmography without electrocardiogram. Journal of healthcare engineering. 2018 Mar 7;2018.

40. Unger T, Borghi C, Charchar F, Khan NA, Poulter NR, Prabhakaran D, Ramirez A, Schlaich M, Stergiou GS, Tomaszewski M, Wainford RD. 2020 International Society of Hypertension global hypertension practice guidelines. Hypertension. 2020 Jun;75(6):1334-57.

41. Elgendi M, Fletcher R, Liang Y, Howard N, Lovell NH, Abbott D, Lim K, Ward R. The use of photoplethysmography for assessing hypertension. NPJ digital medicine. 2019 Jun 26;2(1):60.

42. Kario K. Management of hypertension in the digital era: small wearable monitoring devices for remote blood pressure monitoring. Hypertension. 2020 Sep;76(3):640-50.

43. LaFreniere D, Zulkernine F, Barber D, Martin K. Using machine learning to predict hypertension from a clinical dataset. In2016 IEEE symposium series on computational intelligence (SSCI) 2016 Dec 6 (pp. 1-7). IEEE.

44. Hermida RC, Smolensky MH, Ayala DE, Portaluppi F. Ambulatory Blood Pressure Monitoring (ABPM) as the reference standard for diagnosis of hypertension and assessment of vascular risk in adults. Chronobiology International. 2015 Nov 26;32(10):1329-42.

45. Pierdomenico SD, Cuccurullo F. Prognostic value of white-coat and masked hypertension diagnosed by ambulatory monitoring in initially untreated subjects: an updated meta analysis. American journal of hypertension. 2011 Jan 1;24(1):52-8.

46. Whelton WP. 2017 Guideline for the prevention, detection, evaluation, and management of high blood pressure in adults. J Am Coll Cardiol. 2017.Simonite T. AI Can Help Apple Watch Predict High Blood Pressure, Sleep Apnea.

47. Haugg F, Elgendi M, Menon C. Assessment of blood pressure using only a smartphone and machine learning techniques: A systematic review. Frontiers in Cardiovascular Medicine. 2022 Jun 13;9:894224.

48. David Petronzio. Hampshire AI technology used to take blood pressure. BBC News. 2023. https://www.bbc.com/news/uk-england-hampshire-67134503

49. Miyashita M, Brady M. The health care benefits of combining wearables and AI. Harv. Bus. Rev. 2019 Jun 18.

50. Williams B, Mancia G, Spiering W, Agabiti Rosei E, Azizi M, Burnier M, Clement DL, Coca A, De Simone G, Dominiczak A, Kahan T. 2018 ESC/ESH Guidelines for the management of arterial hypertension: The Task Force for the management of arterial hypertension of the European Society of Cardiology (ESC) and the European Society of Hypertension (ESH). European heart journal. 2018 Sep 1;39(33):3021-104.

51. Whelton PK, Carey RM, Aronow WS, Casey DE, Collins KJ, Dennison Himmelfarb C, DePalma SM, Gidding S, Jamerson KA, Jones DW, MacLaughlin EJ. 2017 ACC/AHA/AAPA/ABC/ACPM/AGS/APhA/ASH/ASPC/NMA/PCNA guideline for the prevention, detection, evaluation, and management of high blood pressure in adults: a report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines. Journal of the American College of Cardiology. 2018 May 15;71(19):e127-248.

52. Samant R, Rao S. Evaluation of artificial neural networks in prediction of essential hypertension. International Journal of Computer Applications. 2013 Jan 1;81(12).

53. LaFreniere D, Zulkernine F, Barber D, Martin K. Using machine learning to predict hypertension from a clinical dataset. In2016 IEEE symposium series on computational intelligence (SSCI) 2016 Dec 6 (pp. 1-7). IEEE.

54. Wu TH, Pang GK, Kwong EW. Predicting systolic blood pressure using machine learning. In7th international conference on information and automation for sustainability 2014 Dec 22 (pp. 1-6). IEEE.

55. Poplin R, Varadarajan AV, Blumer K, Liu Y, McConnell MV, Corrado GS, Peng L, Webster DR. Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. Nature biomedical engineering. 2018 Mar;2(3):158-64.

56. Chaikijurajai T, Laffin LJ, Tang WH. Artificial intelligence and hypertension: recent advances and future outlook. American Journal of Hypertension. 2020 Nov;33(11):967-74.

57. Ioannis Paschalidis. New artificial intelligence program could help treat hypertension. National Science Foundation (NSF). 2023 June

58. Dawes TJ, de Marvao A, Shi W, Fletcher T, Watson GM, Wharton J, Rhodes CJ, Howard LS, Gibbs JS, Rueckert D, Cook SA. Machine learning of three-dimensional right ventricular motion enables outcome prediction in pulmonary hypertension: a cardiac MR imaging study. Radiology. 2017 May;283(2):381-90.

59. Quang D, Chen Y, Xie X. DANN: a deep learning approach for annotating the pathogenicity of genetic variants. Bioinformatics. 2014 Oct 22;31(5):761-3.

60. Zhou J, Troyanskaya OG. Predicting effects of noncoding variants with deep learning–based sequence model. Nature methods. 2015 Oct;12(10):931-4.

61. Zhou J, Theesfeld CL, Yao K, Chen KM, Wong AK, Troyanskaya OG. Deep learning sequence-based ab initio prediction of variant effects on expression and disease risk. Nature genetics. 2018 Aug;50(8):1171-9.

62. Sundaram L, Gao H, Padigepati SR, McRae JF, Li Y, Kosmicki JA, Fritzilas N, Hakenberg J, Dutta A, Shon J, Xu J. Predicting the clinical impact of human mutation with deep neural networks. Nature genetics. 2018 Aug;50(8):1161-70.

63. Huan T, Meng Q, Saleh MA, Norlander AE, Joehanes R, Zhu J, Chen BH, Zhang B, Johnson AD, Ying S, Courchesne P. Integrative network analysis reveals molecular mechanisms of blood pressure regulation. Molecular systems biology. 2015 Apr;11(4):799.

64. Li YH, Zhang GG, Wang N. Systematic characterization and prediction of human hypertension genes. Hypertension. 2017 Feb;69(2):349-55.

65. Alimadadi A, Manandhar I, Aryal S, Munroe PB, Joe B, Cheng X. Machine learning-based classification and diagnosis of clinical cardiomyopathies. Physiological Genomics. 2020 Sep 1;52(9):391-400.

66. Aryal S, Alimadadi A, Manandhar I, Joe B, Cheng X. Machine learning strategy for gut microbiome-based diagnostic screening of cardiovascular disease. Hypertension. 2020 Nov;76(5):1555-62.

67. Held E, Cape J, Tintle N. Comparing machine learning and logistic regression methods for predicting hypertension using a combination of gene expression and next-generation sequencing data. InBMC proceedings 2016 Oct (Vol. 10, No. 7, pp. 141-145). BioMed Central.
68. Rastegar S, Gholamhosseini H, Lowe A, Mehdipour F, Lindén M. Estimating Systolic Blood Pressure Using Convolutional Neural Networks. InpHealth 2019 Jan 1 (pp. 143-149).
69. Pei Z, Liu J, Liu M, Zhou W, Yan P, Wen S, Chen Y. Risk-predicting model for incident of essential hypertension based on environmental and genetic factors with support vector machine. Interdisciplinary Sciences: Computational Life Sciences. 2018 Mar;10:126-30.
70. Maxwell A, Li R, Yang B, Weng H, Ou A, Hong H, Zhou Z, Gong P, Zhang C. Deep learning architectures for multi-label classification of intelligent health risk prediction. BMC bioinformatics. 2017 Dec;18:121-31.
71. Koren G, Nordon G, Radinsky K, Shalev V. Machine learning of big data in gaining insight into successful treatment of hypertension. Pharmacology Research & Perspectives. 2018 Jun;6(3):e00396.
72. Guthrie NL, Berman MA, Edwards KL, Appelbaum KJ, Dey S, Carpenter J, Eisenberg DM, Katz DL. Achieving rapid blood pressure control with digital therapeutics: retrospective cohort and machine learning study. JMIR cardio. 2019 Mar 12;3(1):e13030.
73. João da Silva V, da Silva Souza V, Guimarães da Cruz R, Mesquita Vidal Martínez de Lucena J, Jazdi N, Ferreira de Lucena Junior V. Commercial devices-based system designed to improve the treatment adherence of hypertensive patients. Sensors. 2019 Oct 18;19(20):4539.
74. Miller DD. Machine intelligence in cardiovascular medicine. Cardiology in Review. 2020 Mar 1;28(2):53-64.
75. Padmanabhan S, Tran TQ, Dominiczak AF. Artificial intelligence in hypertension: seeing through a glass darkly. Circulation Research. 2021 Apr 2;128(7):1100-18.
76. Krittanawong C, Johnson KW, Rosenson RS, Wang Z, Aydar M, Baber U, Min JK, Tang WW, Halperin JL, Narayan SM. Deep learning for cardiovascular medicine: a practical primer. European heart journal. 2019 Jul 1;40(25):2058-73.
77. Liu Y, Li Z, Xiong H, Gao X, Wu J. Understanding of internal clustering validation measures. In2010 IEEE international conference on data mining 2010 Dec 13 (pp. 911-916). IEEE.
78. Handelman GS, Kok HK, Chandra RV, Razavi AH, Huang S, Brooks M, Lee MJ, Asadi H. Peering into the black box of artificial intelligence: evaluation metrics of machine learning methods. American Journal of Roentgenology. 2019 Jan;212(1):38-43.

How to cite this article: Singh Anjali, Verma Narsingh. Department of Physiology, King George's Medical University, Lucknow, UP, India. Hypertens J. 2023;10(1):2-6.

Source of support: Nil, Conflicts of interest: None