IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

COMPARING VARIOUS NEURAL BASED LEARNING MODELS FOR HEALTHCARE APPLICATIONS

Kadaru Deepashikha, Computer Science Engineering, Jawaharlal Nehru Technological University Hyderabad, Hyderabad

ABSTRACT

Having access to quality health care is crucial to surviving in life. However, getting an appointment with a doctor when you're sick can be difficult. The health care sector is expanding and has a profound impact on many facets of human existence. The healthcare sector is developing in tandem with technological innovation. Rapid technological advancements in the medical sciences promise improved methods of disease prevention, diagnosis, and treatment. Artificial intelligence (AI) is undergoing a sea change due to its numerous applications; for instance, it is reshaping the healthcare industry by allowing for better monitoring of patients with chronic diseases. Researchers have their work cut out for them as they try to streamline the architecture and management of intelligent delivery systems as a whole. The vast majority of these systems are driven by cutting-edge learning algorithms like Convolution Neural Network. The Convolutional Neural Network (CNN) algorithm is frequently used as an illustrative example of DL architecture. With the arrival of CNN hardware accelerators and a subsequent increase in the quantity of available annotated data, the field of CNN research and development has experienced a recent uptick, resulting in benchmarks being implemented on a wide range of different applications. For this meta-analysis, researchers looked for publications published between January 1, 2012 and June 6, 2022 in the databases Ovid-MEDLINE, Embase, Science Citation Index, and Conference Proceedings Citation Index. It was considered valid study to compare the diagnostic precision of deep learning models to that of healthcare professionals utilising medical imaging.

Key words: Neural network, Healthcare, Deep Learning, CNN.

1. INTRODUCTION

Recent developments in data analytics using wireless sensing systems have resulted in positive advances across a wide range of fields, including remote healthcare, agriculture technology, smart trackers, and augmented reality. The main forces behind data analysis are state-of-the-art machine learning and deep learning algorithms. Feed-forward artificial neural networks are one of the most well-known implementations of Convolution Neural Network (CNN) approaches. Inspiring the interneuron pattern of connectivity in this type of network is the visual cortex of an animal's brain. Individual neurons in the visual cortex have a limited "receptive field" that only receives information from a certain region. Receptive fields of neurons with nodes at opposite ends of their connections may overlap to cover the entire visual field. It was previously shown [1] that a 3D convolution approach often employed in CNNs can be used to estimate quantitatively the reaction of different neurons to the stimuli inside its receptive area.

Increasingly, doctors are turning to AI in an effort to address some of the field of medicine's most pressing problems. Based on what we already know, it looks like we will be able to solve some of the most important problems in healthcare right now. One of the most promising areas of AI research is machine learning. The health care sector is expanding rapidly and has far-reaching implications. Consistent with other sectors of the economy, the health care sector is advancing. Better methods of prevention, diagnosis, and treatment are all on the horizon as a result of the fast convergence of technology and the medical sciences. Emergency room wait times can be predicted with this technology, which is being used by the healthcare administration. According to medical professionals, promptness in making a correct diagnosis is of utmost importance, as this can have a significant positive impact on the health of the patient [2]. These days, much healthcare documentation is done digitally. Keeping up with the volume of incoming data necessitates a fast, reliable, and secure electronic method of storing and filing information. Thus, it is clear that the future would benefit from combining machine learning with the medical sciences. Precision medicine tries to "make sure that the right medicine is given to the right patient at the right time" by taking into account a patient's molecular traits, environment, electronic health records (EHRs), and way of life[3].

Some people have even thought that AI applications could eventually replace whole areas of medicine or make new jobs for doctors, like "information specialists," in the health domain. However, due to its reliance on human interpretation and growing resource constraints, medical imaging is becoming less and less of a reliable diagnostic tool. Even in low- and middle-income countries, the demand for diagnostic imaging is outstripping the supply of specialists.

2. LITERATURE REVIEW

"Deep learning," a subfield of machine learning, is a neural network that attempts to simulate the way the human brain works. Recently, Deep Neural Network (DNN) models and other Machine Learning approaches have gained popularity in the healthcare industry because to the growing complexity of healthcare data. The fact that this is an image collection means that machine learning could prove quite helpful in making diagnoses. Machine learning algorithms, such as neural networks, can be used to evaluate medical images obtained by medical imaging modalities. In a standard Deep Neural Network (DNN) [4], an input value is weighted and bias-corrected before being fed into a non-linear activation function like ReLu or softmax. Accordingly, DNN training seeks to maximise the network's weights in a way that minimises the loss function [5].

Table1.Different ML and DLTechniquesforDiagnosisofVariousDiseases

Disease	Author	Technique used	Dataset	Accuracy	Ref
Heart Disease	Apurb Rajdhan (2020)	Random Forest	UCI develand dataset	90.16%	[6]
	Archana Singh(2020)	K-nearest neighbour	UCI repository dataset	87%	[7]
	Abhijeet Jagtap(2019)	SVM	UCI dataset	64.4%	[8]
	Harshit Jindal (2021)	KNN	UCI repository dataset	87.5	[9]
Diabetes Disease	Nesreen Samer El_Jerja wi (2018)	ANN	Documentation of the Association of diabetic's city of Urmia	87.3%	[10]
	Safial Islam Ayon (2019)	Deep Neural Network	Pima Indian diabetes dataset	98.35%	[11]
	Aishwarya Mujumdae (2019)	Logistic Regression		96%	[12]

	(2019)				
	Amani Yahyaoui (2020)	Random Forest	Pima Indian Diabetes dataset	83.67%	[13]
Liver Disease	A. K. M. Sazzadur Rahman (2019)	Logistic Regression	dataset from the UCI Machine Learning Repository. In addition, the original dataset was collected from the northeast of Andhra Pradesh, India	75%	[14]
	M. Banu Priya (2018)	J.48 and Bayesnet	Indian Liver Patient Dataset	95.04 % and 90.33 %	[15]
	Dr.S.Vijayarani	SVM	Indian Liver Patient Dataset(ILPD)	79.66%	[16]
	Md.Irfan	K-nearest neighbour	Indian Liver Patient Dataset(ILPD)	73.97%	[17]
Malaria Disease	Gautham Shekar(2020)	Basic CNN, VGG-19 Frozen CNN, and VGG-19 Fine Tuned CNN		94%,92% and 96%	[18]
	Krit Sriporn(2020)	CNN	The data were collected from a thin blood smear on a slide containing malaria from the hospital by using a microscope. The total sample comprised 201 patients, of which 151 were infected and 50 patients were not.	96.85%	[19]
	Soner Can Kalkan	CNN	U.S National Library of Medicine and used consists of 27,558 cell images	95%	[20]

3. APPLICATION OF CNN IN INTELLIGENT HEALTHCARE

In healthcare, Neural Networks have been utilised for decades. They aid in the discovery of a previously unseen pattern in healthcare data, which in turn improves the accuracy and timeliness with which an illness can be diagnosed [21]. The success of CNN in extracting spatial features has led to its rise in popularity as a deep learning algorithm [22]. CNN is useful in several fields, including linguistics [23], facial recognition [24], and computer vision [25]. Drug discovery, medicine, medical imaging, and the genome are just a few examples of how CNN is influencing the healthcare industry [26].

Some uses for radiology include:

- CT scans for the detection of lung cancer.
- Identifying and classifying tumours automatically (mammography scans, MRI, or CT).
- Analyzing Brain Images (both in health and disease).
- Profiling gene expression in a variety of malignancies (one molecular signature was found recently for hepatocellular carcinomas).
- Prostate, lung, and MS CAD systems are among those attempting to adopt deep learning methodologies.
- Analysis of medical images for the purpose of segmenting anatomical structures (this varies a lot, from the prostate to brain substructures, and abdominal organs to the heart).

Automated microbiological analysis is a significant area where deep learning has the potential to significantly improve medicine [27]. Commonly done in a medical lab, this method still requires human intervention to check if bacteria grow in a Petri dish and identify the species.

Traditional image recognition techniques have been unreliable for use in analysing microorganisms [28]. In contrast, deep learning algorithms perform exceptionally well in this respect. It was proposed by Talo [29] that automatic bacterial picture classification may be achieved by the use of a deep learning-based algorithm. In addition, they used transfer learning to speed up CNN's training process.

It is a significant step forward to automate microbiological analysis with the help of deep learning, which will allow many patients to receive their test result sooner (medical labs working 24/7 is of high importance for people with urgent health needs), cheaper (without humans being involved, medical labs will be able to cut cost on the process), and with greater confidence in their diagnosis (due to minimised risk of a human error happening in the lab) [30, 31]. Labs conducting industrial microbiology research reap similar rewards. The healthcare industry is extremely diverse, and it would be impossible to cover all of its facets in a single essay. Consequently, we focus on how CNN can be used in the medical field specifically.

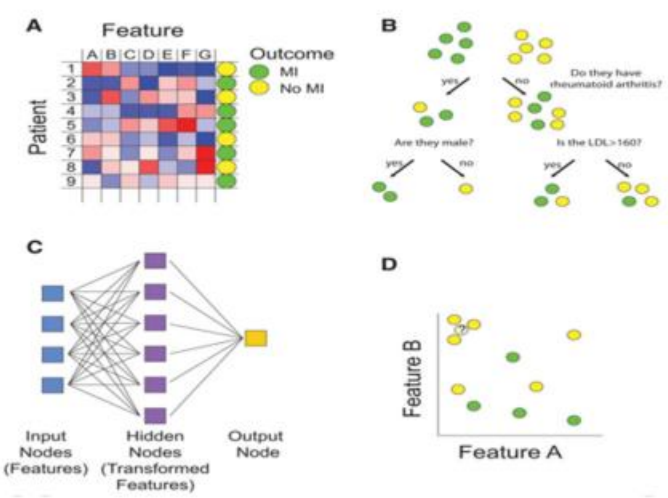

Fig. 1. An overview of drug discovery process using deep learning.

3.1 Applications of Deep Learning in Medicine

Algorithms based on deep learning have been significant in the advancement of medical science [32]. To find a new drug is a procedure that is not only lengthy and difficult, but also extremely costly. Current estimates place the total cost of developing a new drug at $2.5 billion, with an average time to market of over 12 years [33, 34]. Furthermore, only around one in ten drugs ever developed really receives regulatory approval. Machine learning is being incorporated into the drug discovery process by researchers in an effort to increase productivity, decrease development time, and cut expenses significantly [35, 36]. Additionally, this indicates that a considerable portion of the time, resources, and money currently being invested in traditional methods of drug discovery could be redirected to other projects with higher potential for return on investment or to the development of innovative new technologies.

The massive volume of new biological data being generated every day, from which useful information must be retrieved, represents a potential bottleneck for machine learning. With the current state of technology, it is practically difficult to efficiently handle the up to 10,000 pieces of published content produced daily by the world's biomedical journals [37]. Other businesses are analysing data from healthy and sick patient samples with machine learning to discover new biomarkers and therapeutics. Using machine learning, scientists may extract these potentially valuable targets from biological data and put into practise the first form of tailored treatment.

Many new companies have arisen as a result of the use of machine learning into the drug development process, which has helped researchers shorten the time and money needed to bring a novel drug to market [38]. All of these cutting-edge methods will eventually help us decipher the molecular blueprint of each individual patient, paving the way for precision medicine.

While it would be a huge undertaking to implement a drug discovery system powered by deep learning, the time and money saved would be well worth it. The incorporation of a deep-learning or AI model into the drug discovery process is essential for the creation of a novel compound's early development system. Developing a personalised method for processing precise prediction criteria for hitherto unknown molecules is the most important step in constructing a drug discovery system using deep learning [39].

Incorporating deep learning principles, these algorithms will reliably foretell how various medication molecules will interact with certain proteins. All of their information comes from other sources, such similar experiments and simulations (see Fig. 1). By linking together these parameter references, it will be able to forecast whether a molecule is bio-active or not with up to 99 percent accuracy in a fraction of the time it would take using typical quantum mechanical calculations. This approach is analogous to performing only a few dozen experiments to estimate the activity of hundreds of substances before fully evaluating them. Screening candidate molecules is now done over a thousand times faster than with previous calculations [40], which is why so many pharmaceutical companies are using these technologies for early research.

4. RESULTS COMPARISON ANALYSIS

Table 2: Model training and validation for the 32 included studies

	Target condition	Reference standard	Same method for assessing reference standard across samples	Type of internal validation	External validation
Abbasi-Sureshjani et al (2018)	Diabetes	Laboratory testing	Yes	Random split sample validation	No
Adams et al (2019)	Hip fracture	Surgical confirmation	Yes	Random split sample validation	No
Ardila et al (2019)	Lung cancer	Histology; follow-up	No	NR	Yes
Ariji et al (2019)	Lymph node metastasis	Histology	Yes	Resampling method	No
Ayed et al (2015)	Breast tumour	Histology	Yes	Random split sample validation	No
Becker et al (2017)	Breast tumour	Histology; follow-up	No	Study 1: NA Study 2: temporal split-sample validation	Yes
Becker et al (2018)	Breast tumour	Histology; follow-up	No	Random split sample validation	No
Bien et al (2018)	Knee injuries	Expert consensus	Internal validation dataset: yes External validation dataset: NR	Stratified random sampling	No
Brinker et al (2019)	Melanoma	Histology	Yes	Random split sample validation	Yes
Brown et al (2018)	Retinopathy	Expert consensus	Yes	Resampling method	Yes
Burlina et al (2017)	Age-related macular degeneration	Expert consensus	Yes	Resampling method	No
Burlina et al (2018)	Age-related macular degeneration	Reading centre grader	Yes	NR	No
Burlina et al (2018)	Age-related macular degeneration	Reading centre grader	Yes	NR	No

Byra et al (2019)	Breast tumour	Histology; follow-up	No	Resampling method	Yes
Cao et al (2019)	Prostate cancer	Histology; clinical care notes or imaging reports	Yes	Resampling method	No
Chee et al (2019)	Femoral head osteonecrosis	Clinical care notes or imaging reports	Yes	NR	Yes
Choi et al (2019)	Breast tumour	Histology; follow-up	No	NA	Yes
Choi et al (2018)	Liver fibrosis	Histology	Yes	Resampling method	Yes
Ciompi et al (2017)	Lung cancer	Expert consensus	Yes	Random split sample validation	Yes
Codella et al (2017)	Melanoma	Histology	No	Random split sample validation	No
Coudray et al (2018)	Lung cancer	Histology	Yes	NR	Yes

De Fauw et al (2018)	Retinal disease	Follow-up	Yes	Random split sample validation	No
Ding et al (2019)	Alzheimer's disease	Follow-up	No	NR	Yes
Dunnmon et al (2019)	Lung conditions	Expert consensus	Yes	Resampling method	No
Ehteshami Bejnordi et al (2017)	Lymph node metastases	Histology	No	Random split sample validation	Yes
Esteva et al (2017)	Dermatological cancer	Histology	No	Resampling method	No
Fujioka et al (2019)	Breast tumour	Histology; follow-up	No	NR	No
Fujisawa et al (2019)	Dermatological cancer	Histology	No	Resampling method	No
Gómez-Valverde et al (2019)	Glaucoma	Expert consensus	Yes	Resampling method	No
Grewal et al (2018)	Brain haemorrhage	Expert consensus	Yes	NR	No
Haenssle et al (2018)	Melanoma	Histology; follow-up	No	NR	No
Hamm et al (2019)	Liver tumour	Clinical care notes or imaging reports	Yes	Resampling method	No
Han et al (2018)	Onychomycosis	Histology; expert opinion on photography	No	Random split sample validation	Yes
Han et al (2018)	Skin disease	Histology; follow-up	No	Random split sample validation	Yes
Hwang et al (2018)	Pulmonary tuberculosis	Laboratory testing; expert opinion	Yes	NR	Yes

Figure 2 displays the summary ROC curves of these 25 investigations in a hierarchical format. After pooling data from all relevant trials, researchers found that deep learning algorithms had a sensitivity of 88% (95% CI: 85-79%) and that human doctors had a sensitivity of 79% (74%-83%). When comparing the pooled specificity of deep learning algorithms and that of healthcare professionals, the former came up at 93% (92%-95%), while the latter was 88% (82%-91%).

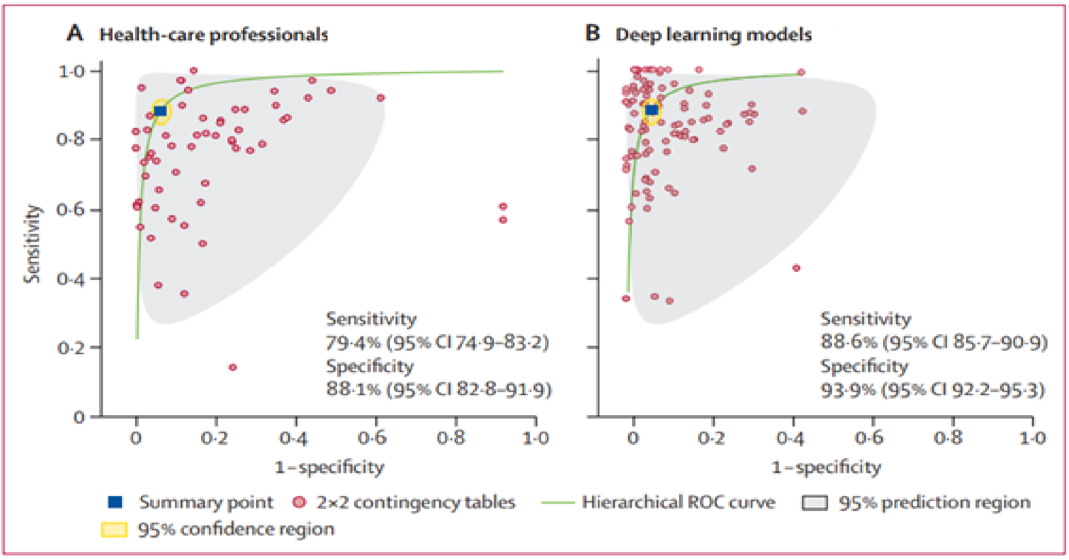

Figure 2: Hierarchical ROC curves of all studies included in the meta-analysis (25 studies)
ROC=receiver operating characteristic

In order to evaluate the efficacy of deep learning algorithms to that of healthcare experts, 25 studies were conducted, but only 14 of those studies employed the same sample for out-of-sample validation (54 tables for healthcare professionals vs. 25 tables for deep learning algorithms) (figure 3).

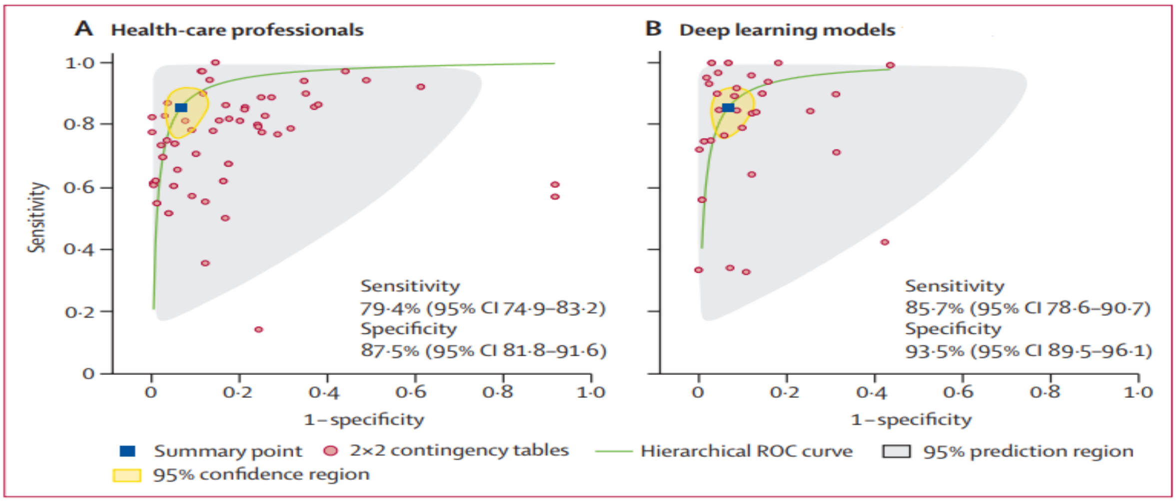

Figure 3: Hierarchical ROC curves of studies using the same out-of-sample validation sample for comparing performance between health-care professionals and deep learning algorithms (14 studies)
ROC=receiver operating characteristic.

Overall, the sensitivity was 85.7 percent (95.5 percent confidence interval [CI]: 78.6 to 90.7) for deep learning algorithms and 80.4 percent (74.9% to 83.2 percent) for doctors and nurses. The overall specificity for deep learning algorithms was 93.5 percent (89.5 percent to 96.1 percent) while for human doctors it was 87.5 percent (81.8 percent to 91.6 percent).

CONCLUSION

Machine learning and deep learning algorithms provide numerous benefits in the medical field. They are more effective and quicker than current technologies and help in illness prevention, diagnosis, and treatment. They have been proven both theoretically and practically. Providing healthcare is becoming increasingly difficult and expensive. To fix these problems, a number of machine learning methods are employed. There is a great deal of promise in applying deep learning algorithms for disease diagnosis. Based on the results of this preliminary meta-analysis, we tentatively assert that deep learning algorithms are as accurate as healthcare professionals, while also noting the need for further research into the practical application of these tools. An overstated claim from a poorly planned or badly reported study could damage the credibility and route to impact of such diagnostic algorithms, according to the more relevant result concerning methodology and reporting. Through this analysis, we hope to draw attention to some of the more salient methodological and reporting concerns that researchers should keep in mind. These concerns are important for assuring the quality of studies on deep learning diagnostics, or any other machine learning technique, so that the performance of these algorithms may be evaluated in a way that benefits patients and health systems in everyday practise.

REFERENCES

1. Rehman, S.U., et al.: Unsupervised pre-trained filter learning approach for efficient convolution neural network. Neurocomputing 365, 171–190 (2019)
2. Precision Medicine Initiative (NIH). https://www.nih.gov/pre cisionmedicine-initiative-cohort-program (12 November 2016, date last accessed).
3. Lyman GH, Moses HL. Biomarker tests for molecularly targeted therapies — the key to unlocking precision medicine. N Engl J Med 2016;375:4–6.
4. J. Schmidhuber, Deep learning in neural networks: an overview, Neural networks. 61 (2015) 85–117.
5. W.Y.B. Lim, N.C. Luong, D.T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, et al., Federated learning in mobile edge networks: a comprehensive survey, IEEE Commun. Surv. Tutorials (2020).
6. Rajdhan, Apurb& Agarwal, Avi& Sai, Milan &Ghuli, Poonam. (2020). Heart Disease Prediction using Machine Learning. International Journal of Engineering Research and. V9. 10.17577/IJERTV9IS040614.
7. Singh, Archana & Kumar, Rakesh. (2020). Heart Disease Prediction Using Machine Learning Algorithms. 452-457. 10.1109/ICE348803.2020.9122958.
8. Jagtap, A., Malewadkar, P., Baswat, O. and Rambade, H., 2019. Heart disease prediction using machine learning. International Journal of Research in Engineering, Science and Management, 2(2), pp.352-355.
9. Jindal, Harshit & Agrawal, Sarthak &Khera, Rishabh & Jain, Rachna &Nagrath, Preeti. (2021). Heart disease prediction using machine learning algorithms. IOP Conference Series: Materials Science and Engineering. 1022. 012072. 10.1088/1757-899X/1022/1/012072.
10. El_Jerjawi, Nesreen& Abu-Naser, Samy. (2018). Diabetes Prediction Using Artificial Neural Network. Journal of Advanced Science. 124. 1- 10.
11. Ayon, Safial& Islam, Md. (2019). Diabetes Prediction: A Deep Learning Approach. International Journal of Information Engineering and Electronic Business. 11. 21-27. 10.5815/ijieeb.2019.02.03.
12. Mujumdar, Aishwarya &Vaidehi, V.. (2019). Diabetes Prediction using Machine Learning Algorithms. Procedia Computer Science. 165. 292-299. 10.1016/j.procs.2020.01.047.
13. Yahyaoui, Amani & Rasheed, Jawad & Jamil, Akhtar &Yesiltepe, Mirsat. (2019). A Decision Support System for Diabetes Prediction Using Machine Learning and Deep Learning Techniques. 10.1109/UBMYK48245.2019.8965556.
14. Rahman, A. K. M. &Shamrat, F.M. &Tasnim, Zarrin& Roy, Joy & Hossain, Syed. (2019). A Comparative Study On Liver Disease Prediction Using Supervised Machine Learning Algorithms. 8. 419- 422.
15. Priya, M.B., Juliet, P.L. and Tamilselvi, P.R., 2018. Performance analysis of liver disease prediction using machine learning algorithms. International Research Journal of Engineering and Technology (IRJET), 5(1), pp.206-211.
16. Mohan, Vijayarani. (2015). Liver Disease Prediction using SVM and Naïve Bayes Algorithms.
17. Kannapiran, Thirunavukkarasu& Singh, Ajay & Irfan, Md & Chowdhury, Abhishek. (2018). Prediction of Liver Disease using Classification Algorithms. 1-3. 10.1109/CCAA.2018.8777655.
18. Shekar, Gautham; Revathy, S.; Goud, Ediga Karthick (2020). [IEEE 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI) - Tirunelveli, India (2020.6.15-2020.6.17)] 2020 4th International Conference on Trends in Electronics and Informatics (ICOEI)(48184) - Malaria

Detection using Deep Learning. , (), 746– 750. doi:10.1109/ICOEI48184.2020.9143023

19. Sriporn, Krit & Tsai, Cheng-Fa & Tsai, Chia-En& Wang, Paohsi. (2020). Analyzing Malaria Disease Using Effective Deep Learning Approach. Diagnostics (Basel, Switzerland). 10. 10.3390/diagnostics10100744.

20. Kalkan, Soner Can; Sahingoz, OzgurKoray (2019). [IEEE 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT) - Istanbul, Turkey (2019.4.24-2019.4.26)] 2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT) - Deep Learning Based Classification of Malaria from Slide Images. , (), 1– 4. doi:10.1109/EBBT.2019.8741702

21. Lin, Q., Tu, S., Waqas, M., ur Rehman, S., Chang, C.C.: Tracking areas planning based on spectral clustering in small cell networks. IET Commun. 13, 1921–1927 (2019)

22. Tu, S., et al.: Security in fog computing: A novel technique to tackle an impersonation attack. IEEE Access 6, 74993–75001 (2018)

23. Wu, H., Shen, G., Lin, X., Li, M., Zhang, B., Li, C.Z.: Screening patents of ICT in construction using deep learning and NLP techniques. Engineering, Construction and Architectural Management (2020)

24. Han, W., et al. ContextNet: Improving convolutional neural networks for automatic speech recognition with global context. arXiv preprint arXiv:2005.03191 (2020)

25. Ling, H., Wu, J., Huang, J., Chen, J., Li, P.: Attention-based convolutional neural network for deep face recognition. Multimedia Tools Appl. 79(9–10), 5595–5616 (2019). https://doi.org/ 10.1007/s11042-019-08422-2

26. Baskin, I.I.: The power of deep learning to ligand-based novel drug discovery. Expert Opinion on Drug Discovery, pp. 1–10 (2020)

27. Tu, S., et al.: ModPSO-CNN: an evolutionary convolution neural network with application to visual recognition. Soft Comput. 4, 1–2 (2020)

28. Yang, Z., Zhang, Y.-J., Rehman, S., Huang, Y.: Image captioning with object detection and localization. In: Zhao, Y., Kong, X., Taubman, D. (eds.) ICIG 2017. LNCS, vol. 10667, pp. 109–118. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-71589-6_10

29. Talo, M.: An Automated Deep Learning Approach for Bacterial Image Classification. arXiv preprint arXiv:1912.08765 (2019)

30. Brown, C., et al.: An Automated, Cost-Effective Optical System for Accelerated Antimicrobial Susceptibility Testing (AST) using Deep Learning. arXiv preprint arXiv:2005. 11454 (2020)

31. Hakim, Z., Ierasts, T., Hakim, I., D'Penha, A., Smith, K.P., Caesar, M.C.: Connecting data to insight: a pan-canadian study on AI in healthcare. Healthc. Q. (Toronto, Ont.), 23, 13–19 (2020)

32. Porumb, M., Stranges, S., Pescapè, A., Pecchia, L.: Precision medicine and artificial intelligence: a pilot study on deep learning for hypoglycemic events detection based on ECG. Sci. Rep. 10, 1–16 (2020)

33. Latif, J., Xiao, C., Tu, S., Rehman, S.U., Imran, A., Bilal, A.: Implementation and use of disease diagnosis systems for electronic medical records based on machine learning: a complete review. IEEE Access. 8, 150489–150513 (2020)

34. Monshi, M.M.A., Poon, J., Chung, V.: Deep learning in generating radiology reports: a survey. Artif. Intell. Med. p. 101878 (2020)

35. Zhavoronkov, A., Vanhaelen, Q., Oprea, T.I.: Will artificial intelligence for drug discovery impact clinical pharmacology? Clin. Pharmacol. Ther. 107, 780–785 (2020)

36. Sarode, K.D.: Applications of deep learning in drug discovery. In: Vyas, R. (ed.) Advances in Bioengineering, pp. 73–91. Springer, Singapore (2020). https://doi.org/10.1007/978-981- 15-2063-1_4

37. Cukier, S., et al.: Checklists to detect potential predatory biomedical journals: a systematic review. BMC Med. 18, 1–20 (2020)

38. Bagherian, M., Sabeti, E., Wang, K., Sartor, M.A., Nikolovska-Coleska, Z., Najarian, K.: Machine learning approaches and databases for prediction of drug–target interaction: a survey paper. Briefings Bioinform. (2020)

39. Lee, C.Y., Chen, Y.P.P.: Prediction of drug adverse events using deep learning in pharmaceutical discovery. Briefings Bioinform. 22(2), 1884–1901 (2020)

40. Réda, C., Kaufmann, E., Delahaye-Duriez, A.: Machine learning applications in drug development. Comput. Struct. Biotechnol. J. 18, 241–252 (2020)

41. Abbasi-SureshjaniS,DashtbozorgB,terHaarRomenyBM,FleuretF.Exploratorystudyondirectpredictionofdiabetesusingdeep residual networks. In: VipIMAGE 2017. Basel: SpringerInternationalPublishing,2018:797–802.

42. AdamsM,ChenW,HolcdorfD,McCuskerMW,HowePD,GaillardF.Computer*vs*human:deeplearningversusperceptualtrainingforthedetectionofneckoffemurfractures. *JMedImagingRadiatOncol*2019;**63:**27–32.

43. ArijiY,FukudaM,KiseY,etal.Contrast-enhancedcomputedtomographyimageassessmentofcer

vicallymphnodemetastasisinpatients with oral cancer by using a deep learning system ofartificial intelligence. *Oral Surg Oral Med Oral Pathol Oral Radiol*2019;**127:**458–63.

44. AyedNGB,MasmoudiAD,SellamiD,AbidR.New developmentsinthediagnosticprocedurestoreduceprospectivebiopsiesbreast.2015 International Conference on Advances inBiomedicalEngineering(ICABME);Beirut,Lebanon;Sept16–18,2015:205–08.

45. BeckerAS,MarconM,GhafoorS,WurnigMC,FrauenfelderT,BossA.Deeplearninginmammography:diagnosticaccuracyofamultipurpose image analysis software in the detection of breastcancer. *Invest Radiol*2017; **52:**434–40.

46. BienN,RajpurkarP,BallRL,etal.Deep-learning-assisteddiagnosisforkneemagneticresonanceimaging:developmentandretrospectivevalidationofMRNet.*PLoSMed*2018;**15:**e1002699.

47. BrinkerTJ,HeklerA,EnkAH,etal.Aconvolutional neuralnetwork trained with dermoscopic images performed on par with145dermatologistsinaclinicalmelanomaimageclassificationtask.*EurJCancer*2019;**111:**148–54.

48. Burlina P, Pacheco KD, Joshi N, Freund DE,Bressler NM.Comparing humans and deep learning performance for gradingAMD: a study in using universal deep features and transfer learningforautomatedAMDanalysis.*ComputBiolMed*2017;**82:**80–86.

49. BurlinaP,JoshiN,PachecoKD,FreundDE,KongJ, BresslerNM.Utility of deep learning methods for referability classification ofage-relatedmacular degeneration.*JAMA Ophthalmol*2018; **136:**1305–07.

50. BurlinaPM,JoshiN,PachecoKD,FreundDE,KongJ,BresslerNM.Use of deep learning for detailed severity characterization andestimation of 5-year risk among patients with age-related maculardegeneration.*JAMA Ophthalmol*2018;**136:** 1359–66.

51. ByraM,GalperinM,Ojeda-FournierH,etal.Breastmassclassification in sonography with transfer learning using a deepconvolutionalneuralnetworkandcolorconversion.*MedPhys*2019;**46:**746–55.

52. Cao R,BajgiranAM,Mirak SA,etal.Jointprostate cancerdetectionandgleasonscorepredictioninmp-MRIviaFocalNet. *IEEETransMedImaging*2019;publishedonlineFeb27.DOI:10.1109/TMI.2019.2901928.

53. CheeCG,KimY,KangY,etal.Performanceofadeep learningalgorithmindetectingosteonecrosisofthefemoralheadondigitalradiography:acomparisonwithassessmentsbyradiologists. *AJRAmJRoentgenol*2019;publishedonlineMarch27.DOI:10.2214/AJR.18.20817.

54. ChoiJS,HanB-K,KoES,etal.Effectofadeeplearningframework-based computer-aided diagnosis system on thediagnosticperformanceofradiologistsindifferentiatingbetweenmalignant and benignmasses on breastultrasonography. *KoreanJRadiol*2019;**20:**749.

55. ChoiKJ,JangJK,LeeSS,etal.Developmentandvalidationofadeep learning system for staging liver fibrosis by using contrastagent-enhancedCTimagesintheliver.*Radiology*2018;**289:**688–97.

56. CiompiF,ChungK,vanRielSJ,etal.Towardsautomaticpulmonarynodulemanagementinlungcancerscreeningwithdeeplearning.*SciRep*2017;**7:**46479.

57. CodellaNCF,NguyenQB,PankantiS,etal.Deeplearningensemblesformelanomarecognitionindermoscopyimages.*IBMJResDev*2017;**61:**5:1–5:15.

58. Coudray N, Ocampo PS, Sakellaropoulos T, et al. Classification andmutationpredictionfromnon-smallcelllungcancerhistopathologyimagesusingdeeplearning.*NatMed*2018;**24:**1559–67.

59. DeFauwJ,LedsamJR,Romera-ParedesB,etal.Clinicallyapplicabledeep learning for diagnosis and referral in retinal disease. *Nat Med*2018;**24:**1342–50.

60. Ding Y, Sohn JH, Kawczynski MG, et al. A deep learning model topredict a diagnosis of Alzheimer disease by using 18F-FDG PET ofthe brain.*Radiology* 2019;**290:** 456–64.

61. DunnmonJA,YiD,LanglotzCP,RéC,RubinDL,LungrenMP.Assessment of convolutional neural networks for automatedclassification ofchestradiographs. *Radiology*2019;**290:** 537–44.

62. EhteshamiBejnordiB,VetaM,JohannesvanDiestP, etal.Diagnosticassessmentofdeeplearningalgorithmsfor detectionoflymph node metastases in women with breast cancer. *JAMA* 2017;**318:**2199–210.

63. Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classificationofskincancerwithdeepneuralnetworks.*Nature*2017;**542:**115–18.

64. Fujioka T, Kubota K, Mori M, et al. Distinction between benign andmalignant breast masses at breast ultrasound using deep

65. learningmethodwithconvolutionalneuralnetwork. *JpnJRadiol*2019;

37:466–72.

66. FujisawaY,OtomoY,OgataY,etal.Deep-learning-based,computer-aidedclassifierdevelopedwithasmalldatasetofclinicalimages surpasses board-certified dermatologists in skin tumourdiagnosis. *Br J Dermatol*2019; **180:** 373–81.

67. Gómez-Valverde JJ, Antón A, Fatti G, et al. Automatic glaucomaclassificationusingcolorfundusimagesbasedonconvolutionalneural networks and transfer learning. *Biomed OptExpress* 2019;**10:**892–913.

68. GrewalM,SrivastavaMM,KumarP,VaradarajanS. RADnet:radiologist level accuracy using deep learning for hemorrhagedetectioninCTscans.2018IEEE15thInternationalSymposiumonBiomedicalImaging(ISBI2018);Washington,DC,USA; April4–7,2018:281–84.

69. HaenssleHA,FinkC,SchneiderbauerR,etal.Managainstmachine:diagnosticperformanceofadeeplearningconvolutionalneural networkfor dermoscopicmelanomarecognitionincomparisonto58dermatologists.*AnnOncol*2018;**29:**1836–42.

70. HammCA,WangCJ,SavicLJ,etal.Deeplearningfor livertumordiagnosis part I: development of a convolutional neural networkclassifierformulti-phasicMRI.*EurRadiol*2019;**29:**3338–47.

71. HanSS,KimMS,LimW,ParkGH,ParkI,ChangS E.Classification of the clinical images for benign and malignantcutaneoustumorsusingadeeplearningalgorithm. *JInvestDermatol*2018;**138:**1529–38.

72. HanSS,ParkGH,LimW,etal.Deepneuralnetworksshowanequivalent and often superior performance to dermatologists inonychomycosisdiagnosis:automaticconstructionofonychomycosisdatasetsbyregion-basedconvolutionaldeepneuralnetwork. *PLoSOne*2018;**13:**e0191493.

72. HwangEJ,ParkS,JinK-N,etal.Developmentandvalidationofadeep learning–based automatic detection algorithm for activepulmonarytuberculosisonchestradiographs.*ClinInfectDis*2018;publishedonlineNov12.DOI:10.1093/cid/ciy967.