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Review Article

From Data to Decisions: The Impact of AI in Modern Healthcare

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A B S T R A C T

Artificial intelligence (AI) is revolutionising healthcare by enhancing diagnostics, personalised medicine, and administrative efficiency. Leveraging advanced techniques such as machine learning, neural networks, and natural language processing, AI systems outperform traditional methods in tasks like medical imaging, disease prediction, and clinical decision support. However, challenges such as explainability, data privacy, ethical considerations, and integration into existing workflows limit widespread adoption. This paper explores the applications of AI in healthcare, its benefits, and the associated barriers, emphasising the need for transparent, ethical, and patient-centric AI systems. Addressing these challenges can unlock AI's full potential to improve healthcare outcomes and accessibility globally.

Keywords: Artificial Intelligence in Healthcare, AI in Medicine, Machine Learning in Healthcare, Deep Learning in Medicine, Healthcare Informatics

Introduction

Artificial intelligence (AI) is making significant strides in the healthcare sector, with its applications rapidly expanding across various domains.[16] AI technologies are poised to transform clinical practices by improving diagnostic accuracy, enhancing personalised treatment plans, and streamlining administrative processes. For example, machine learning algorithms and deep learning models have demonstrated exceptional capabilities in analysing medical images, detecting diseases, and providing actionable insights, often outperforming human experts in certain tasks. These advancements can help reduce healthcare costs by automating routine tasks, improving resource allocation, and enabling earlier interventions through predictive analytics.[2]

Despite its immense potential, the integration of AI into healthcare is not without challenges. One of the primary concerns is data privacy, as AI systems require access to vast amounts of patient data, raising issues about data security and consent. Furthermore, the "black-box" nature of many AI algorithms, especially deep learning models, complicates their explainability.[9] Clinicians and patients alike need a clear understanding of how AI systems arrive at their conclusions to trust their recommendations. This lack of transparency poses a significant barrier to widespread adoption, particularly in clinical settings where decisions directly impact patient care. Finally, the integration of AI systems into existing clinical workflows remains a complex task, requiring seamless collaboration between technology and healthcare professionals to ensure that AI tools complement rather than disrupt established practices.[5]

This paper explores the role of AI in healthcare, examining its transformative potential, the benefits it offers, and the challenges that must be addressed for successful implementation.

Applications Of Ai In Healthcare

Enhancing Diagnostics

AI-powered systems are redefining diagnostics by identifying patterns in medical imaging, genetic data, and other clinical records.[8] These tools excel in detecting early signs of diseases such as cancer, neurological disorders, and cardiac conditions. Machine learning models analyse vast datasets, offering insights that surpass traditional diagnostic methods.[4]

In the diagnostic phase, a significant portion of AI research focuses on analysing data from diagnostic imaging, genetic testing, and electrodiagnostic methods. Radiologists, for instance, have been encouraged by experts like Jha and Topol to adopt AI tools for interpreting complex diagnostic images due to their ability to process large volumes of information. Similarly, researchers such as Li et al have explored the application of AI in identifying genetic abnormalities linked to cancer. Additionally, Shin et al designed an electrodiagnostic support system to pinpoint neural injuries effectively.

Beyond imaging and genetic data, physical examination notes and clinical laboratory results also serve as vital data sources. Unlike imaging and

genetic data, these contain extensive unstructured textual information, such as clinical notes, which are challenging to process directly. AI applications in this context often involve transforming unstructured data into structured formats, such as electronic medical records (EMRs).[15] For instance, Karakülah and colleagues utilised AI to extract phenotypic features from case reports, significantly improving the accuracy of diagnosing congenital anomalies(fig 1).

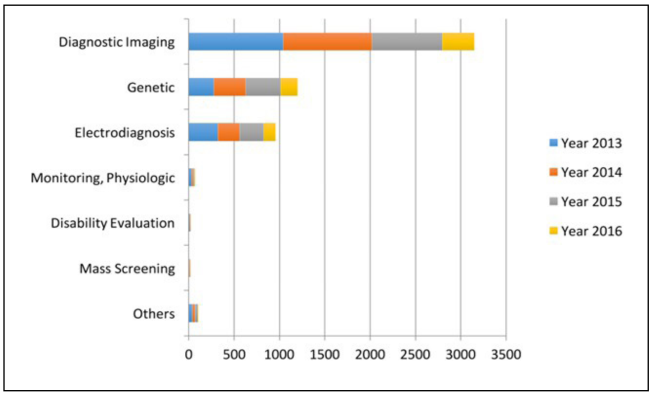

Figure 1.The data types considered in the artificial intelligence artificial (AI) literature

Optimising Treatment Plans

AI supports personalised medicine by tailoring treatment protocols to individual patient profiles. Advanced algorithms process data from past cases, ongoing research, and patient-specific factors to recommend therapies with the highest probability of success

AI tools can primarily be categorised into two types. The first category includes machine learning (ML) techniques that work with structured data, such as medical imaging, genetic information, and electrophysiological (EP) data. In healthcare, ML algorithms are employed to group patients based on shared characteristics or predict the likelihood of specific health outcomes. The second category involves natural language processing (NLP) methods, which focus on extracting useful information from unstructured data like clinical notes and medical literature. NLP converts textual data into structured, machine-readable formats, enabling analysis by ML algorithms.[16]

A clear workflow illustrates how clinical data is generated, enriched through NLP techniques, and analysed using ML to inform clinical decision- making. This process begins and ends with real- world clinical activities, ensuring that AI applications address practical medical challenges and enhance clinical practice. Ultimately, the success of AI in healthcare hinges on its ability to respond to and solve real-world clinical problems.[6]

Streamlining Administrative Tasks

Healthcare providers benefit from AI's ability to automate administrative processes, such asmanaging patient records, scheduling, and claims processing. These solutions reduce manual errors, save time, and allow professionals to focus more on patient care(fig 2).

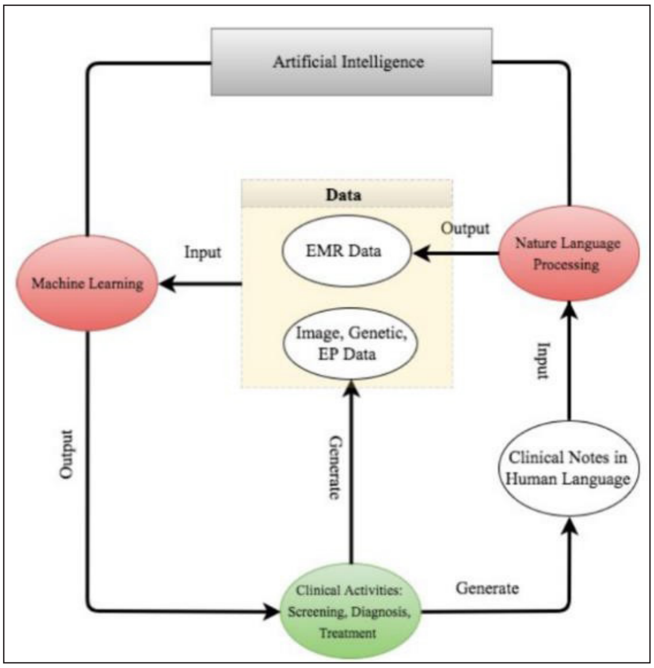

Figure 2.The road map from clinical data generation to natural language processing data enrichment, to machine learning data analysis, to clinical decision making. EMR, electronic medical record; EP, electrophysiological

AI research in healthcare has predominantly focused on a few key disease categories: cancer, neurological disorders, and cardiovascular diseases. This concentration is logical, as these conditions are among the leading causes of mortality worldwide, making early detection and diagnosis vital to improving patient outcomes. AI's capabilities in analysing imaging, genetic, electrophysiological (EP), and electronic medical record (EMR) data make it particularly effective for addressing these diseases.

- **Cancer:** AI systems like IBM Watson for Oncology have demonstrated reliability in aiding cancer diagnosis through rigorous validation studies. Additionally, clinical image analysis using AI has enabled precise identification of skin cancer subtypes.[12]
- **Neurology:** Advances in AI have led to the development of systems to restore motor control in individuals with quadriplegia and interfaces that leverage spinal motor neuron activity to control upper-limb prosthetics, showcasing its potential in neurological rehabilitation.
- **Cardiology:** AI applications have proven effective in diagnosing heart diseases through cardiac imaging. For instance, Artery's Cardio DL, an FDA-approved AI tool, automates ventricle segmentation in cardiac MRI images, streamlining diagnosis and treatment planning.

Beyond these areas, AI has shown promise in other medical fields. For example, it has been used to diagnose congenital cataracts through ocular imaging and to detect diabetic retinopathy using retinal fundus photographs.

The paper also explores how AI methodologies, including machine learning and natural language processing, contribute to these advancements. Subsequent sections delve into AI's applications in neurology, particularly in early disease detection, treatment planning, and prognosis prediction. Finally, future opportunities for AI in healthcare are discussed, highlighting its transformative potential across various domains(fig 3).

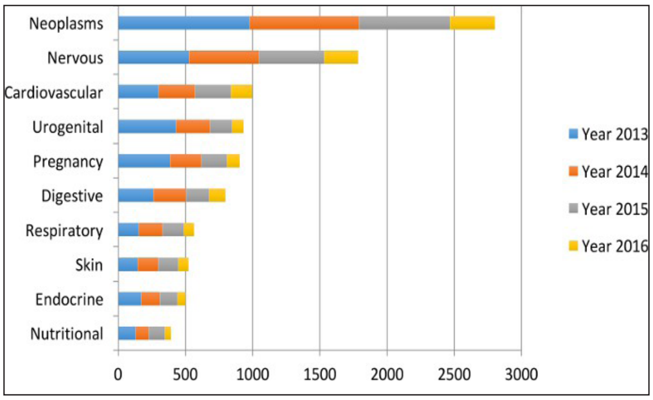

Figure 3.The leading 10 disease types considered in the artificial intelligence (AI) literature

Improving Patient Engagement

AI enhances patient engagement through chatbots, reminders, and mobile applications. These tools improve medication adherence, encourage lifestyle changes, and provide real-time support, fostering better health outcomes.

Patient engagement and adherence have long been recognised as critical challenges in healthcare, often referred to as the "last mile" problem. This issue represents the gap between effective treatment plans and achieving optimal health outcomes. Studies consistently show that the more actively patients participate in managing their health, the better the results in terms of medical, financial, and overall experience metrics. However, many patients struggle to make the necessary behavioral changes, such as following prescribed medication regimens, attending follow-up appointments, or adopting healthier lifestyles.

Noncompliance remains a significant barrier, with surveys revealing that over 70% of healthcare professionals report less than half of their patients being fully engaged. Furthermore, 42% of respondents indicated that fewer than one-fourth of their patients show high levels of engagement.

AI has shown potential in addressing this issue by personalising and contextualising patient care. Machine learning algorithms and business rules engines are being utilised to create tailored interventions that drive meaningful actions at critical moments. For example, targeted messaging alerts and personalised reminders help prompt patients to adhere to treatment plans.

Another area of focus involves designing predictive models that anticipate patient behavior. Using data from electronic health records (EHRs), wearable devices, smartphones, and conversational AI tools, AI systems can recommend individualised care strategies by comparing patient data with effective treatment pathways for similar cases. These recommendations can then be shared with healthcare providers, care teams, or directly with patients, ensuring more proactive and informed care delivery.

Ethical and Technological Challenges

The Need for Explainability

AI systems, particularly those based on deep learning, are often criticised for their lack of transparency. Explainable AI seeks to address this by making algorithms' decisions interpretable, enabling clinicians and patients to trust and act on the insights provided.

From a technological standpoint, explainability in AI involves two critical aspects: the methods used to achieve it and its application in medical AI development. Explainability can either be an intrinsic feature of certain algorithms or approximated through additional techniques, particularly for complex systems like artificial neural networks

(ANNs), which are often considered "black-box" models. While numerous techniques now exist to make these systems more interpretable, inherently explainable models, such as linear and logistic regression, are generally more accurate in their transparency. However, these simpler models often fall short in performance when compared to advanced methods like ANNs, which present a trade-off between performance and explainability—a key challenge in developing clinical decision support systems.

Some researchers argue that this trade-off is an artifact of suboptimal modeling approaches, suggesting that advancements in methodology could reduce the need for compromise. Nevertheless, the preference for high-performing modern algorithms in medical AI underscores the need for better explainability methods tailored to these systems. Approaches must evolve to balance performance with interpretability, addressing the needs of multiple stakeholders, including developers, clinicians, and patients.

For developers, explainability tools are essential for verifying that an AI system's predictions are based on meaningful data rather than irrelevant metadata. A well-known example is a non-medical classification model designed to differentiate between huskies and wolves, which mistakenly relied on the snowy backgrounds of wolf images rather than the animals' features. Similar "Clever Hans" phenomena have been observed in healthcare, such as a model at Mount Sinai Hospital that accurately identified high-risk patients during testing but failed in external settings.[11]

The issue arose because the model based its predictions on metadata from specific X-ray machines rather than clinically relevant image features. Explainability methods help identify and rectify such errors before deployment, ensuring the model's reliability and saving development time and costs.

It is also important to note that explainability methods for developers differ from those intended for end-users, such as clinicians and patients. For developers, these methods can employ more intricate approaches and visualisations to offer deeper insights into a model's workings. By refining explainability techniques, AI systems can deliver not only high performance but also the transparency required to build trust and ensure usability across diverse healthcare applications.

Data Bias and Equity

AI models can unintentionally perpetuate biases if trained on non-representative datasets. This may lead to disparities in healthcare delivery. Addressing this requires diverse and comprehensive training data.

The legal perspective on the explainability of AI in healthcare raises key questions, particularly regarding its legal requirements. Transparency and traceability, especially in healthcare, must meet high standards due to the sensitive nature of patient data. AI technologies, such as machine learning and deep learning, offer the potential to greatly improve healthcare by enhancing diagnostic accuracy, detecting anomalies, and providing decision support. However, the use of AI in healthcare involves challenges related to data privacy, security, patient consent, and autonomy, all of which must comply with relevant laws and regulations.[9]

From a legal standpoint, data handling—its acquisition, storage, transfer, processing, and analysis—must align with current legal frameworks, which evolve alongside technological advances. Even if AI solutions comply with these requirements, there remains the question of whether explainability is required. Specifically, should doctors and patients have access not only to the AI- generated results but also to an understanding of how these results were derived, including the assumptions and characteristics that shaped them? Furthermore, the inclusion of additional stakeholders, such as regulatory bodies, may necessitate a deeper understanding of the algorithms used.

There are three core legal areas where explainability is relevant: informed consent, certification and approval of medical devices, and liability. Informed consent, which is legally required for the processing of personal health data, involves providing patients with adequate information about the procedures and risks involved. AI-driven diagnostic tools complicate this process, as patients may need information about how AI models operate. While doctors can explain basic principles, such as the types of data AI inputs and the general functioning of algorithms, it remains difficult to define the exact level of detail required.

Developing a framework to define the "right" level of explainability for specific use cases is essential, as it also impacts the training and professional development needed for healthcare providers.

Regarding certification and approval, regulatory bodies like the FDA and Medical Device Regulation (MDR) have yet to clearly define the requirements for explainability in AI-driven medical devices.

While the FDA's Total Product Life Cycle (TPLC) approach emphasises the need for transparency, it does not specifically mandate explainability. Similarly, the MDR calls for accountability and transparency but leaves the specifics of AI-based systems' traceability and explainability unclear. As AI technologies evolve, these regulations are expected to become more precise, eventually requiring manufacturers to provide detailed information about the models, data, and development processes involved in AI-based medical devices.

The General Data Protection Regulation (GDPR) in the European Union also raises the question of whether explainable AI is necessary when handling patient data. The current phrasing of the GDPR is ambiguous, but future amendments may require clearer guidelines promoting explainability.

Finally, the issue of patient awareness and legal liability arises. If clinical decision support systems (CDSS) rely on AI, patients should be informed about its role in treatment decisions. From a legal perspective, physicians may be required to explain their use of AI tools and the reasoning behind overriding AI recommendations. Legal scholars suggest that explainability could be critical in avoiding medical malpractice lawsuits, with courts expected to provide clarity as AI systems become more integrated into healthcare.[13]

In conclusion, while AI holds immense promise for improving healthcare, its integration into clinical practice necessitates careful legal consideration. The need for explainability in AI systems is crucial to protect patient rights, ensure transparency, and prevent potential harm. As AI technologies continue to advance, establishing clear legal standards for explain ability will be essential in balancing innovation with regulatory oversight.[14]

Privacy and Security

AI systems require access to sensitive patient data, raising concerns about privacy and cybersecurity. Ensuring compliance with data protection regulations is crucial for maintaining patient trust.

Patient engagement and adherence have long been recognised as the critical “last mile” in healthcare, representing the final hurdle between suboptimal and optimal health outcomes. The more actively patients engage in their health and care, the better the overall results, including utilisation, financial efficiency, and patient experience. These challenges are increasingly being addressed through big data and AI technologies. A significant issue arises when patients fail to follow prescribed treatments or medications. In a survey of over 300 healthcare leaders, more than 70% reported that fewer than 50% of their patients were highly engaged, and 42% noted that less than 25% of their patients demonstrated high engagement.

Given that increased patient involvement tends to lead to better health outcomes, it raises the question of whether AI-driven solutions can effectively personalise and contextualise care. There is a growing focus on using machine learning and business rules engines to facilitate tailored interventions throughout the care process. This includes deploying messaging alerts and relevant, targeted content that encourages patients to take action at critical moments in their treatment.

Another important area of development in healthcare is designing the “choice architecture” to influence patient behavior in a proactive manner, based on real-world evidence. By leveraging data from electronic health record (EHR) systems, biosensors, smartwatches, smartphones, conversational interfaces, and other devices, AI can provide personalised recommendations. These recommendations, which compare a patient’s data with similar treatment pathways for other cohorts, can be delivered to healthcare providers, patients, nurses, call center agents, or care coordinators.

Healthcare providers and hospitals often develop care plans using their clinical expertise, aiming to improve a patient’s condition, whether for chronic or acute health issues. However, these plans can be ineffective if patients do not make the necessary behavioral changes, such as losing weight, scheduling follow-up visits, filling prescriptions, or adhering to treatment plans. Noncompliance—when patients do not follow medical advice—remains a major challenge in achieving successful health outcomes.

Legal and Regulatory

The regulatory environment for AI in healthcare remains underdeveloped. Questions around liability, certification, and approval processes create barriers to its widespread adoption.

Future Directions

Advancements in AI Algorithms

Future innovations in machine learning and natural language processing will further improve AI’s ability to process complex datasets. These advancements will unlock new possibilities in diagnostics and personalised medicine.

AI techniques that have proven beneficial in medical applications, categorising them into three groups: classical machine learning (ML), recent deep learning methods, and natural language processing (NLP) techniques.[10]

Classical Machine Learning

Machine learning uses data analysis algorithms to extract useful features from various types of patient data, which can include demographic details such as age, gender, and medical history, as well as more specific data like diagnostic images, genetic expressions, physical examination results, and medication. These inputs are used to predict certain outcomes such as disease progression or patient survival. In this context, the patient’s traits are represented by Xij, and the desired outcome by Yi.

There are two major categories in machine learning: unsupervised learning and supervised learning. Unsupervised learning primarily focuses on feature extraction and is useful for identifying patterns within data without considering the outcomes. Supervised learning, on the other hand, involves learning from both the input traits and known outcomes, which allows the algorithm to predict future outcomes based on past data. A recent innovation, semi-supervised learning, blends unsupervised and supervised methods, making it effective for situations where some outcome data may be missing.

- **Unsupervised Learning:** Techniques like clustering and principal component analysis (PCA) fall under this category. Clustering involves grouping patients with similar traits, while PCA is used to reduce data dimensionality by projecting it onto a few principal components without significant loss of information. These methods are especially useful when the data consists of high-dimensional traits, such as in genomics.
- **Supervised Learning:** This approach takes into account the outcomes along with patient traits and aims to build predictive models. Common algorithms used include linear regression, logistic regression, decision trees, random forests, and support vector machines (SVM). Supervised learning is highly relevant in medical applications because it can directly inform clinical decision- making. For example, it can predict clinical outcomes like disease progression or the likelihood of a patient developing a specific condition based on their traits(fig 4).

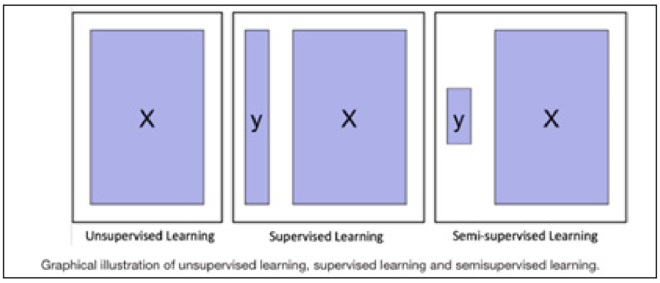

Figure 4.Graphical illustration of unsupervised learning, supervised learning and semi supervised learning

Support Vector Machine (SVM)

SVM is a popular supervised learning technique, especially for binary classification tasks, where the goal is to categorise subjects into two groups. The decision rule is based on finding an optimal boundary that separates the data points belonging to different classes. This is done by determining the weights associated with each input feature (X_{in}) that define this boundary. The optimal classification is achieved when the separation between the groups is maximised, minimising misclassification errors.

An important advantage of SVM is that it guarantees finding a global optimum solution due to its convex optimisation nature. This makes SVM particularly well-suited for medical applications where accurate classification is critical. For instance, SVM has been used to identify imaging biomarkers in neurological and psychiatric diseases, assist in cancer diagnosis, and even support early detection of Alsheimer's disease.

In practice, SVM works by calculating a decision function (ai) for each data point and classifying it based on whether ai is greater than or less than sero. The goal is to adjust the weights (wj) in a way that minimises classification errors while ensuring a clear distinction between the two groups. Overall, SVM and other supervised learning techniques have shown promise in medical fields, where they help to identify patterns in patient data, predict clinical outcomes, and support diagnostic Processes (fig 5).

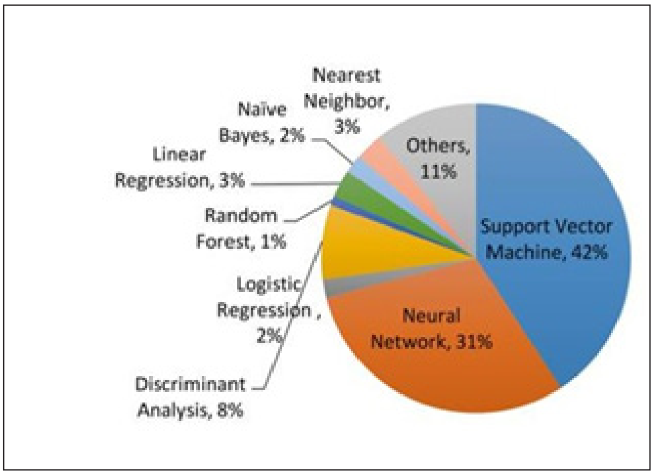

Figure 5.The machine learning algorithms used for imaging (upper), genetic (middle) and electrophysiological (bottom) data

Integration with Clinical Workflows

To maximise its impact, AI must be seamlessly embedded into healthcare workflows. This requires collaboration between technology developers and healthcare providers to create user-friendly interfaces and ensure compatibility with existing systems.

Neural Networks

Neural networks can be considered as an advancement of linear regression, designed to capture more intricate non-linear relationships between input variables and outcomes. Unlike linear regression, which is limited to linear associations, neural networks use multiple hidden layers to combine pre-specified functions to model complex relationships. The objective of training a neural network is to minimise the average error between the predicted outcome and the actual data.

For example, Mirtskhulava et al. utilised neural networks for stroke diagnosis, with input variables such as symptoms like arm or leg paraesthesia, confusion, vision problems, and mobility issues, along with a binary outcome indicating whether the patient had a stroke. The model output is the probability of stroke, which is calculated based on a weighted combination of these symptoms, and the weights are adjusted through optimisation methods like gradient descent to minimise the prediction error(fig 6).

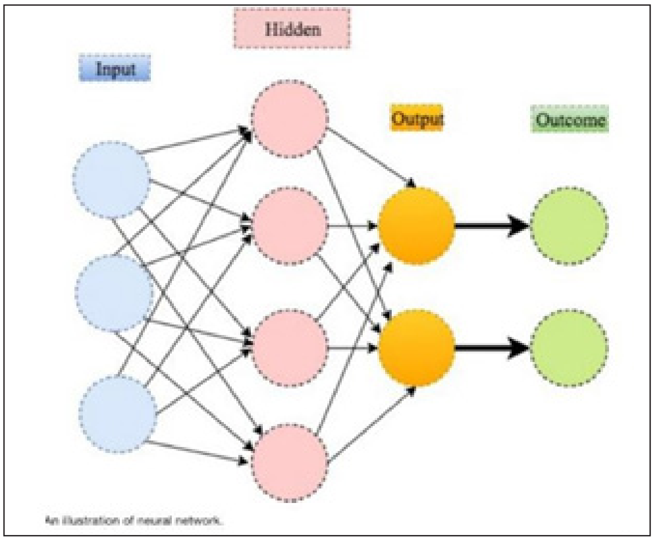

Figure 6.An illustration of neural network

Similar methods have been used in cancer diagnosis, where Khan et al. applied neural networks to classify tumor categories based on gene data, while Dheeba et al. predicted breast cancer using texture information from mammographic images. Hirschauer et al. developed a more sophisticated neural network to diagnose Parkinson's disease by analysing motor symptoms, non-motor symptoms, and neuroimaging data (fig 7).

Deep Learning: A New Era of Machine Learning

Deep learning represents a modern extension of neural networks, consisting of multiple layers, which allow the model to capture even more complex patterns in data. Recent advancements in computing technology have made it feasible to build deep neural networks with many layers, enabling them to handle large and high-dimensional datasets effectively. This

capability has been a key factor in the growing popularity of deep learning, especially with the increasing volume and complexity of available medical data.[10]

In the healthcare domain, deep learning has been widely applied, particularly in the analysis of imaging data. Convolutional Neural Networks (CNNs) are among the most popular deep learning algorithms, especially useful for high-dimensional data such as images. CNNs work by passing image pixel values through multiple convolution and pooling layers to identify hierarchical patterns, ultimately leading to accurate predictions (fig 8).

The data are generated through searching the deep learning in healthcare and disease category on PubMed. For instance, CNNs have been employed to diagnose congenital cataracts by analysing ocular images, with over 90% accuracy. Esteva et al. used CNNs to detect skin cancer from clinical images with high sensitivity and specificity. Similarly, Gulshan et al. applied CNNs for the detection of diabetic retinopathy from retinal images, demonstrating comparable performance to experienced clinicians in diagnosing both normal and disease cases (fig 9).

Natural Language Processing (NLP)

While image, electrophysiological (EP), and genetic data are structured and easily processed by machine learning algorithms, much of the clinical data exists as unstructured text, such as clinical notes, discharge summaries, and laboratory reports. NLP aims to process and extract valuable insights from this textual information to support clinical decision-making.

An NLP pipeline generally involves two key steps: text processing and classification. The text processing phase identifies disease-relevant keywords within clinical notes, leveraging historical databases and clinical guidelines. These keywords are then used in the classification step to assist in decision-making processes, such as diagnosing diseases or determining treatment plans(fig 10).

For example, Fiszsman et al. demonstrated that NLP could help identify potential antibiotic needs by analysing chest X-ray reports. Similarly, NLP has been used to monitor adverse effects in laboratory results and to assist in diagnosing conditions like cerebral aneurysms, achieving high accuracy rates in identifying both normal and abnormal cases.

These advancements in NLP show promise for improving clinical efficiency, disease diagnosis, and treatment management by effectively extracting relevant information from unstructured clinical data.

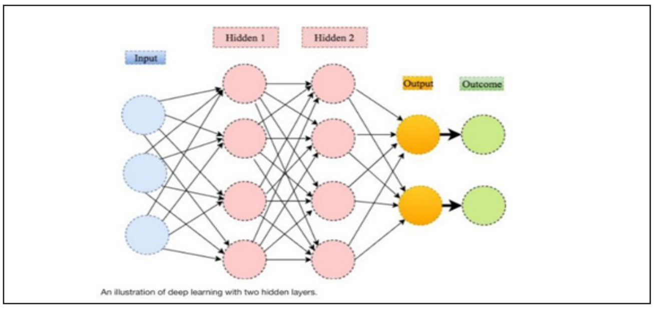

Figure 7.An illustration of deep learning with two hidden layer

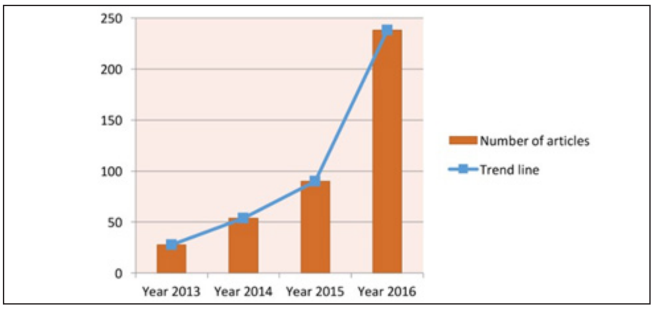

Figure 8.Current trend for deep learning

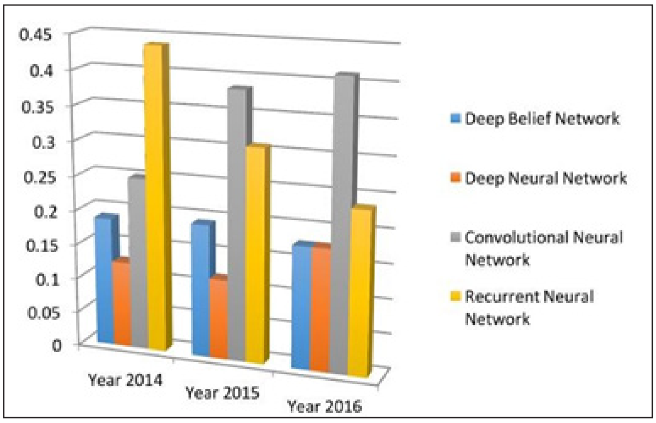

Figure 9.The four main deep learning algorithm and their popularities

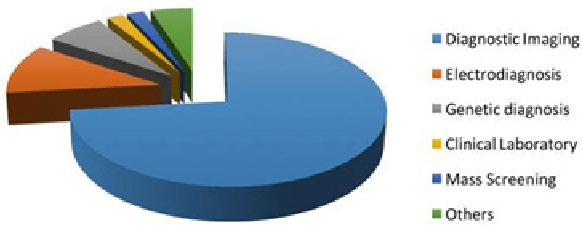

Figure 10.The data sources for deep learning

Conclusion

In conclusion, while AI holds immense potential to revolutionise healthcare, its impact on employment is likely to be gradual and less disruptive than initially anticipated. Although AI can automate certain tasks in fields like radiology and pathology, human expertise remains crucial in various aspects of patient care and moreover, challenges related to data availability, regulatory frameworks, and the explainability of AI algorithms need to be addressed to ensure the safe and effective integration of AI into clinical practice.

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