Official Journal of Erciyes University Faculty of Medicine

DOI: 10.14744/cpr.2024.25381
J Clin Pract Res 2024;46(6):527–536

Applications of Deep Learning Techniques in Healthcare Systems: A Review

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ABSTRACT

Artificial intelligence (AI) is the ability of machines to carry out tasks by imitating human intelligence. In recent years, AI methods have begun to be applied in many different areas, with healthcare being one of the most prominent. Diagnosis, treatment, patient care, new drug production, and preventive care can be listed as some of the applications of AI in healthcare. In this review, deep learning methods, which are a sub-branch of AI, are mentioned. Deep learning methods frequently used in the literature are convolutional neural networks (CNNs), stacked autoencoders (SAEs), and recurrent neural networks (RNNs). These deep learning methods include CNNs for image recognition and classification, SAEs for unsupervised feature learning and dimensionality reduction, and RNNs for analyzing sequential data like time-series. However, it should be noted that these methods can also be applied to other application areas. This paper presents studies in the literature on medical image analysis, drug discovery and development, and remote patient monitoring in which these deep learning methods are used.

Keywords: Artificial intelligence, deep learning, healthcare, review, smart systems.

Cite this article as:
Ozcan T, Toprak AN, Aruk İ, Sahin O, Ozcan I. Applications of Deep Learning Techniques in Healthcare Systems: A Review. J Clin Pract Res 2024;46(6):527–536.

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Submitted: 29.04.2024
Revised: 29.05.2024
Accepted: 14.08.2024
Available Online: 14.10.2024

Erciyes University Faculty of Medicine Publications - Available online at www.jcpres.com

INTRODUCTION

Artificial intelligence (AI) is the study of creating or programming computer learning models by imitating human intelligence.[1] The use of AI is increasing in direct proportion to developing technology. AI methods are also used in the field of health, which contains different types of data. Healthcare is in a new era where abundant biomedical data plays an increasingly important role.[2]

The use of artificial intelligence in healthcare has the potential to offer significant benefits, such as improved diagnosis and diagnostic accuracy, increased speed and efficiency, enhanced predictive care, and personalized treatment. However, there are also several challenges that need to be addressed. These include concerns about data security and privacy, limitations related to training data and generalization, legal regulations and responsibilities, ethical considerations, and the transparency and understandability of the algorithms. It is important to recognize both the potential benefits and the associated risks and to work on solutions to effectively address these challenges.

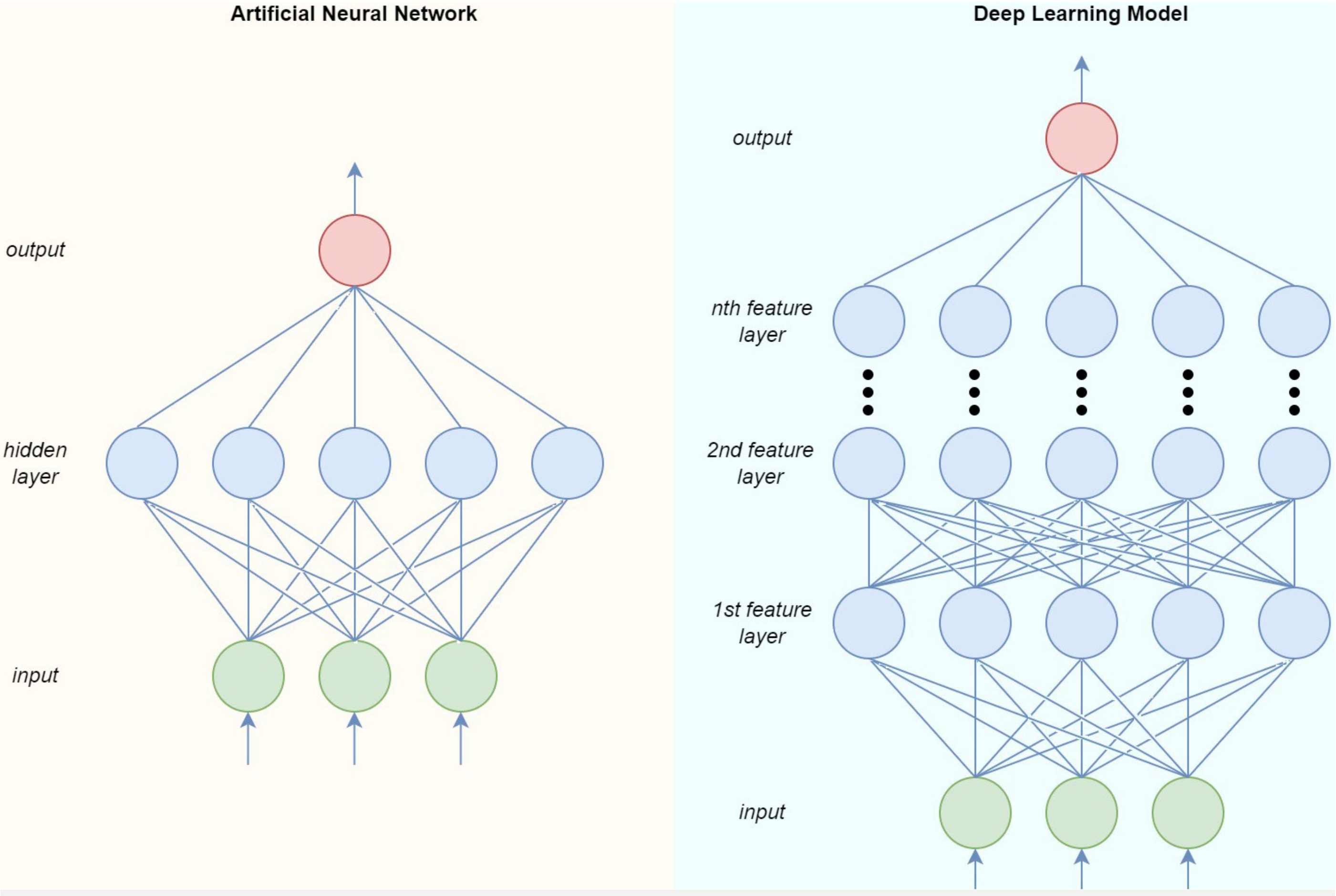

Figure 1. The architectures of simple artificial neural network (ANN) and deep neural network (DNN).[2]

Deep learning approaches, one of the AI-based methods, are frequently used in AI applications in health. Among these methods, convolutional neural networks (CNNs), stacked autoencoders (SAEs), and recurrent neural networks (RNNs) are widely preferred. CNNs are specialized artificial neural networks that contain at least one convolution layer.[3] They are end-to-end methods that perform feature extraction and classification systems together. On the other hand, SAEs are another neural network approach. This method tries to convert input data into an output similar to the input.[4] RNN, another deep learning approach examined in this article, performs processing in the next step using the output calculated in the previous step.[5]

AI helps provide solutions to many different issues in the field of healthcare. In this review, we will focus on AI applications in health, specifically medical image analysis, drug discovery and development, and remote patient monitoring. Under the title of medical image analysis, the focus is on studies related to breast cancer, brain cancer, heart diseases, lung cancer, eye diseases, and skin cancer.

The paper's main contributions are as follows:

- Popular AI methods frequently used in the field of health
- Classification of health problems solved using deep learning methods.

METHODOLOGY

This review aims to identify and analyze the applications of well-known deep learning algorithms in healthcare systems. We conducted a literature search to gather relevant and up-to-date information. We utilized the Web of Science search engine to identify relevant studies published from 2020 onwards in journals indexed in the Science Citation Index (SCI) and Science Citation Index Expanded (SCIE) databases. Our search strategy included a combination of keywords: "deep learning," "healthcare systems," "medical image analysis," and "health applications in deep learning." We focused on articles with a success rate of 90% or more to ensure the inclusion of impactful research. From the selected articles, we extracted information on the specific deep learning algorithms used, the

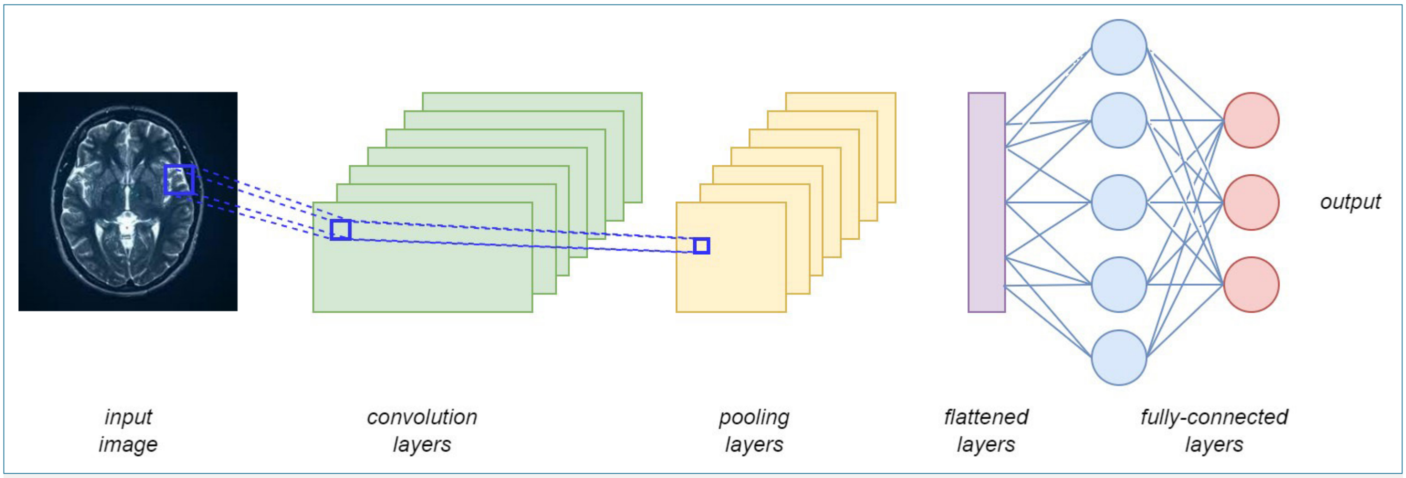

Figure 2. An example of convolutional neural network (CNN) architecture.[8]

healthcare application domain (e.g., medical image analysis, drug discovery and development, etc.), and the reported outcomes or findings.

DEEP LEARNING MODELS

Deep learning is a mechanism that mimics the human learning strategy and thus can perform complex tasks in computer systems. This system, which is based on artificial neural networks (ANNs) learning from a large amount of data, has many more layers than ANNs.[6] It gets its name "deep" due to the multiple layers in neural networks. ANNs consist of connected neurons, similar to how the human brain works. Deep learning models work to train the connections between these neurons. An example of ANN and deep neural networks (DNNs) architecture is presented in Figure 1.

Deep learning methods have been successfully used in various application areas such as image recognition, natural language processing, big data, autonomous vehicles, medical image processing, voice processing, robotics, financial analysis, and energy efficiency.[7]

Three of the most popular and frequently used deep learning models in healthcare are presented in detail in the subsections. These methods are CNNs, SAEs, and RNNs.

Convolutional Neural Networks

Convolutional Neural Networks are a type of artificial neural network that uses at least one convolutional layer to process information. CNNs work similarly to how the human brain processes vision, using small, moving filters to analyze visual information.[3]

CNNs utilize the convolution operator, which works by sliding a filter over the image and calculating a combination of pixels at each filter location to learn features of images. This allows the filter to highlight certain image features.[3] CNNs use a classification layer to classify images based on extracted features, predicting the class to which the image belongs. An example of CNN architecture[8] is presented in Figure 2.

CNNs are used in healthcare sectors such as medical imaging, disease diagnosis, neurological disease diagnosis, drug development, health records analysis, health monitoring devices, and radiology.

Stacked Autoencoders

An autoencoder is a type of neural network that attempts to convert input data into an output similar to the input.[4] Stacked autoencoders consist of a series of autoencoders connected together. SAE was proposed by Hinton and Salakhutdinov in 2006.[4] This deep learning method is designed for dimensionality reduction and feature extraction.

SAEs are used in various applications, including diagnosis, treatment, research, image analysis, natural language processing, and data analysis. An example of SAE architecture is shown in Figure 3.

Recurrent Neural Networks

Recurrent Neural Networks, which perform processing in the next step using the output calculated in the previous step, was proposed by Williams and Zipser in 1989.[5] Unlike traditional neural networks that use input data only once, RNNs can process data in a series of steps. RNNs are particularly useful for applications where the output depends on previous calculations, such as machine translation, natural language processing, and speech recognition.[9]

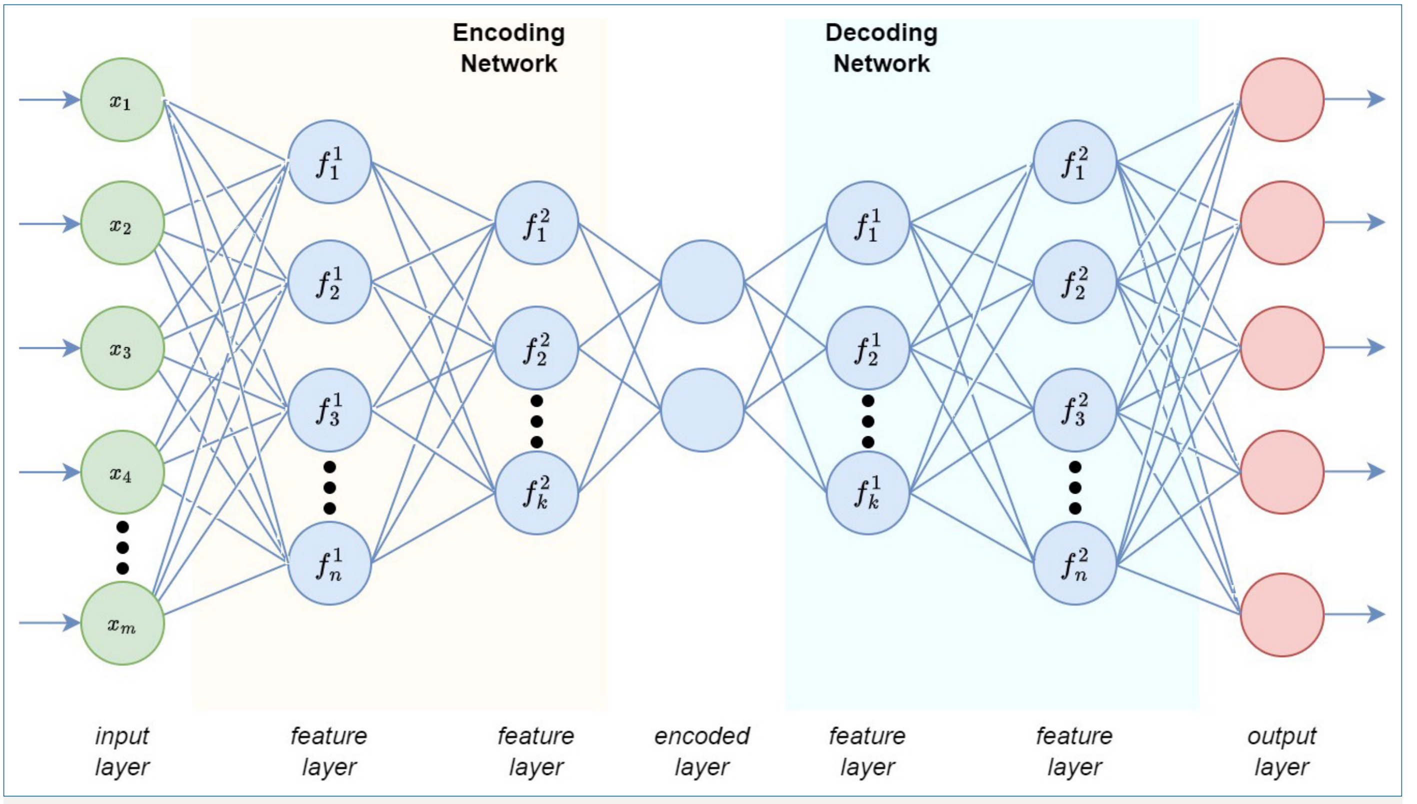

Figure 3. An example of stacked autoencoder (SAE) architecture.[4]

RNNs share the same weights across all steps. This algorithm has the ability to memorize sequential events and model time dependence.[9] An example of RNN architecture[10] is presented in Figure 4.

The differences between the CNNs, SAEs, and RNNs, which are introduced as deep learning methods in this review, are presented in Table 1.

DEEP LEARNING APPLICATIONS IN HEALTHCARE STUDIES

Deep learning has revolutionized healthcare by providing powerful tools for analyzing complex medical data and enabling the development of innovative applications that improve patient care. Its ability to extract meaningful insights from vast and intricate datasets has led to its widespread adoption in various healthcare aspects, from medical imaging analysis to drug discovery and personalized medicine. This section focuses on popular deep-learning applications in healthcare systems. Table 2 provides a summary of the literature studies mentioned. It shows key information such as the field of study, authors, publication year, deep learning technology used, and the reported accuracy rates.

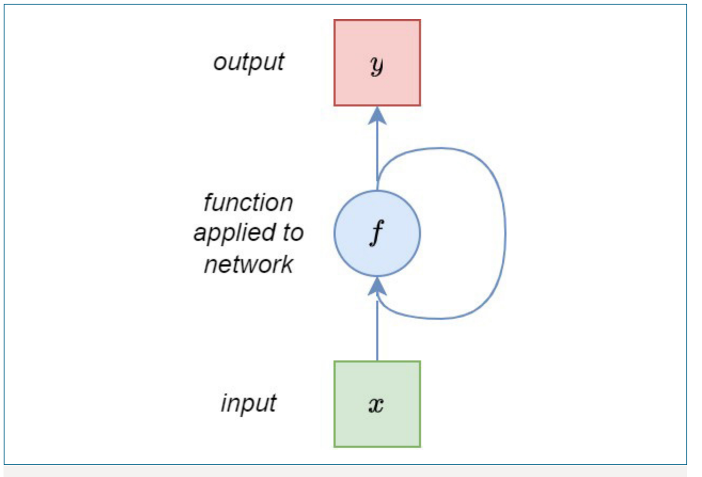

Figure 4. An example of recurrent neural network (RNN) architecture.[10]

Medical Image Analysis

Deep-learning algorithms have demonstrated remarkable abilities in analyzing medical images, including magnetic resonance imaging (MRIs), computed tomography (CT) scans, and X-rays. This has significantly improved disease detection,

Table 1. The differences between popular deep learning techniques

Feature	Convolutional neural networks (CNNs)	Stacked autoencoders (SAEs)	Recurrent neural networks (RNNs)
Task	Speech recognition Image recognition Natural language processing	Anomaly detection Unsupervised learning Dimensionality reduction	Natural language processing Speech recognition
Data	Spatial or temporal	Unlabeled	Sequential
Strength	Feature extraction Pattern recognition	Efficient data representation	Long-range dependencies
Weaknesses	Not well-suited for unstructured data	Requires large amounts of labeled data	Sensitive to long time delays

diagnosis, and treatment planning. Deep learning models can effectively identify subtle patterns and anomalies within medical images, aiding healthcare professionals in making accurate diagnoses.

Breast Cancer

Breast Cancer (BC) is a type of cancer that starts in the breast. It is characterized by the uncontrolled growth of cells in the breast tissue. Approximately 85% of BC cases originate in the epithelial cells of the ducts, while 15% begin in the lobules of the breast. If breast cancer is not detected early, it can spread to nearby lymph nodes and other organs in the body. Breast cancer ranks among the primary contributors to cancer-related fatalities among women globally.[11]

Studies conducted thus far have demonstrated that early detection and treatment of breast cancer can enhance a patient's prospects for recovery and diminish the likelihood of mortality. Experts have suggested using screening methods as the most accurate way to diagnose breast cancer early. Different Medical Imaging Modalities (MIM) are used to perform breast cancer diagnosis. The commonly employed screening methods encompass Histopathological (HP) images, Breast Ultrasound (BUS), Breast Magnetic Resonance Imaging (BMRI), Computed Tomography scans, Positron Emission Tomography (PET) scans, Digital Mammography (DM), and Thermography.[11]

In a recent study, Obayya et al.[12] developed an arithmetic optimization algorithm for histopathological breast cancer classification based on deep learning. The approach involved utilizing a deep belief network (DBN) classifier with the Adamex hyperparameter optimizer for the classification of breast cancer. The algorithm demonstrated an accuracy of 96.77%.

Jabeen et al.[13] proposed a framework for classifying breast cancer from ultrasound images using deep learning (DL). They utilized a pre-trained DarkNet-53 model for feature extraction and then applied reformed gray wolf (RGW) and reconstructed differential evolution (RDE) optimization algorithms to select the most optimal features. Finally, the selected features were classified using machine learning (ML) techniques. Their framework achieved an accuracy of 99.1% on the Breast Ultrasound Images (BUSI) dataset.

Brain Cancer

Brain tumors are a leading cause of cancer-related deaths, necessitating prompt and accurate diagnosis for effective treatment. However, recognizing brain tumors in medical images such as MRI and CT scans is challenging due to the complex brain structure and the high variability in tumor tissue appearance. Therefore, developing computer-assisted diagnosis techniques is crucial to aid radiologists in identifying and distinguishing different types of tumors. Several deep learning-based brain tumor classification and segmentation methods have been presented in the literature to assist radiologists in their diagnostic analysis.[14]

In a recent study, Pedada et al.[15] proposed a modified U-Net structure for brain tumor detection based on residual networks using periodic shuffling in the encoder part of the original U-Net and subpixel convolution in the decoder part. With the model evaluated on two datasets, they achieved segmentation accuracies of 93.40% and 92.20%. Wang et al.[16] proposed a CNN model trained on labeled optical coherence tomography (OCT) images and co-occurrence matrix features for brain cancer diagnosis, achieving 93.31% sensitivity and 97.04% specificity.

Saha et al.[17] developed a CNN model to extract deep features from MR images. Their study divides brain cancers into four classes: Glioma, Meningioma, Pituitary, and non-cancerous. The model achieved 97.90% accuracy for the Glioma class, 98.94% for Meningioma, 98.92% for the Pituitary class, and 98.00% for non-cancerous.

Heart Diseases

Cardiovascular diseases (CVDs) have risen to become a leading global cause of death. Initially presenting with mild symptoms, CVDs worsen gradually over time. As these diseases progress, individuals often suffer from fatigue, difficulty breathing, swelling in the ankles, fluid retention, and other associated symptoms.

Table 2. Summary of critical data extracted from the literature

Field of study	Authors	Year	Method	Result
Breast cancer	Obayya et al.[12]	2023	DBN	96.77% (accuracy)
	Jabeen et al.[13]	2022	CNN RGW RDE	99.1% (accuracy)
Brain cancer	Pedada et al.[15]	2023	U-Net CNN	93.40% (accuracy) 92.20% (accuracy)
	Wang et al.[16]	2023	CNN	93.31% (sensitivity) 97.04% (specificity)
	Saha et al.[17]	2023	CNN	97.90% (accuracy) 98.94% (accuracy) 98.92% (accuracy) 98.00% (accuracy)
Heart diseases	Ali et al.[19]	2020	Ensemble DL and feature fusion	98.5% (accuracy)
	García-Ordás et al.[20]	2023	CNN	90% (accuracy)
Lung cancer	Shah et al.[22]	2023	CNN	95% (accuracy)
	Said et al.[23]	2023	CNN	97.83% (accuracy) 98.77% (accuracy)
	Pandit et al.[24]	2023	CNN Adam Opt.	99.5% (accuracy)
Eye diseases	Guo et al.[26]	2021	MobileNetV2	96.2% (accuracy)
	Shankar et al.[27]	2020	SDL	99.28% (accuracy)
	Hassan et al.[28]	2023	CNN	98.36% (sensitivity) 96.15% (specificity)
Skin cancer	Tembhurne et al.[30]	2023	Contourlet Transform LBP Histogram	93% (accuracy)
	Hussain et al.[31]	2023	CNN	95% (accuracy)
	Jansen et al.[32]	2023	CNN	98.57% (accuracy)
Drug discovery and development	Wu et al.[35]	2023	FP-GNN	91% (accuracy)
	D'Souza et al.[36]	2023	CNN	93% (accuracy)
Remote patient monitoring	Jeyaraj and Nadar.[38]	2022	DNN	97.2%
	Hannah et al.[39]	2022	CNN	98%

DBN: Deep belief network; CNN: Convolutional neural network; RGW: Reformed gray wolf; RDE: Reconstructed differential evolution; DL: Deep learning; SDL: Synergic deep learning; FP-GNN: Fingerprint graph neural network.

Clinical approaches like blood tests, electrocardiography (ECG) signals, and medical imaging serve as highly effective means for diagnosing cardiovascular diseases.[18]

In one of the recent studies, Ali et al.[19] proposed an intelligent healthcare system that utilizes ensemble deep learning and feature fusion approaches for predicting heart disease. They evaluated the proposed system utilizing heart disease data and compared it to conventional classifiers utilizing feature fusion, feature selection, and weighting techniques. The system attained an accuracy rate of 98.5%.

García-Ordás et al.[20] developed a model using deep learning methods and feature augmentation techniques to assess the risk of patients developing cardiovascular disease. They obtained a precision value of 90%.

Lung Cancer

Lung cancer ranks as the foremost cause of cancer-related deaths worldwide, with the highest mortality rates attributed to it. It occurs when abnormal cells multiply uncontrollably in the lungs. Medical imaging techniques are crucial in clinical settings, playing an essential role in the screening, diagnosis, and treatment of lung cancer.[21]

In a recent study, Shah et al.[22] combined multiple CNN models to detect potentially cancerous lung nodules from different CT scan images. By combining multiple CNNs, they achieved a result with 95% accuracy. Said et al.[23] proposed a system for early lung cancer diagnosis in CT scan imaging. The suggested system consists of two components: segmentation, which involves segmenting 3D CT scan images, and classification, where the segmented images are classified as benign or malignant. The results showed that the system achieved 97.83% accuracy in segmentation and 98.77% accuracy in classification.

In their study, Pandit et al.[24] aimed to reduce the processing time and improve the overall accuracy of predicting lung cancer by incorporating multi-domain images into the pooling layer of the CNN. They proposed a method that utilized multi-domain images and the Adam optimization algorithm. The method yielded a lung cancer classification accuracy of 99.5%.

Eye Diseases

Deep learning algorithms possess the ability to detect various eye ailments, including cataracts, glaucoma, macular degeneration, diabetic retinopathy (DR), and retinoblastoma. Fundus images and optical coherence tomography images are frequently employed for diagnosing eye conditions.[25]

In their study, Guo et al.[26] proposed a model for discriminating four common eye diseases using the MobileNetV2 architecture. They implemented a visualization approach to emphasize the regions most correlated with disease labels, enhancing the model's interpretability. Experimental results showed that the system achieved an average accuracy of 96.2%, sensitivity of 90.4%, and specificity of 97.6%. Shankar et al.[27] introduced an automated model for detecting and classifying diabetic retinopathy in fundus images using deep learning. The method consists of three main steps: preprocessing, segmentation, and classification. In the preprocessing stage, edge noise is eliminated. Segmentation then identifies functional regions in the image using histogram-based methods. Finally, the synergic deep learning (SDL) model is used to classify DR fundus images into different levels. Experimental results on the Messidor dataset demonstrated that the model outperformed existing models in classification performance.

In their study, Hassan et al.[28] proposed an enhanced optical coherence tomography (EOCT) model to classify retinal OCT images. The experimental results obtained performance values with a sensitivity of 98.36% and a specificity of 96.15%.

Skin Cancer

Skin cancer, identified by the abnormal growth of skin cells, stands as one of the most common types of cancer worldwide. It encompasses three main types: squamous cell skin cancer (SCC), basal cell skin cancer (BCC), and melanoma. The first two types are classified as non-melanoma and rarely result in death. On the other hand, melanoma stands out as the deadliest type of skin cancer. Recent research has seen a widespread utilization of DL techniques in identifying skin cancer through dermoscopic images.[29]

In their research, Tembhurne et al.[30] presented a method that integrates ML and DL techniques for detecting skin cancer. They used a DL model to extract features from images and an ML model to process them using methods like Contourlet Transform and Local Binary Pattern Histogram. By combining manual and automatic features, their model achieved an accuracy of 93% in identifying both benign and malignant types of cancer.

Hussain et al.[31] conducted a study wherein they trained and assessed various deep learning models utilizing transfer learning for a dataset aimed at localizing native nail melanoma. Seven CNN architectures using dermoscopic image datasets were trained and tested on classifying skin lesions for melanoma detection. They achieved an accuracy value of over 95%. In their study, Jansen et al.[32] developed a deep learning-based method for detecting melanoma metastasis on histological tissue sections of sentinel lymph nodes collected from clinical routine. They detected a clinically significant metastasis of at least 0.1 mm to initiate treatment with a sensitivity of 98.57%.

Drug Discovery and Development

Drug discovery is a complex process that involves multiple scientific disciplines to identify and develop new therapeutic agents for specific diseases. This process is both time-consuming and expensive, often taking more than a decade from discovery to approval.[33] The use of AI in drug discovery has recently gained significant attention due to its potential to reduce the time and cost associated with developing new drugs. As deep learning technology improves and data accumulates, it is increasingly being utilized at all stages of drug development. Deep learning technologies and applications are becoming more prevalent in drug discovery, particularly in areas such as drug-target interactions (DTIs), drug-drug similarity interactions (DDIs), drug sensitivity and responsiveness, and the prediction of drug side effects.[34]

In their study, Wu et al.[35] developed a total of 832 classification models using the fingerprint graph neural network (FP-GNN) deep learning method to predict the inhibitory activity of compounds against targets and tumor cell lines. Compared with classical methods, the FP-GNN model showed overall prediction performance of 91%, 88%, and 91% for test sets of targets, academic-sourced, and National Cancer Institute's 60 (NCI-60) cancer cell lines, respectively.

In a separate study, D'Souza et al.[36] introduced a deep-learning approach for predicting unknown drug-target interactions. They utilized only one-dimensional Simplified Molecular Input Line Entry System (SMILES) representations of drugs and protein subsequences derived from binding pocket data. Their model, which was trained on binding site residues, showed performance comparable to that of basic shallow methods. This approach proves to be computationally superior to traditional machine learning models as it eliminates the need for constructing similarity matrices.

Remote Patient Monitoring

Remote patient monitoring (RPM) is a healthcare tool aiding medical professionals in overseeing individuals with chronic or acute conditions from afar, offering assistance to elderly individuals in their residences, and overseeing patients in hospital settings. RPM applications use traditional ML and DL methods to detect and predict vital signs, detect early deterioration in patients' health, and classify patients' physical activities. In RPM solutions, popular technologies such as cloud computing, Internet of Things (IoT), wearables, sensors, and blockchain are frequently utilized. Patient monitoring systems focus on extracting human vital signs such as heart rate, pulse rate, respiratory rate, blood pressure, and blood oxygen volume.[37]

In their study, Jeyaraj and Nadar[38] developed an IoT application-based physiological signal monitoring system. A DNN-based accurate signal prediction algorithm is used in the system. They prototyped an advanced electronic component using a smart sensor for signal measurement and National Instruments myRIO for smart data acquisition. They achieved an average accuracy value of 97.2% in the experimental setup with the prototype.

In another study, Hannah et al.[39] delved into the application of blockchain-powered deep neural networks to improve the velocity and dissemination of healthcare data within the healthcare management framework. Employing a DL model, they categorized brain ailments into benign or malignant. The research encompassed three specific categories of brain disorders: Alzheimer's disease (AD), mild cognitive impairment, and normal cognitive function, aiming to forecast the benign or malignant nature of the brain disorder. The results showed that the proposed method responded with 98% accuracy.

CONCLUSION

Deep learning is an emerging powerful technique with the potential to revolutionize the healthcare industry. In recent years, DL has provided effective solutions for discovering and developing drugs, optimizing clinical workflows, improving remote patient monitoring, and analyzing medical images. This paper has focused on the healthcare challenges addressed using DL with promising results, including analyzing medical images with high accuracy and creating personalized treatment plans for individual patients.

In the future, researchers may focus on developing and integrating efficient technologies to meet the hardware requirements. Improving the DL models is necessary to build more effective systems. Therefore, creating well-defined general architectures that work with different types of health data is essential to solving complex problems in healthcare systems. Additionally, implementing DL models in terms of Explainable Artificial Intelligence (xAI) can help in describing an AI model, its expected impact, and potential biases.

Author Contributions: Concept – TO, ANT, OS, İA, IO; Design – TO, ANT, OS, İA, IO; Supervision – TO, ANT, OS, İA, IO; Analysis and/or Interpretation – TO, IO, ANT; Literature Search – TO, IO, ANT; Writing – TO, ANT, İA, IO; Critical Reviews – TO, ANT.

Conflict of Interest: The authors have no conflict of interest to declare.

Use of AI for Writing Assistance: Not declared.

Financial Disclosure: The authors declared that this study has received no financial support.

Peer-review: Externally peer-reviewed.

REFERENCES

1. Boden MA. Artificial intelligence. 1st edition. Elsevier; 1996.
2. Miotto R, Wang F, Wang S, Jiang X, Dudley, JT. Deep learning for healthcare: review, opportunities, and challenges. Brief Bioinform 2018; 19(6): 1236-46.
3. Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Communications ACM 2017;60(6): 84-90.
4. Hinton GE, Salakhutdinov RR. Reducing the dimensionality of data with neural networks. Science 2006; 313(5786): 504-7.
5. Williams RJ, Zipser D. A learning algorithm for continually running fully recurrent neural networks. Neural Computation 1989; 1(2): 270-80.
6. Deng L, Yu D. Deep learning: methods and applications. Foundations and trends® in Signal Processing 2014; 7(3-4):

197-387.

7. Yapici MM, Tekerek A, Topaloglu N. Literature review of deep learning research areas. Gazi Mühendislik Bilim Derg 2019; 5(3): 188-215.
8. Sarvamangala DR, Kulkarni RV. Convolutional neural networks in medical image understanding: a survey. Evol Intel 2022; 15(3): 1-22.
9. Kaya U, Yılmaz A, Dikmen Y. Deep Learning Methods used in the field of Health. European J Scie and Techn 2019; 16: 792-808.
10. Katte T. Recurrent neural network and its various architecture types. Int J Res Scie Innovation 2018; 5(3): 124-9.
11. Abhisheka B, Biswas SK, Purkayastha B. A comprehensive review on breast cancer detection, classification and segmentation using deep learning. Arch Computat Methods Eng 2023; 30(8): 5023-52.
12. Obayya M, Maashi MS, Nemri N, Mohsen H, Motwakel A, Osman AE, et al. Hyperparameter optimizer with deep learning-based decision-support systems for histopathological breast cancer diagnosis. Cancers (Basel) 2023; 15(3): 885.
13. Jabeen K, Khan MA, Alhaisoni M, Tariq U, Zhang YD, Hamza A, et al. Breast cancer classification from ultrasound images using probability-based optimal deep learning feature fusion. Sensors 2022; 22(3): 807.
14. Muhammad K, Khan S, Del Ser J, De Albuquerque VHC. Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey. IEEE Trans Neural Netw Learn Syst 2020; 32(2): 507-22.
15. Pedada KR, Rao B, Patro KK, Allam JP, Jamjoom MM, Samee NA. A novel approach for brain tumour detection using deep learning based technique. Biomed Signal Processing Contr 2023; 82: 104549.
16. Wang N, Lee CY, Park HC, Nauen DW, Chaichana KL, Quinones-Hinojosa A, et al. Deep learning-based optical coherence tomography image analysis of human brain cancer. Biomed Optics Express 2023; 14(1): 81-8.
17. Saha P, Das R, Das SK. BCM-VEMT: Classification of brain cancer from MRI images using deep learning and ensemble of machine learning techniques. Multimed Tools Appl 2021; 82(28): 44479-506.
18. Jafari M, Shoeibi A, Khodatars M, Ghassemi N, Moridian P, Alizadehsani R, et al. Automated diagnosis of cardiovascular diseases from cardiac magnetic resonance imaging using deep learning models: A review. Comp Bio Med 2023; 160: 106998.
19. Ali F, El-Sappagh S, Islam SR, Kwak D, Ali A, Imran M, et al. A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Inform Fusion 2020; 63: 208-22.
20. García-Ordás MT, Bayón-Gutiérrez M, Benavides C, Aveleira-Mata J, Benítez-Andrades JA. Heart disease risk prediction using deep learning techniques with feature augmentation. Multimed Tools Appl 2023; 82(1): 1-15.
21. Huang S, Yang J, Shen N, Xu Q, Zhao Q. Artificial intelligence in lung cancer diagnosis and prognosis: Current application and future perspective. Semin Cancer Biol 2023; 89: 30-7.
22. Shah AA, Malik HAM, Muhammad A, Alourani A, Butt ZA. Deep learning ensemble 2D CNN approach towards the detection of lung cancer. Scientific Reports 2023; 13(1): 2987.
23. Said Y, Alsheikhy AA, Shawly T, Lahza H. Medical images segmentation for lung cancer diagnosis based on deep learning architectures. Diagnostics 2023; 13(3): 546.
24. Pandit BR, Alsadoon A, Prasad PWC, Al Aloussi S, Rashid TA, Alsadoon OH, et al. Deep learning neural network for lung cancer classification: enhanced optimization function. Multimed Tools Appl 2023; 82(5): 6605-24.
25. Sebastian A, Elharrouss O, Al-Maadeed S, Almaadeed N. A survey on deep-learning-based diabetic retinopathy classification. Diagnostics 2023; 13(3): 345.
26. Guo C, Yu M, Li J. Prediction of different eye diseases based on fundus photography via deep transfer learning. J Clin Med 2021; 10(23): 5481.
27. Shankar K, Sait ARW, Gupta D, Lakshmanaprabu SK, Khanna A, Pandey HM. Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model. Pattern Recognit Lett 2020; 133: 210-6.
28. Hassan E, Elmougy S, Ibraheem MR, Hossain MS, AlMutib K, Ghoneim A, et al. Enhanced deep learning model for classification of retinal optical coherence tomography images. Sensors 2023; 23(12): 5393.
29. Bhatt H, Shah V, Shah K, Shah R, Shah M. State-of-the-art machine learning techniques for melanoma skin cancer detection and classification: a comprehensive review. Intell Med 2023; 3(03): 180-90.
30. Tembhurne JV, Hebbar N, Patil HY, Diwan T. Skin cancer detection using ensemble of machine learning and deep learning techniques. Multimed Tools Appl 2023; 82(18): 27501-24.
31. Hussain M, Fiza M, Khalil A, Siyal AA, Dharejo FA, Hyder W, et al. Transfer learning-based quantized deep learning

models for nail melanoma classification. Neural Comp Appl 2023; 35(30): 22163-78.

32. Jansen P, Baguer DO, Duschner N, Arrastia JL, Schmidt M, Landsberg J, et al. Deep learning detection of melanoma metastases in lymph nodes. Eur J Cancer 2023; 188: 161-70.

33 Paul D, Sanap G, Shenoy S, Kalyane D, Kalia K, Tekade RK. Artificial intelligence in drug discovery and development. Drug Discov Today 2021; 26(1): 80-93.

34. Askr H, Elgeldawi E, Aboul Ella H, Elshaier YAMM, Gomaa MM, Hassanien AE. Deep learning in drug discovery: an integrative review and future challenges. Artif Intell Rev 2023; 56(7): 5975-6037.

35. Wu J, Xiao Y, Lin M, Cai H, Zhao D, Li Y, et al. DeepCancerMap: A versatile deep learning platform for target-and cell-based anticancer drug discovery. European J Med Chemistry 2023; 255: 115401.

36. D'Souza S, Prema KV, Balaji S, Shah R. Deep learning-based modeling of drug-target interaction prediction incorporating binding site information of proteins. Interdisciplinary Sciences: Comp Life Scie 2023; 15(2): 306-15.

37. Shaik T, Tao X, Higgins N, Li L, Gururajan R, Zhou X, et al. Remote patient monitoring using artificial intelligence: Current state, applications, and challenges. WIRE's Data Mining Knowl Discov 2023; 13(2): e1485.

38. Rajan Jeyaraj P, Nadar ERS. Smart-monitor: Patient monitoring system for IoT-based healthcare system using deep learning. IETE J Res 2022; 68(2): 1435-42.

39. Hannah S, Deepa AJ, Chooralil VS, BrillySangeetha S, Yuvaraj N, Arshath Raja R, et al. Blockchain-based deep learning to process Iot data acquisition in cognitive data. Biomed Res Int 2022; 2022: 5038851. Retraction in: Biomed Res Int 2023; 2023: 9768789.