The Role of Machine Learning and Deep Learning in Revolutionizing Healthcare: A Review

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Additional material is published online only. To view please visit the journal online.

Cite this as: Ahmed W. The Role of Machine Learning and Deep Learning in Revolutionizing Healthcare: A Review. Premier Journal of Artificial Intelligence 2025;3:100010

DOI: https://doi.org/10.70389/PJAI.100010

Received: 1 January 2025

Revised: 17 January 2025

Accepted: 18 January 2025

Published: 5 February 2025

Ethical approval: N/a

Consent: N/a

Funding: No industry funding

Conflicts of interest: N/a

Author contribution: Waqas Ahmed – Conceptualization, Writing – original draft, review and editing

Guarantor: Waqas Ahmed

Provenance and peer-review: Commissioned and externally peer-reviewed

Data availability statement: N/a

ABSTRACT

The healthcare system has been transformed due to artificial intelligence, deep learning, and machine learning, which have improved diagnostic power, predictive analytics, and patient monitoring. The main models applied in healthcare are Convolutional Neural Networks (CNNs), Support Vector Machines, and Transformers and Recurrent Neural Networks (RNNs), which play a role in predicting disease, genomics, and medical imaging. CNN explains a higher level of accuracy in medical imaging where Long and Short-term Memory and RNN are developed to identify chronic diseases based on large amounts of structured and unstructured data. The transformers assist in processing many genomic datasets and clinical texts to enhance personalized medicine. The model assesses the disease pattern before the progression of symptoms in the body makes treatment possible. It impacts patient outcomes, operational efficiency, and healthcare accessibility, benefiting patients and healthcare systems. In future learning, emerging trends like explainable AI and federated learning can reshape the healthcare system to increase clinical understanding, transparency, and trust for decision-making.

Keywords: Machine learning in healthcare, Deep learning in healthcare, Convolutional neural networks in medical imaging, Predictive analytics in healthcare, Remote patient monitoring

Introduction

The healthcare sector faces continuous challenges of increased costs, limited access to quality care, inefficient processes, and an increasing chronic burden.[1] The current trends in healthcare indicate a global demand for efficient, personalized, predictive healthcare solutions based on the integration of advanced technologies for addressing such issues.[2] The development of modern technology, including artificial intelligence (AI), deep learning (DL), and machine learning (ML), has come up with quick healthcare delivery, personalized drug development, diagnostics power, and patient management.[3]

ML and DL Significance in Healthcare

The current development of ML and DL in healthcare is a reason for increased accuracy of outcomes, disease progression prediction, task automation, earlier diagnosis of disease, and patient management for further treatment plans.[4] These technologies have reshaped the healthcare systems through telemedicine and genomic analysis.[5] Modern healthcare techniques depend on X-rays, CT scans, and MRIs to analyze the anomalies in the data. AN earlier diagnosis of cardiac disease, neurological issues, and cancer also makes these technologies significant for healthcare.[6] ML models analyze the patient data in the form of lifestyle factors, medical history, and genetic information to assess the likelihood of the specific disease.[7] It led to providing intervention strategies and personalized prevention.[8]

Objectives and Scope of Systematic Review

I. To critically analyze ML and DL for addressing main challenges like disease diagnosis, patient care optimization, and treatment prediction
II. To identify and categorize the state-of-the-art ML and DL models used in healthcare applications, evaluating their strengths, limitations, and performance in different medical domains.
III. To explore integrating ML/DL techniques with existing healthcare systems, including electronic health records (EHRs), medical imaging, wearable devices, and genomics.
IV. To propose future research directions and challenges in leveraging ML and DL for personalized medicine, remote healthcare, and health data security.

Background

ML is a subset of AI based on developing algorithms that create learning systems from data and improve time without proper programming.[9] The primary focus of creating the models is to find the patterns and develop the prediction or decisions based on large datasets. ML methods range from supervised learning methods that are trained models on labeled data for unsupervised learning to assess the hidden patterns without reinforcement learning and predefined labels that optimize the action with the help of trial and error.[10]

DL employs neural networks to stimulate human decision-making and process increasingly complicated data.[11] Researchers[12] elaborated that DL is an advanced branch of ML that uses neural networks to stimulate human decision-making by processing vast amounts of complicated data.[13] DL works in multilayered neural networks where every layer cuts the intangible features from the input data. Such a hierarchal learning process establishes the DL as powerful for speech and image recognition, complex problem solving, and natural language processing.[14] However, in healthcare, DL applications vary from medical image analysis to discovering new drug compounds and forecasting patient outcomes.[15]

The historical progression of ML and DL in healthcare can be drawn from the earlier usage of statistical models and rule-based expert systems from the 1970s to the 1980s.[16,17] These systems aim to assist healthcare professionals in decision-making, but it was limited by data availability and computational power. A turning point was marked in the 2000s with the advent of big data and advancements in computational capabilities that enabled the development of sophisticated ML algorithms.[18] Furthermore, DL gained power in the 2010s, followed by neural network architecture breakthroughs and the availability of large annotated datasets. ML and DL continuously drive innovation in pathology, radiology, predictive analytics, and genomics that shape the future of personalized care and precision medicine. The technologies have elaborated on the notable potential in healthcare by increasing the accuracy of diagnostics, disease progression prediction, optimization of treatment plans, and automation of administrative tasks. From a former cancer detection, genomic analysis, and applications of telemedicine, ML and DL are redeveloping the modern healthcare landscape.

The data processing and analysis of traditional methods are based on structured data collected from laboratory results or EHRs. For further data analysis, traditional methods apply statistical tools, including descriptive analysis and rule-based methods. The primary focus of the analysis process is to identify past patterns and trends. Conversely, AI-based approaches handle both structured and unstructured data in the form of medical images, genomics, and patient notes. ML and DL learn patterns separately from huge amounts of data. Future outcomes are predicted and generated by real-time information. The complexity and depth of traditional analytical methods, such as manual feature selection and queries, are pre-defined, and surface-level information is gained from traditional methods.

Conversely, ML and DL find complicated and hidden relations without human intervention, and advanced techniques can analyze high-dimensional and nonlinear data from in-depth insights. AI-driven methods continuously improve results due to the increased availability of data, but traditional methods need human input for consistent monitoring and updates of data. The scalability and speed of the traditional methods show slower processing for large data sets, but ML and DL can get quick results, and scalability becomes easier in healthcare systems. This increases the decision-making capacity of ML and DL.

Applications of ML and DL in Healthcare

Disease Diagnosis and Prediction

AI-driven models play a vital role in detecting cancer; the DL model includes convolutional neural networks (CNNs) that excel at analyzing medical images like CT scans, MRIs, and mammograms.[19] Medical imaging processing assists in detecting lung, breast, and skin cancers. The models can recognize tumors at earlier stages by achieving outstanding outcomes for radiologists. For example, Google's AI system indicates a 5% reduction in the false positive and 11% control in the false negative results for breast cancer identification compared to traditional radiology techniques.[20] ML algorithms also predict the onset of diabetes by assessing patient data like blood glucose levels, family history, and BMI.

Long and short-term memory (LSTM) and recurrent neural networks (RNNs) process the time series data by offering consistent and personalized monitoring and risk assessment.[21] IBM Waston is an AI-powered tool implemented to provide predictive insights for diabetes complications. Furthermore, the DL algorithms assist in diagnosing neurological diseases like Parkinson's, epilepsy, and Alzheimer's.[22] The analysis of brain scans and patients' histories is easier through DM models as these models work to detect the earlier signs of cognitive decline among patients. For example, PET scans followed by DL can achieve 95% accuracy in predicting the progression of Alzheimer's disease.[23]

The performance of CNNs is achieved through diagnostic accuracy rates of 92–97% in imaging for cancer detection compared to 85–90% in traditional radiology.[24] Support vector machines (SVMs) are applied for diabetes tests that have achieved an accuracy of 80–85%; however, collective methods like Random Forst (RF) can achieve 90% accuracy.[25,26] LSTMs and RNNs determine almost 94% accuracy to predict a seizure, outperforming the classical statistical methods by 10–15%.[27] The ML and DL integration in healthcare increases diagnostic precision and reduces the time needed for analysis, ultimately improving the patient's outcomes and assisting in further advancement in personalized medicine.

Medical Imaging

The CNNs have a significant transformation of medical imaging that increases the speed and accuracy of CT, MRI, and X-ray interpretation.[28] Furthermore, these techniques extract complicated features from data imaging, enabling precise abnormalities detection. CT scans and MRIs are applied for the scans to detect brain lesions, tumors, and lung diseases.[29] The study by[30,31] added that the DL system is useful in recognizing lung nodules in CT scans with a higher accuracy of almost 94%, which assists in diagnosing lung cancer earlier. The chest X-rays analyzed by the DL-powered systems diagnose pneumonia, fractures, and tuberculosis. The CNN model developed by Stanford University has diagnosed pneumonia from chest X-rays with a higher level of accuracy.

Google Health's AI is used to detect breast cancer, where the DL model minimizes false positive results by 5.7% and false negative results by 9.4%.[32,33] Researchers[34] showed that Aidoc, RapidAI, and Viz.ai are AI systems examining CT scans to detect intracranial pulmonary embolisms and hemorrhages that enable quicker triage and enhance patient outcomes.[35] narrated the Zebra Medical Vision and its AI, which interpret millions of medical scans for detecting cardiovascular conditions, bone fractures, and liver disease and achieve accuracy compared to radiologists. It provides automated solutions to assess critical solutions that improve patient outcomes by managing early interventions.

 DOI: https://doi.org/10.70389/PJAI.100010 | Premier Journal of Artificial Intelligence 2025;3:100010

Personalized Medicine

ML algorithms predict a diverse number of datasets to predict the future response of patients to various treatments.[7] The DL models identified the genetics of tumor profiles for finding the effective regimens of chemotherapy, enhancing the treatment efficacy, and minimizing the adverse effects. Predictive analytics works to find the high-risk patients who benefit from early interventions. The DL algorithms process the genomic data to uncover the mutations associated with the disease that enable targeted therapy development.[24] Precision medicine in oncology leverages AI to match cancer patients with tailored drugs for their exclusive genetic makeup. IBM Watson for Genomics explains the genetic data used to guide oncologists in selecting personalized cancer treatments that significantly improve survival rates.[36] However, AI-based platforms participate in the multi-choice data of proteomics, genomics, and metabolomics that directly suggest holistic treatment approvals. The approach increases the precision of drug discovery and development through novel therapies.

Remote Patient Monitoring

The application of the Internet of Things (IoT) and wearable devices transforms remote patient monitoring (RPM) through real-time health data that enables a continuous and timely detection of health problems.[37] Smartwatches, biosensors, and fitness trackers assist in monitoring vital signs like glucose level, heart rate, and blood pressure. Such IoT-enabled devices disseminate data to healthcare providers, reducing hospital visits and enabling remote monitoring. For example, wearable ECG monitors help detect arrhythmias to alert patients and doctors in a short time.[38]

RNNs and CNNs process the consistent data streams to find the patterns linked with worsening health conditions.[39] DL models can assess heart failure predictions before the symptoms appear, allowing timely intervention. Furthermore, researchers[40] showed that RPM based on IoT and AI increases patient engagement, minimizes healthcare costs, and increases outcomes by permitting the proactive management of chronic conditions.

State-of-the-Art ML/DL Models in Healthcare

Overview of Popular Models

SVMs are used in health care to classify tasks like disease prediction and patient risk stratification.[41] The ability to manage high-dimensional data makes it effective to identify the complicated patterns within medical datasets. Furthermore, CNNs excel in medical imaging by extracting unique features from MRIs, X-rays, and CT scans. It is a layered architecture that assists in the hierarchical learning of features, resulting in revolutionary treatment in pathology and radiology.[42] RNNs and LSTM are models developed and designed to manage sequence-based data analysis, making them ideal for monitoring the patient's value and predicting future health issues based on historical health records.[43] Furthermore, researchers[44,45] found that transformers are developed from natural language processing and have proven and effective clinical text analysis and genomics. They can handle prolonged sequences of data using increased performance in large-scale biometric datasets.

Comparative Analysis of ML/DL Models

Medical imaging is dominated by CNNs that outperform traditional image processing techniques.[46] Their ability to detect and classify anomalies with accuracy rates of 95% has made them crucial for dermatology and radiology.[47] Regarding predictive analytics, LSTM, and RNN models are useful for predicting chronic diseases that capture temporal dependencies within health data.[43] Such models provide timely and accurate predictions for conditions like diabetes, neurological disorders, and cardiovascular disease. On the other hand, for text analysis and genomics, transformers offer matchless efficiency in genomics through large dataset processing in a short time, and they aid in the sequencing and mutation detection of genes. For clinical text analysis, transformers accurately extract critical information, increasing the decision-making process for personalized medicine.[44]

Performance Metrics

The metrics indicate the overall model (ML, DL) correctness, which is important for general diagnostics. Sensitivity is recall, a critical measure in the oncology field that assesses the sensitivity and ability of the model to correctly find true positive cases that ensure every detail is considered.[48] Specificity focuses on true negative identification as it minimizes false positive outcomes. It is important to reduce unnecessary anxiety and treatments. The F1 score balances the recall and precision, providing a clear view of the model performance. These are particularly useful when dealing with imbalanced datasets commonly found to predict rare diseases.

Case Study

Mayo Clinic, a famous healthcare provider, is integrating ML and DL technologies within its operations to improve patient outcomes.[49] A prominent application is the DL algorithm, which was used to analyze medical imaging to detect diseases like cancer and cardiovascular issues earlier. Implementing CNNs in the clinic has achieved a higher accuracy level in finding anomalies in CT scans, X-rays, and MRIs that are incomparable with traditional diagnostic methods.[50] DL models have assisted in reducing imaging errors by finding precise patterns that human radiologists can overlook. This comes with critical results of earlier detection, leading to better treatment. Furthermore, the clinic uses predictive analytics to find patients at risk of heart failure. Further aspects are about personalized treatment plans using genomic data and patient health records, where AI assists in tailored treatment plans and improves therapy efficacy. The weaknesses are data challenges, algorithm bias, and integration issues.[51] ML models need a huge amount of high-quality data as variability in the data formats or incomplete records can minimize the reliability of the model. Models are also trained based on biased datasets that can result in healthcare delivery disparities. For example, minority groups may be underrepresented in the data, leading to reduced data prediction accuracy.[50] ML and DL implementation in the clinic's workflow can also disrupt the current system, which might require infrastructure and training-based investments.

Integration of AI in Healthcare Systems

Challenges in Integrating ML/DL with EHR

The introduction of ML and DL in EHR and the clinical workflows leads to increased challenges by delaying the seamless adoption of healthcare settings.[52] A primary issue in data interoperability is that EHR systems usually operate in diverse platforms with varying formats and structures of data.[53] It is difficult to consolidate the standardized data for ML and DL models. A lack of standardization of data extraction and model deployment increases complications needed for the extensive pre-processing to ensure systems-based compatibility.[24] Further, the highly sensitive nature of healthcare data demands rigorous measures for protecting patient privacy. It is critical to balance the data security and model performance as deanonymization and de-identification techniques usually minimize the data utility, affecting the accuracy of the model. Furthermore, complaints with strict regulations like the General Data Protection Regulation (GDPR) in Europe increase data access and usage complications.[54] This is due to the legal systems demanding robust data governance practices that can reduce innovations and switch operational costs.

Healthcare professionals-based resistance is also a barrier to AI integration. Healthcare professionals can suspect AI-generated recommendations if the model decision-making lacks explainability and transparency.[17] Such skepticism emphasizes the requirement for explainable AI (XAI) solutions with clear and interpretable information that can increase confidence and trust among medical professionals. Furthermore, the AI tool's integration within existing clinical workflows can also interrupt the pre-defined processes. It requires considerable restraint, customization, and allocation of resources.

Use of AI in Telemedicine and Remote Healthcare Delivery

The revolution of AI in telemedicine and remote healthcare delivery process is a way to increase diagnostic accuracy, improve patient monitoring optimization, and implement real-time virtual consultations.[5] The most impactful applications of AI in telehealth are with the help of AI-powered virtual assistants and chatbots that conduct initial patient assessments, triage symptoms, and provide basic medical advice. Automating such tasks reduces workloads and leads to complicated and more focused cases.[26] RPM elaborates on the critical area where AI adds value and algorithms analyze the data assembled from the wearable devices that directly alter the healthcare professionals to find anomalies and real-time health risks. Remote scanning and evaluation are possible through AI-driven tools that provide a second opinion and increase the diagnostic process.[8] The analysis of huge datasets is helpful for improved radiological assessments and accuracy.

Future Directions and Research Challenges

The prospects that can be followed as opportunities are a collaboration between institutions to create high-quality and large-scale datasets that can improve the generalization and accuracy of the model. Transferring domain and learning adaption can offer model optimization with a limited amount of data that can directly increase performance across various clinical settings. Emerging trends like XAI and federated learning can reshape healthcare. It can also increase the transparency, clinical understanding, and trust model decisions to increase the adoption rate.

Furthermore, federated learning can allow models for decentralized data training without compromising patient privacy, promote collaboration across healthcare institutions, and adhere to data protection regulations. Moreover, real-world implementation and scalability can be addressed to ensure seamless integration with current EHR workflows and systems.

Conclusion

The revolutionary AI models in healthcare showed immense potential for growth in assessing, predicting, and monitoring diseases. Healthcare professionals can monitor cancer at earlier stages, which can further reduce the burden of treatment. Machine learning and deep learning models employ advanced techniques to analyze vast quantities of structured and unstructured data to discern disease patterns. By utilizing laboratory tests and other indicators, these models predict the likelihood of various diseases, such as diabetes, epilepsy, cardiac issues, and Alzheimer's disease, before the manifestation of symptoms.

However, compliance issues can reduce the data collection process as the GDPR has some restrictions on data collection. The privacy issues, interoperability, and professional resistance can be reduced to enable the seamless addition of these models. Healthcare delivery and remote evaluations are possible through such models as wearable devices, and IoT is another source to manage patients remotely.

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