Frontiers in Health Informatics
ISSN-Online: 2676-7104
2024; Vol 13: Issue 3
www.healthinformaticsjournal.com
Open Access

Pretrained Model: A Transfer Learning Approach for Early Prediction of Chronic Diseases

Pooja Yadav[1], Hemant Yadav[2]*, S.C. Sharma[3]
[1]Department of Computer Sc. and Information Technology, FET, MJP Rohilkhand University, Bareilly, 243006, Uttar Pradesh, India
[2]Department of Computer Science, Future Institute of Engineering and Technology, Bareilly, Uttar Pradesh, India
[3]Electronics & Computer Discipline, DPT, IIT Roorkee, Uttarakhand, India
[1]erpoojafet15@gmail.com, [1]pooja.yadav@mjpru.ac.in
[2]drhemantyadav22@gmail.com
[3]subhash.sharma@pt.iitr.ac.in

Cite this paper as: Pooja Yadav, Hemant Yadav, S.C. Sharma (2024) Pretrained Model: A Transfer Learning Approach for Early Prediction of Chronic Diseases. *Frontiers in Health Informatics, 13* (3), 190-.202

Abstract
Transfer learning, mainly through pre-trained models, has gained traction as a promising approach for the early prediction of chronic diseases using medical data. In this study, we investigate the challenges and complexities associated with applying pretrained models in the healthcare domain. Leveraging a pre-trained model trained on diverse datasets, we explore the transferability of knowledge to the field of chronic disease prediction. This study emphasizes the role of the pre-trained model and transfers Learning their advantages and disadvantages as well as reveals several critical challenges in the healthcare sector.

Keywords: *Chronic Disease, Deep Learning, Transfer Learning, Pre-trained model, Prediction Model, data-driven*

Introduction

Recent breakthroughs in computer technology have resulted in the development of algorithms that allow computers to execute human functions more quickly and automatically. Data mining (DM), Machine Learning (ML), and Deep Learning (DL) are examples of Artificial Intelligence (AI) tools that have demonstrated impressive effectiveness in analyzing existing data. Artificial intelligence-based technologies, particularly in the medical profession, are utilized in diagnosing or treating a wide range of disorders because they deliver quick and powerful results [1]. Chronic illnesses are becoming more common and lethal all around the world. Thus, early diagnosis has become an essential field of study to improve patient survival rates. Several investigations have revealed categorization systems for predicting certain diseases [2]. Diabetes is now one of the world's most common, chronic, and, owing to complications, fatal diseases. Diabetes identification at an early stage is critical for prompt treatment since it can halt disease development [3].

Diabetes is generally diagnosed when the glucose concentration in the blood exceeds the usual threshold. This is owing to the pancreas's inability to execute its function in the human body adequately. If the pancreas cannot use the insulin it produces or does not make enough of it, the person's blood sugar increases. Diabetes can harm several organs, including the eyes, heart, kidneys, and blood vessels [1][4]. Advances in new technologies involving computers are outpacing expectations. There is tremendous potential in digital healthcare to eliminate human error, enhance therapeutic results, and track data across time. AI approaches in detecting and forecasting several diseases, including cancer, heart, lung, kidney, skin, genetic, and brain problems, outperform doctors without human error. AI technologies, such as ML and DL algorithms, are widely employed in predicting and diagnosing various illnesses, particularly those whose diagnosis is based on images [5][6]. ML enables computers to do medical professional duties. ML is a set of methods for discovering patterns in data on its own and then using those methods to anticipate future data or make decisions in uncertain situations. The key feature of ML is that it is data-driven, with little human intervention in decision-making. When new data is added, the system learns by analyzing previous data and making predictions [7]. In medical image recognition, DL is a popular branch of ML. DL expands the ML technique in which fundamental concepts are employed sequentially to construct a deep structure with numerous processing layers. In a word, deep learning is the application of machine learning to enormous volumes of data [8][9][10][11].

DL algorithms have shown modest success in identifying diseases by examining medical images, which are rich in data that has been annotated [12]. Convolutional Neural Network (CNN) is the most often used model in DL-based medical diagnosis/detection applications. CNN models are top-rated because of their extensive structure and the highest level of feature representation [1]. Although the CNN architecture is end-toend, raw data are provided as input, and classifications are acquired as output[13]. As a result, the planned architecture is critical to the effectiveness of the CNN model [14]. The most prevalent challenge in training CNN models is a lack of labeled datasets [15]. Transfer learning (TL) algorithms have proven excellent performance when dealing with information with annotations. Even when the dataset is minimal, it uses and transmits data from the source domain to the target domain. There are several techniques to transfer learning that end up resulting in a variety of performance estimates in clinical issues such as diagnosis, detection, and classification [12] TL is frequently used to solve medical image analysis problems, such as exporting the weights (learned parameters) of a model (well-trained CNN) created on an extensive dataset like ImageNet. TL is frequently accomplished by freezing or fine-tuning the convolution layers (Conv layer) while training the fully connected (FC) layer from the beginning (using the clinical dataset) [16]. As previously indicated, ImageNet's pre-trained models' learned features are not the same as medical imaging characteristics; hence, the utility of TL from these models may be restricted [17]. Predicting chronic diseases using pre-trained models involves leveraging existing DL models trained on large datasets to perform specific tasks. While there might not be a universal pre-trained model for all chronic diseases, existing models can also adapt for the prediction of specific diseases. This work underscores the potential of pre-trained models as a powerful tool in different applications, especially in early disease prediction, and encourages future investigations to harness the full potential of transfer learning in healthcare. By bridging the gap between data-driven AI and clinical practice, the aim is to contribute to the ongoing efforts to transform healthcare through innovative technology, as shown in Fig. 1 [18].

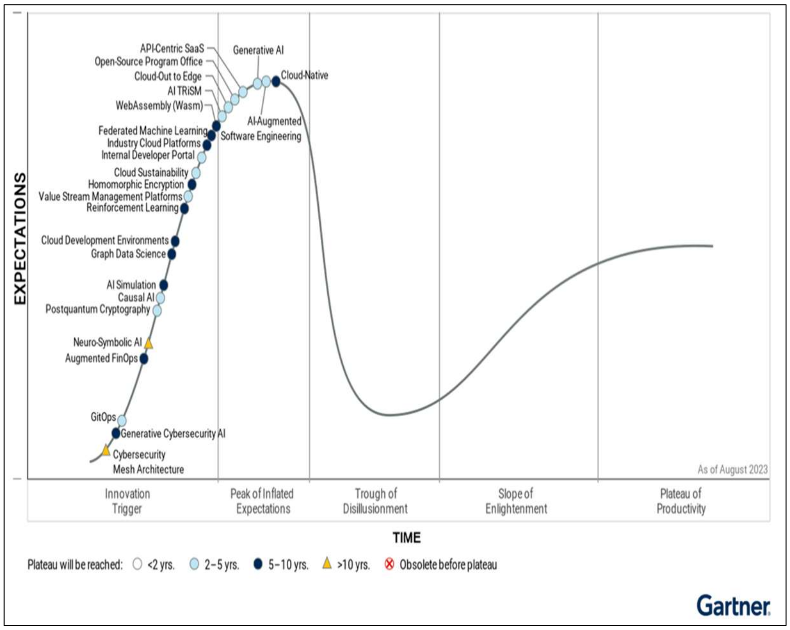

Fig. 1: Hype Cycle for Emerging Technologies, 2023

1.0.1 Some Pre-Trained models are

In many data-driven research [19][20][21][22] the direct usage of pre-trained CNN architectures showed advantages in terms of performance at ease. However, transfer learning applications have been utilized nowadays, and popular CNN designs like AleNet, ResNet, GoogleNet, Xception, VGGNet, DenseNet, EfficientNet-B0, etc.

The architecture defines the fundamental structure of the neural network, including the arrangement of layers, the number of neurons or filters, the connections between layers, weights, feature extraction, transfer Learning, memory, and more. Table 1 summarizes the critical aspects like the number of layers, depth, activation function, and processor of pre-trained models, which can vary depending on the specific model and its intended application. Selecting an appropriate pre-trained model based on the task and domain is essential to achieve the best results.

Table 1: Architecture of some pre-trained model [keras applications]

Model	**Full Name**	**Size (MB)**	**Depth**	**No. Conv layers**	**No. Pool layers**	**Fully Connected Layer**	**Type of Pooling**	**Activation Function**	**Resource Requirements**
AlexNet (2012)	Convolutional neural network	240	8	5	3	3	Max pooling	Relu	GPU, CPU
VGG16 (2014)	Visual Geometry Group	528	16	13	5	3	Max Pooling, Global avg	Relu	GPU

DenseNet 201 (2017)	Dense Convolution Network	80	201	200	1	1	Max Pooling, Avg pooling, Global avg	Relu, Softmax,	GPU
ResNet50 (2015)	Residual Network	98	50	49	1	1 FC / 16 Residual Blocks	Max Pooling, Global avg	Relu	CPU then GPU
GoogLeNet (2014)	InceptionNet V1	27	22	22	2	1	Max pooling	Relu	GPU, CPU
Xception (2017)	Extreme Inception	88	36	36	1	1	Max pooling	Relu, linear	GPU, CPU
EfficientNetB0 (2019)	EfficientNet-Base0	20	16	16	0	9	Max pooling	Swish	GPU
MobileNetV2 (2018)	**Mobile Network Version 2.**	16	53	52	0	1	Global Avg	Relu	GPU, CPU

Methodology

The steps shown in Fig. 2 used in pre- trained model have provided valuable insights and highlighted the importance of data preprocessing, model fine-tuning, and domain

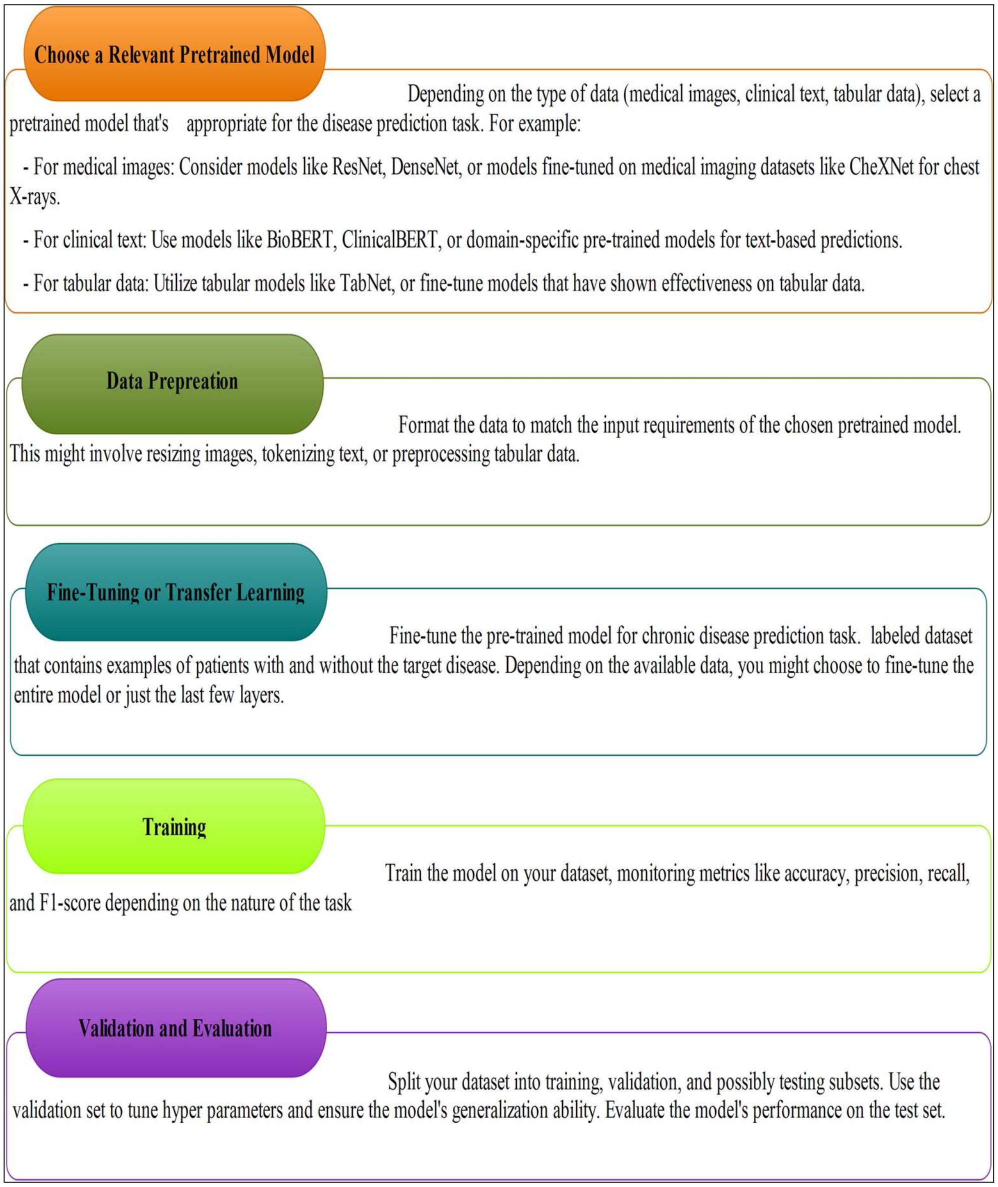

Fig. 2: Step by Step working of a pre-trained model

adaptation in the success of this approach. Moreover, the interpretability of the pretrained model's predictions has opened up opportunities for clinicians to gain deeper insights into the factors contributing to disease onset and progression.

Performance of Pre-trained Model in Disease Prediction Model

The performance of a pre-trained model in a disease prediction task depends on several factors, including the quality and quantity of the data, the specific disease being predicted, the choice of a pre-trained model, and the fine-tuning process. The performance of a pre-trained model in disease prediction depends on the particular context and the effort put into data collection, preprocessing, fine-tuning, and model evaluation. Moreover, continuous monitoring and updates may be required to maintain model performance as new data becomes available or as clinical practices evolve. Table 2 depicted the performance of some pre-trained models for disease prediction.

Table 2: Performance of Pre-trained Mode

S.N.	Year	Ref.	Model	Disease	Dataset	Accuracy
1	2021	[17]	Lightweight model , Xception, ResNet,	Diabetes Foot Ulcer	DFU	97.5, 98.9, 99.4
2	2021	[23]	DenseNet-201 , Inception-ResNet-V2 Inception-V3	Skin lesions	HAM10000	98, 97, 96
3	2021	[24]	DenseNet-121, DenseNet-169, DenseNet-201	COVID-19	Covid data set	86 (90.05), 84 (91.54), 86 (95.52)
4	2020	[25]	DenseNet-121, DenseNet-169, DenseNet-201	Multiple Sclerosis	MS Images	97.10, 96.60, 98.5
5	2023	[1]	ResNet18, ResNet50 CNN-SVM	Diabetes	PIMA	80.86, 80.47, 92.7
6	2023	[26]	DNN + PCA + LR	Heart	Cleveland dataset	93.33
7	2022	[27]	VGGNet16, MobileNetV2, InceptionResNetV2, ResNet152V2, and DenseNet201.	Skin diseases.	Skin Image dataset	95.84
8	2023	[28]	Multi-task deep learning (MTDL) CapsNet	Alzheimer's disease	Structural MRI data	96 (Binary classifi cation) 93(Multi classifi cation)
9	2023	[29]	ANN, KNN, DT, NB, CNN, SVM, LR, RF	Lung Disease	Chest X-ray	95
10	2021	[30]	VGG19, ResNet50V2, and DenseNet201	Pneumonia, COVID-19,	Chest X-ray images	93(VGG), 87(ResNet), 100(Dense Net) 98(VGG) 99(ResNet) 100(Dense Net)

				Tuberculosis (TB)		95.5(VGG) 95.7(ResNet) 95.9(Dense Net)

Advantages and Disadvantages of Pre-trained Model

Pre-trained Models are in trend nowadays but still every pre-trained model offers several advantages and disadvantages, depending on their application and context. Some of them are depicted in Fig. 3 and Fig. 4. Pre-trained models have found numerous applications in the medical sector, revolutionizing how healthcare professionals diagnose, treat, and manage patients[35]. These models leverage the power of DL and large-scale datasets to make accurate predictions and assist medical professionals in various tasks, as shown in Fig. 5.

Fig. 3: Advantages of pre-trained Model

Challenges and their solution of AI in Medical

Artificial Intelligence (AI) has the potential to revolutionize the healthcare industry by improving patient outcomes and reducing costs. However, there are several challenges associated with the widespread adoption of AI in medicine. Although there are several benefits, the present obstacles and limits of AI in the medical field are shown in Table
3.

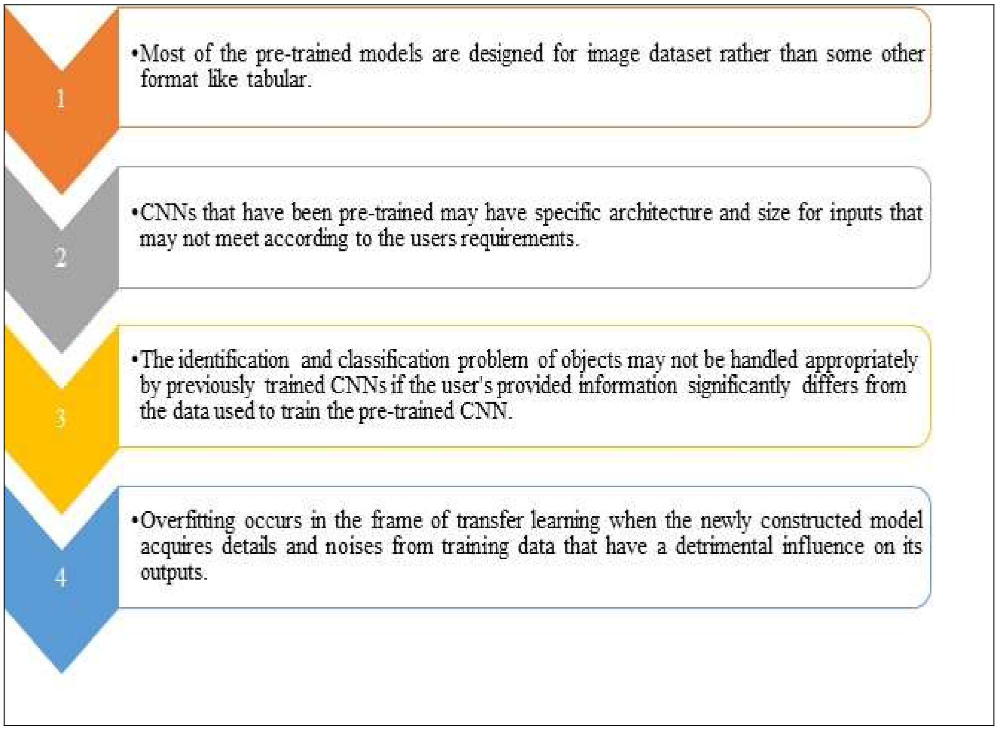

Fig. 4: Disadvantages of pre-trained Model

Table 3: Challenges for applying AI-based approach in the medical field [32][33][34]

S.N.	Challenges	Explanation	Solution
1	Data Augmentation and Preprocessing	AI algorithms are the need for massive data and error-free data in training phases which is not always practical in most diseases.	Data must be accurate and free from error. Apply data augmentation techniques like rotation, translation, and flipping alongside data normalization and proper handling of missing values.
2	Lack of Quality Data	A large amount of data is necessary in the field of medicine in order to make the best possible use of it. this is due to a lack of electronic health records (EHR) and other resources. The data supplied in the form of medical images is insufficient in quantity to be used to test.	Data must be bias-free in terms of age and, gender. To maintain the record in the form of EHR and highresolution images.

3	Data annotation / Data Labelling	The practice of identifying specific bits of training data (whether text, photos, audio, or video) to assist machines in comprehending what is in it and what is significant is known as data annotation. This labeled data is then utilized to train models. It is time-consuming and highly costly	Using Automation tools and crowdsourcing.
4	Complexity of computation	A further obstacle in this field is the complexity of computation and layout in DL-based models.	Model compression approaches like as pruning, quantization, and low-rank factorization are one possible answer for lowering the complexity of computation and architecture in DL models.
5	Low-Contrast Images	The examination of patterns and features in low-contrast photographs is likewise a difficult assignment.	Histogram Equalization (HE) is one of the enhancement techniques used to increase contrast.
6	Privacy	When putting data into artificial intelligence systems, patient privacy must be considered seriously.	An efficient encryption scheme should be used.
7	Hyperparameter Tuning [4][11]	It is a time-consuming operation, especially since there are so many factors to set and monitor in order to achieve the best outcomes.	Tune (change) the hyperparameters so that they result in a very good performance on the test data
8	Interpretability and Explainability	Understanding the working of AI models and the reason behind the decisions is vital in critical applications such as healthcare	To explain model predictions, use strategies such as LIME (Local Interpretable Model-Agnostic Explanations) or SHAP (SHapley Additive Explanations).

9	AI adoption in healthcare [36]	To make sure AI-based technology reaches and benefits patients, it is critical to keep a focus on clinical application and patient outcomes, enhance approaches for algorithmic interpretability, and get a deeper knowledge of human-computer interactions.	Prioritizing data privacy and security with correct prediction and explanation
10	Robust Regu-lation	The creation of the requisite regulatory frameworks is a critical component to attaining safe and successful AI algorithm deployment.	Tools strategies and regulatory follow in the medical sector.
11	Collaboration	AI in medicine requires a multidisciplinary approach that involves collaboration between clinicians, computer scientists, and data analysts.	Official rules and regulations should be incorporated and some regular monitoring should be adhered to in order to ensure privacy

Conclusion

In conclusion, this study demonstrates the potential of pre-trained models and TL techniques in the early prediction of chronic diseases. This work shows that leveraging existing knowledge from large datasets can significantly improve prediction accuracy, especially when labeled data for a specific disease is limited. The brief study about the pre-trained model presented in this paper offers a promising avenue for healthcare practitioners and researchers to enhance disease prediction and ultimately improve patient outcomes. The main aim of this paper is to discuss the pre-trained model and TL, their advantages and disadvantages also emphasize the challenges of AI-based approaches in the medical field. Also, compile the results of some pre-existing work related to disease prediction models using pre-trained models. As further research is needed to explore the generalizability of pre-trained models across different chronic diseases and diverse patient populations. Additionally, efforts should be directed toward ensuring the ethical and responsible use of patient data in the healthcare domain. While pre-trained models offer great promise, privacy and security considerations remain paramount.

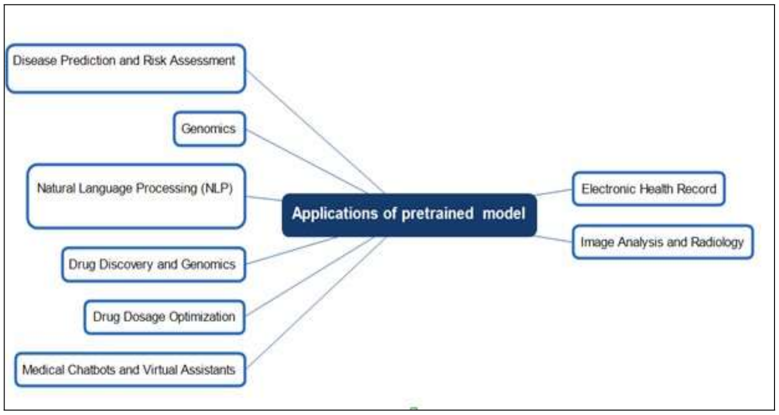

Fig. 5: Applications of pre-trained Model [31]

References

1. M.F. Aslan, K. Sabanci, A novel proposal for deep learning-based diabetes prediction: Converting clinical data to image data. Diagnostics **13**(4), 796 (2023)
2. J. Rashid, S. Batool, J. Kim, M. Wasif Nisar, A. Hussain, S. Juneja, R. Kushwaha, An augmented artificial intelligence approach for chronic diseases prediction. Frontiers in Public Health **10**, 860396 (2022)
3. H. Zhou, R. Myrzashova, R. Zheng, Diabetes prediction model based on an enhanced deep neural network. EURASIP Journal on Wireless Communications and Networking **2020**, 1–13 (2020)
4. P. Yadav, S. Sharma, R. Mahadeva, S.P. Patole, Exploring hyper-parameters and feature selection for predicting non-communicable chronic disease using stacking classifier. IEEE Access (2023)
5. G. Uysal, M. Ozturk, Hippocampal atrophy based alzheimer's disease diagnosis via machine learning methods. Journal of Neuroscience Methods **337**, 108669 (2020)
6. A.Z. Woldaregay, E. ˚Arsand, S. Walderhaug, D. Albers, L. Mamykina, T. Botsis, G. Hartvigsen, Data-driven modeling and prediction of blood glucose dynamics: Machine learning applications in type 1 diabetes. Artificial intelligence in medicine **98**, 109–134 (2019)
7. R. Cao, A.M. Bajgiran, S.A. Mirak, S. Shakeri, X. Zhong, D. Enzmann, S. Raman, K. Sung, Joint prostate cancer detection and gleason score prediction in mp-mri via focalnet. IEEE transactions on medical imaging **38**(11), 2496–2506 (2019)
8. X. Xi, X. Meng, L. Yang, X. Nie, G. Yang, H. Chen, X. Fan, Y. Yin,
9. X. Chen, Automated segmentation of choroidal neovascularization in optical coherence tomography images using multi-scale convolutional neural networks with structure prior. Multimedia Systems **25**, 95–102 (2019)
10. Y. Rizk, N. Hajj, N. Mitri, M. Awad, Deep belief networks and cortical algorithms: A comparative study for supervised classification. Applied computing and informatics **15**(2), 81–93 (2019)
11. C. Bhatt, I. Kumar, V. Vijayakumar, K.U. Singh, A. Kumar, The state of the art of deep learning models in medical science and their challenges. Multimedia Systems **27**(4), 599–613 (2021)
12. P. Yadav, S. Sharma, Hfbo-kselm: Hybrid flash butterfly optimization-based kernel softplus extreme learning machine for classification of chronic kidney disease. The Journal of Supercomputing pp. 1–24 (2023)

13. Z. Ardalan, V. Subbian, Transfer learning approaches for neuroimaging analysis: A scoping review. Frontiers in Artificial Intelligence **5**, 780405 (2022)
14. N. Arora, P. Yadav, K. Tripathi, S. Sharma, in *2023 International Conference on Device Intelligence, Computing and Communication Technologies,(DICCT)* (IEEE, 2023), pp. 351–355
15. M.F. Aslan, K. Sabanci, A. Durdu, A cnn-based novel solution for determining the survival status of heart failure patients with clinical record data: numeric to image. Biomedical Signal Processing and Control **68**, 102716 (2021)
16. L. Alzubaidi, M.A. Fadhel, O. Al-Shamma, J. Zhang, Y. Duan, Deep learning models for classification of red blood cells in microscopy images to aid in sickle cell anemia diagnosis. Electronics **9**(3), 427 (2020)
17. A.S.O.Z.J.S.J.D.Y. Alzubaidi L, Fadhel MA, Robust application of new deep learning tools: an experimental study in medical imaging. Multimed Tools and Application **81**(10), 13289–13317 (2022)
18. L. Alzubaidi, Y. Duan, A. Al-Dujaili, I.K. Ibraheem, A.H. Alkenani, J. Santamar´ıa, M.A. Fadhel, O. Al-Shamma, J. Zhang, Deepening into the suitability of using pre-trained models of imagenet against a lightweight convolutional neural network in medical imaging: An experimental study. PeerJ Computer Science **7**, e715 (2021)
19. Gartner Places Generative AI on the Peak of
20. Inflated Expectations on the 2023 Hype Cycle for Emerging Technologies gartner.com.
21. https://www.gartner.com/en/newsroom/press-releases/
22. 2023-08-16-gartner-places-generative-ai-on-the-peak-of-inflated-expectations-on-the-2023-hype-cycle-fo (2023). [Accessed 16-09-2023]
23. P. Pradhan, B. Kumar, S. Mohan, Comparison of various deep convolutional neural network models to discriminate apple leaf diseases using transfer learning. Journal of Plant Diseases and Protection **129**(6), 1461–1473 (2022)
24. P. Pradhan, B. Kumar, in *2022 3rd International Conference for Emerging Technology (INCET)* (2022), pp. 1–5. https://doi.org/10.1109/INCET54531.2022. 9825376
25. P. Pradhan, B. Kumar, in *2021 First International Conference on Advances in Computing and Future Communication Technologies (ICACFCT)* (IEEE, 2021), pp. 13–17
26. M.K. Singh, B. Kumar, in *Computer Vision and Robotics: Proceedings of CVR 2022* (Springer, 2023), pp. 271–283
27. J.P. Villa-Pulgarin, A.A. Ruales-Torres, D. Arias-Garzon, M.A. Bravo-Ortiz, H.B. Arteaga-Arteaga, A. Mora-Rubio, J.A. Alzate-Grisales, E. Mercado-Ruiz, M. Hassaballah, S. Orozco-Arias, et al., Optimized convolutional neural network models for skin lesion classification. Comput. Mater. Contin **70**(2), 2131–2148 (2022)
28. M.K. Bohmrah, H. Kaur, Classification of covid-19 patients using efficient finetuned deep learning densenet model. Global Transitions Proceedings **2**(2), 476– 483 (2021)
29. S.H. Wang, Y.D. Zhang, Densenet-201-based deep neural network with composite learning factor and precomputation for multiple sclerosis classification. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) **16**(2s), 1–19 (2020)

30. D. Hassan, H.I. Hussein, M.M. Hassan, Heart disease prediction based on pre-trained deep neural networks combined with principal component analysis. Biomedical Signal Processing and Control **79**, 104019 (2023)

31. A.N.A. Thohari, L. Triyono, I. Hestiningsih, B. Suyanto, A. Yobioktobera, Performance evaluation of pre-trained convolutional neural network model for skin disease classification. JUITA: Jurnal Informatika **10**(1), 9–18 (2022)

32. S. Venkatasubramanian, J.N. Dwivedi, S. Raja, N. Rajeswari, J. Logeshwaran, A. Praveen Kumar, et al., Prediction of alzheimer's disease using dho-based pretrained cnn model. Mathematical Problems in Engineering **2023** (2023)

33. B.M. Rashed, N. Popescu, Performance investigation for medical image evaluation and diagnosis using machine-learning and deep-learning techniques. Computation **11**(3), 63 (2023)

34. L. Mangeri, G.P. OS, N. Puppala, P. Kanmani, Chest diseases prediction from x-ray images using cnn models: a study. International Journal of Advanced Computer Science and Applications **12**(10) (2021)

35. S. Yang, F. Zhu, X. Ling, Q. Liu, P. Zhao, Intelligent health care: Applications of deep learning in computational medicine. Frontiers in Genetics **12**, 607471 (2021)

36. L. Caviglione, C. Comito, M. Guarascio, G. Manco, Emerging challenges and perspectives in deep learning model security: A brief survey. Systems and Soft Computing p. 200050 (2023)

37. C.J. Kelly, A. Karthikesalingam, M. Suleyman, G. Corrado, D. King, Key challenges for delivering clinical impact with artificial intelligence. BMC medicine **17**, 1–9 (2019)

38. N. Ghaffar Nia, E. Kaplanoglu, A. Nasab, Evaluation of artificial intelligence techniques in disease diagnosis and prediction. Discover Artificial Intelligence **3**(1), 5 (2023)

39. Yadav, P., Sharma, S.C., Yadav, H. (2024). Deep Learning Based Framework for Multi-disease Detection Using CNN-BiLSTM. In: Pant, M., Deep, K., Nagar, A. (eds) Proceedings of the 12th International Conference on Soft Computing for Problem Solving. SocProS 2023. Lecture Notes in Networks and Systems, vol 995. Springer, Singapore. https://doi.org/10.1007/978-981-97-3292-0_47

40. Yadav, H., Yadav, P., Joshi, N., Sharma, S.C. (2024). Smart Healthcare: Paradigm Shift in Industry 5.0 Using AI. In: Arya, R., Sharma, S.C., Verma, A.K., Iyer, B. (eds) Recent Trends in Artificial Intelligence Towards a Smart World. Frontiers of Artificial Intelligence, Ethics and Multidisciplinary Applications. Springer, Singapore. https://doi.org/10.1007/978-981-97-6790-8_3