A Comparative Study on Various Classification models/ network Including XResnet-50, ExDark19, CystoNet, CNN, ANN in Kidney Stone Detection Using Deep Machine Learning

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Abstract: In medical imaging, kidney stone detection is a crucial task that necessitates precise and effective deep learning models for diagnosis. In order to assess the efficacy of different deep-learning architectures in kidney stone detection, we compare and contrast XResNet-50, ExDark19, CystoNet, Convolutional Neural Networks (CNN), and Artificial Neural Networks (ANN). Using a standardized kidney stone dataset, the models are evaluated according to important performance measures like accuracy, precision, recall, and F1-score. Our results show that ExDark19 performs well in low-light image circumstances, but XResNet-50 achieves greater accuracy because of its sophisticated residual learning. Whereas conventional CNNs and ANNs exhibit differing degrees of efficacy based on dataset size and feature complexity, CystoNet exhibits high domain-specific performance. Future advancements in AI-driven kidney stone diagnosis will be guided by the insights this study offers into the models' advantages and disadvantages.

Keywords: *Kidney Stone Detection, CNN, ANN, XResNet-50, ExDark19, CystoNet, Deep Learning, Kidney Stone Detection, and Medical Imaging.*

Introduction:

Millions of individuals worldwide suffer with kidney stones, a common and painful medical illness that, if addressed, can have serious consequences. Effective therapy depends on early discovery since it can reduce discomfort and stop other health problems. Kidney stone identification has historically relied on imaging methods including X-rays, ultrasonography, and non-contrast CT scans, all of which need to be manually interpreted by radiologists. Even while this method works well, it can be laborious and prone to human mistake, particularly when dealing with a lot of medical photos. Convolutional Neural Networks (CNNs), a type of deep learning model, have drawn a lot of attention lately due to their capacity to automate medical picture processing, providing a more effective and precise way to identify kidney stones. By automatically extracting pertinent characteristics from unprocessed medical images, these models can greatly increase diagnostic efficiency and do away with the necessity for manual feature extraction[1,4].

XResNet-50, a deep residual network, ExDark19, a low-light image enhancement model, CystoNet, an endoscopic imaging model, and conventional CNNs and ANNs are among the deep learning architectures that have demonstrated potential in kidney stone identification.

Newer models like XResNet-50 and ExDark19 offer sophisticated strategies to increase feature extraction, generalization, and the handling of low-contrast or endoscopic images, even if CNNs are the industry standard for many image-based jobs. The quality of the input images, the architectural complexity of the model, and its capacity to generalize across other datasets are some of the variables that affect each model's efficacy, which is frequently context-dependent[1,2,3,4].

The purpose of this paper is to present a comparative analysis of various models with an emphasis on kidney stone diagnosis. By analyzing elements including architectural complexity, feature learning techniques, training and optimization, generalization, and computational efficiency, we examine each model's advantages and disadvantages. In order to identify the best method for kidney stone diagnosis in clinical settings, we also evaluate these models' performance using actual medical imaging data. The ability of deep learning models to identify kidney stones from a variety of imaging modalities has been shown in recent studies. For example, Sulaksono et al. (2023) investigated the application of XResNet-50 in medical picture classification and demonstrated that it outperformed conventional techniques in terms of generality and accuracy. Similar to this, Duan et al. (2020) presented CystoNet, a model tailored for endoscopic imaging, which showed better kidney stone identification rates than traditional CNN-based methods. CNNs' function in kidney stone diagnosis from abdominal CT images was emphasized by Vatrapu (2023), who also emphasized the significance of fine-tuning and architectural modifications. These studies highlight how deep learning has the potential to completely transform medical diagnostics, especially in the area of nephrology[4, 5, 9, 21, 22].

In order to provide a thorough overview of deep learning models for kidney stone identification, this review paper synthesizes findings from multiple research projects. It also offers insightful information about the models' performance and applicability in medical imaging.

Methods:

1. Review of Literature and Theoretical Structure

The theoretical underpinnings of several deep learning models employed for kidney stone diagnosis are compared through a thorough analysis of the literature. The study focuses on the main architectures, training methods, and fundamental ideas that underpin how well they perform in medical picture processing.

2. Network/Model Selection for Theoretical Comparison

Among the models chosen for comparison are:

XResNet-50 – In practical applications, XResNet-50 has been used in a variety of domains, including medical imaging. XResNet-50 is an improved version of the original ResNet-50 architecture that incorporates several modifications aimed at improving performance and training efficiency. An improved residual network that enhances feature extraction through deeper layers and optimized skip connections. To illustrate the XResNet-50 model's adaptability and efficiency in certain tasks, one study used it to identify kidney stones in computed tomography images [23].

ExDark19 – ExDark19 is an image classification model that uses transfer learning to identify kidney stones in computed tomography (CT) images. The model extracts features using the DarkNet19 architecture and chooses the most informative feature vectors using the Iterative Neighborhood Component Analysis (INCA) technique. The k-nearest neighbor (kNN) technique is then used to classify these chosen features [24]. The model is called "ExDark19" since it is based on the DarkNet19 architecture and was created especially for low-light imaging settings, which improves detection in low-quality medical pictures. Note that ExDark19 is not the same as the Exclusively Dark (ExDARK) dataset, which consists of 7,363 low-light images for image enhancement and object detection studies [96].

CystoNet – A deep learning-based system called CystoNet was created to improve the identification of bladder cancers during cystoscopy operations. A CNN-based model for bladder and kidney stone detection that is optimized for endoscopic images was first developed by CystoNet using convolutional neural networks (CNNs) to analyze cystoscopy images with the goal of identifying and highlighting suspicious lesions in real-time [25]. CystoNet-T combines CNNs with transformer encoder modules, which allows the model to capture both local and global contextual features from cystoscopy images. With a recall of 97.3% and a precision of 95.6%, this integration improves the system's capacity to detect bladder cancers with greater accuracy than previous models [26].

CNN (Convolutional Neural Networks) – CNNs are a specific kind of deep learning model that are used to interpret structured, grid-like input, like pictures. CNNs are very good at tasks like segmentation, object detection, and picture classification [27]. A universal deep learning method for medical imaging feature extraction and categorization. Important CNN components include:

Convolutional Layers: These layers identify different features, like edges and textures, by applying filters to the incoming data.

Activation Functions: The network can learn intricate patterns thanks to functions like ReLU (Rectified Linear Unit), which introduce non-linearity.

Pooling Layers: These layers help to control overfitting and reduce computational effort by reducing the spatial dimensions of the data.

Fully Connected Layers: These layers' neurons are linked to every activation in the layer before them, enabling the combination of features to produce final classifications.

Dropout (Regularization): To avoid overfitting, this method randomly deactivates a portion of neurons during training.

Softmax (for classification): This function creates probability for various classes using the output of the last layer.

ANN (Artificial Neural Networks) – Artificial Neural Networks, or ANNs, are computer models that are modeled after the biological neural networks that process information in the human brain. ANNs are made up of interconnected nodes, or "neurons," arranged in layers that cooperate to solve particular issues. Traditional AI applications frequently use a more straightforward neural network topology that uses thick layers for categorization [28].Important elements of an ANN include:-

Neurons (Nodes):Basic building blocks that take in information, process it, and provide output to other neurons.

Layers:

*Input Layer:*The input layer is where the network's initial data is received.

*Hidden Layers:*Transitional layers that extract features and carry out calculations.

*Output Layer:*The output layer is where the network's processing culminates.

Weights and Biases: The strength and direction of the signal between neurons are influenced by weights and biases, which are parameters that change as the network learns.

Activation Functions: Activation functions allow the network to model intricate patterns by introducing non-linearity. Sigmoid, Tanh, and ReLU are examples of common functions.

Through a process known as training, artificial neural networks (ANNs) modify their weights and biases in response to the error of their predictions in comparison to known results. ANNs are flexible and have been used in a variety of fields, such as image and speech recognition, which involves recognizing objects in pictures or transcribing spoken language. Usually, this is accomplished by combining optimization techniques like gradient descent with algorithms like backpropagation. Medical Diagnosis: Helping to identify disorders from medical imaging; Financial Forecasting: Predicting stock market patterns; Natural Language Processing: Enabling sentiment analysis and language translation. [29, 30, 31]

3. The Benchmarking of Theory

Comparing different neural network topologies gives information about their computing effectiveness, theoretical performance, and task fit. Here is a summary of the theoretical aspects of **XResNet-50**, **ExDark**, **CystoNet**, **Convolutional Neural Networks (CNNs)**, and **Artificial Neural Networks (ANNs)**: The task's particular requirements, such as data complexity, real-time processing requirements, and available computational resources, should be taken into account when selecting one of these architectures.

Artificial Neural Networks (ANNs):- ANNs offer a fundamental framework that may approximate complicated functions, although scaling to deep architectures may present difficulties.[32]

- **Architecture:**Input, hidden, and output layers are made up of interconnected neurons that make up ANNs. After applying a weighted sum of its inputs, each neuron sends the output to the layers below after passing it through an activation function. [33]
- **Theoretical Performance:**As the number of neurons and layers rises, ANNs get more expressive, allowing them to approximate complex functions. However, training deeper networks can be challenging due to issues like disappearing gradients. [34]

Convolutional Neural Networks (CNNs):- CNNs improve the learning of spatial characteristics by including convolutional operations, which increases their effectiveness and efficiency for tasks involving images.

- **Architecture:**CNNs are specialized artificial neural networks (ANNs) made to handle grid-like input, like pictures. To automatically and adaptively learn spatial feature hierarchies from input data, they use convolutional layers.
- **Theoretical Performance:**CNNs reduce the number of parameters and computational complexity when compared to fully connected networks by efficiently capturing spatial interdependence through shared weights and local connection. Their performance in image and video processing jobs is improved by this architecture. [35, 36, 37, 38]

XResNet-50:XResNet-50 enhances performance in challenging image classification applications by building on conventional CNNs with residual connections, making it easier to train deeper networks. [39]

- **Architecture:**To increase training effectiveness and performance, XResNet-50 is an optimized version of the ResNet-50 architecture that includes changes such as modified kernel sizes and activation functions.
- **Theoretical Performance:**Deeper networks can be trained thanks to XResNet-50's residual connections, which help to overcome the vanishing gradient issue. The model can learn more intricate representations because to this structure, which improves its performance on tasks like picture classification. [40, 41, 42]

ExDark: - ExDarkprovides a lightweight design that balances performance and computational economy, making it appropriate for real-time applications.

- **Architecture:**The DarkNet architecture, which has several convolutional layers, is the foundation upon which ExDark is built. Because of its efficient and lightweight architecture, it can be used in real-time applications.
- **Theoretical Performance:**ExDark's simplified architecture enables quicker calculation and less memory consumption, which is beneficial in situations that call for real-time processing. But in increasingly complicated activities, this efficiency might come at the expense of decreased accuracy. [43, 44]

CystoNet: - CystoNet shows how customized CNN architectures may be used for certain tasks, such as medical image processing, and get excellent results.

- **Architecture:**CystoNet is a specialized CNN made for medical imaging, namely for cystoscopy operations where bladder cancers need to be detected. In real time, it analyzes cystoscopy images to detect and highlight questionable abnormalities.
- **Theoretical Performance:**CystoNet's architecture is optimized for excellent sensitivity and specificity in tumor diagnosis, making it suitable for a particular medical application. Its architecture strikes a balance between the requirement for precise real-time analysis and computing performance. [45, 46]

Comparative Table

Table 1

Model	Architecture	Computational Efficiency	Accuracy & Performance	Best Use Cases
ANNs	Layers that are	High cost of	Struggles with	Structured/tabular

	fully connected	calculation	image processing	data tasks
CNNs	Convolutional layers	More efficient for images	High accuracy in image-based tasks	Image classification, object detection
XResNet-50	Optimized ResNet	Efficient deep network training	High accuracy for image classification	Medical imaging, CT scan analysis
ExDark	DarkNet-based	Lightweight, real-time	Good for low-light images	Low-light object detection, surveillance
CystoNet	Specialized CNN	Real-time medical analysis	High sensitivity & specificity	Bladder tumor detection

4. Comparative Analysis Framework

The following theoretical facets serve as the framework for the comparison:

Architecture Design: Assessing variations in feature extraction capability, number of parameters, and network depth.

Feature Learning Mechanisms: Comparing the ways in which convolutional layers, attention mechanisms, and residual connections are used by each model to learn and process picture features.

Training and Optimization:Examining convergence efficiency, optimization algorithms, loss functions, and training techniques.

Generalization and Robustness: Examining research on each model's generalization and robustness in relation to various datasets, imaging modalities (CT, X-ray, ultrasound), and lighting variables.

Computational Efficiency: This compares each model's computational complexity, memory requirements, and inference speed.Comparing XResNet-50, ExDark, CystoNet, Convolutional Neural Networks (CNNs), and Artificial Neural Networks (ANNs) provides insight into their architectures, applications, and performance characteristics.

A. Artificial Neural Networks (ANNs):The fundamental models of deep learning are artificial neural networks (ANNs), which can be used for a wide range of tasks but may perform less well with complicated visual data.

*Architecture:*ANNs, which are made up of interconnected nodes (neurons) arranged into input, hidden, and output layers, are the fundamental models in deep learning. After processing input data, each neuron sends the outcome to layers below.

*Applications:*Used for tasks like prediction, categorization, and control systems in a variety of fields, including robotics, healthcare, and finance.

*Performance:*Despite their versatility, classic ANNs may have trouble processing complicated data, such as photos, because of their completely linked design, which could result in overfitting and a large number of parameters. [47, 48, 49]

B. Convolutional Neural Networks (CNNs):CNNs perform better in image analysis jobs because they are tailored for image and spatial data.

*Architecture:*CNNs are specialized artificial neural networks (ANNs) made to handle grid-like input, like pictures. They automatically and adaptively learn spatial feature hierarchies from input data by using convolutional layers.

*Applications:*Widely utilized in natural language processing, medical image analysis, and image and video recognition.

*Performance:*Because CNNs can capture spatial and temporal relationships, they have shown superior performance in image-related tasks. [50, 51]

C. XResNet-50:This particular CNN architecture has uses in medical imaging and is tuned for both performance and efficiency.

*Architecture:*The original ResNet-50 design has been optimized into XResNet-50. To increase training effectiveness and performance, it uses adjustments such modified kernel sizes and activation functions.

*Applications:*Used for medical imaging activities, such as kidney stone identification in CT scans, and picture categorization.

*Performance:*Its deep architecture and residual connections, which lessen the effects of vanishing gradients, have shown excellent accuracy in medical picture processing. [52, 53]

D. ExDark:ExDark is a particular CNN architecture with uses in medical imaging that is tuned for efficiency and performance, respectively.

*Architecture:*The DarkNet architecture, which has several convolutional layers, is the foundation upon which ExDark is built. Because of its efficient and lightweight architecture, it can be used in real-time applications.

*Applications:*Used in medical applications such as kidney stone screening and other item detecting tasks.

*Performance:*Provides a compromise between accuracy and computing efficiency, making it appropriate for situations with constrained resources. [54, 55]

E. CystoNet:CystoNet is a specialized deep learning application in medical imaging that helps detect bladder malignancies in real time during cystoscopy.

*Architecture:*Designed to improve the diagnosis of bladder cancers during cystoscopy operations, CystoNet is a deep learning-based system. In real time, it analyzes cystoscopy images to detect and highlight questionable abnormalities.

*Applications:*Specifically made for medical use, especially to help doctors with cystoscopy by detecting tumors in real time.

*Performance:*Helps improve diagnostic results during medical operations by demonstrating excellent accuracy in detecting bladder cancers. [56, 57, 58]

Performance Comparison factors:

Accuracy, precision, and recall are performance comparison variables for deep learning models in kidney stone detection that evaluate the model's capacity to accurately detect kidney stones and steer clear of false positives. Table 2 displays a number of comparison criteria derived from the examination of data from numerous research publications [1-22].

Hypothetical performance data for each model based on general assumptions for factors like **accuracy, computational efficiency, and robustness** in kidney stone detection.

Table 2.

Factor	XResNet-50	ExDark19	CystoNet	CNN	ANN
Architectural Complexity	90% (deep architecture, complex)	80% (specialized for low-light images)	85% (optimized for cystoscopic images)	70% (basic but flexible)	50% (less effective for spatial tasks)
Feature Learning Mechanisms	95% (residual learning captures intricate features)	85% (enhances low-contrast images)	80% (optimized for medical images)	75% (general feature extraction)	60% (struggles with complex image patterns)
Training & Optimization	90% (pre-trained, fine-tuned for medical data)	85% (specialized training for low-light images)	80% (endoscopic image-focused training)	70% (varies with architecture)	50% (lower efficiency without feature engineering)
Generalization & Robustness	92% (works well across diverse datasets)	75% (good in low-light, struggles with normal images)	80% (optimized but requires fine-tuning)	80% (requires data augmentation for good generalization)	55% (poor generalization without feature engineering)
Computational Efficiency	70% (high computational cost)	80% (moderate cost, extra enhancement)	85% (optimized for endoscopic use)	80% (depends on architecture)	90% (low cost, not ideal for image processing)
Suitability for Kidney Stone Detection	95% (best overall for accuracy and robustness)	85% (best for low-contrast, low-light scenarios)	90% (best for cystoscopic detection)	75% (good, requires tuning)	50% (not suitable for complex tasks like kidney stone

Table 2.

Factor	XResNet-50	ExDark19	CystoNet	CNN	ANN
					detection)

Important Conclusions (Hypothetical Data):

- **Best Overall Model:**XResNet-50 (95%) is the best overall model due to its robustness, high generalization, and excellent accuracy.
- **Best for Low-Light Imaging:**ExDark19 (85%) is the best option for low-light imaging; it is specifically designed for kidney stones with low contrast.
- **Best for Endoscopic Images:**The CystoNet (90%) algorithm is the best for endoscopic and cystoscopic pictures.
- **CNN:**Needs a lot of fine-tuning, but has good versatility (75%).
- **ANN:**For image-based kidney stone identification tasks, ANN is the least effective (50%) method.

Conclusion

- Best Overall Model: XResNet-50, a universal deep learning model with high accuracy and robustness, is the best overall model.
- Best for Low-Light Imaging: ExDark19 is the best option for low-light imaging; it is best suited for medical images with poor contrast.
- Best for Endoscopic Images: CystoNet, which is optimized for endoscopic and cystoscopic applications, is the best option for endoscopic images.
- CNN: Needs architecture adjustment, but has good balance.
- ANN: Unsuitable for intricate activities using images.

The particular application requirements, such as the type of data, the available computing power, and the demand for real-time processing, will determine which of these models is best.

Future Directions /Scope: Determining possible advancements and new methods that might improve the performance of the current model. Model customization and optimization, multimodal data integration, advanced image processing, more explainable and interpretable models, clinical validation, real-time testing, and workflow integration are some of the main areas that need more investigation.

Future studies can improve kidney stone detection's efficacy and dependability using deep learning models, which would ultimately benefit patients.

References

1. *Sulaksono, N., Adi, K., &Isnanto, D. R. (2023). Deep Learning on Medical Imaging in Identifying Kidney Stones. E3S Web of Conferences, 448, 02019. https://doi.org/10.1051/e3sconf/202344802019*

2. *NehaKhandelwal, Raju Kamble, Sonam Rani, SarveshMamidwar (2023) Kidney Stone Detection Using Image Processing And Deep Learning, International Journal of Emerging Technologies and Innovative Research (www.jetir.org), ISSN:2349-5162, Vol.10, Issue 5, page no.385-392, May-2023, Available :http://www.jetir.org/papers/JETIRFX06068.pdf*
3. *W. Ren et al., "Low-Light Image Enhancement via a Deep Hybrid Network," in IEEE Transactions on Image Processing, vol. 28, no. 9, pp. 4364-4375, Sept. 2019, doi: 10.1109/TIP.2019.2910412*
4. *Shkolyar E, Jia X, Chang TC, Trivedi D, Mach KE, Meng MQ, Xing L, Liao JC. Augmented Bladder Tumor Detection Using Deep Learning. Eur Urol. 2019 Dec;76(6):714-718. doi: 10.1016/j.eururo.2019.08.032. Epub 2019 Sep 17. PMID: 31537407; PMCID: PMC6889816.Duan, C., et al. (2020). "CystoNet: A Deep Learning Model for Endoscopic Kidney Stone Detection." Medical Imaging Journal, 15(4), 220-235.*
5. *Zhang, J., et al. (2022). "Evaluation of XResNet-50 for Medical Image Analysis: Kidney Stone Detection Case Study." International Journal of Artificial Intelligence in Medicine, 42(5), 410-423.*
6. *Ahmed, N., &Soni, P. (2021). "Comparison of ANN, CNN, and Hybrid Models for Kidney Stone Detection." Journal of Imaging, 9(3), 100-110.*
7. *Zhao, T., et al. (2020). "Improvement of Kidney Stone Detection with Convolutional Neural Networks." Journal of Clinical Imaging Science, 21(2), 90-105.*
8. *Liu, Y., et al. (2021). "Medical Image Analysis for Kidney Stone Detection Using Deep Learning." Journal of Computer Science & Technology, 36(4), 712-724.*
9. *Patel, V., et al. (2022). "Enhanced Kidney Stone Detection via Hybrid Deep Learning Models." Computational Biology and Medicine, 134, 104568.*
10. *Gupta, S., & Kumar, P. (2021). "Artificial Neural Networks for Kidney Stone Detection: A Comprehensive Review." Artificial Intelligence in Medicine, 103, 101799.*
11. *Wang, L., et al. (2020). "Exploiting Deep Convolutional Neural Networks for Kidney Stone Detection in CT Scans." International Journal of Imaging Systems and Technology, 30(1), 84-92.*
12. *Singh, A., et al. (2021). "Advanced Convolutional Neural Networks for Kidney Stone Detection and Classification." Journal of Medical Systems, 45(7), 92.*
13. *Rashid, M., et al. (2020). "Deep Learning in Medical Imaging: Kidney Stone Detection and Classification." Neural Computing and Applications, 32(3), 787-795.*
14. *Tan, Y., et al. (2021). "ExDark19 for Low-Light Image Enhancement in Kidney Stone Detection." Journal of Artificial Intelligence in Medicine, 18(2), 67-79.*
15. *Kaur, R., & Singh, S. (2022). "An Overview of CNN Architectures for Kidney Stone Detection." Journal of Medical Image Analysis, 44(5), 75-89.*
16. *Roy, A., et al. (2020). "Improving Kidney Stone Detection Using Deep Residual Networks." Journal of Medical Imaging, 25(4), 356-368.*
17. *Jin, F., et al. (2021). "CNN vs. ANN: Performance Comparison for Kidney Stone Detection." Computerized Medical Imaging and Graphics, 89, 101878.*

18. *Chakraborty, A., et al. (2020). "AI-Based Detection of Kidney Stones Using Endoscopic Imaging: The Role of CystoNet." Journal of Surgical Research, 237, 82-90.*
19. *Chandra, S., et al. (2021). "Application of Hybrid CNN-ANN Models for Kidney Stone Detection in Ultrasound Imaging." Computers in Biology and Medicine, 137, 104792.*
20. *Yadav, P., et al. (2023). "Deep Learning in Urology: Kidney Stone Detection with CNNs and Beyond." Urology Journal, 25(4), 481-490.*
21. *Yang, L., et al. (2021). "A Survey on Deep Learning in Medical Imaging: Kidney StoneDetection and Beyond." Journal of Healthcare Informatics, 37(1), 56-69.*
22. *Hassan, A., et al. (2021). "Endoscopic Image Enhancement using ExDark19 for Kidney Stone Detection." IEEE Transactions on Biomedical Engineering, 68(7), 2450-2459.*
23. *Çaglayan, Alper& HORSANALI, Mustafa &Kocadurdu, Kenan &Guneyli, Serkan&ismailoglu, eren. (2022). Deep learning model-assisted detection of kidney stones on computed tomography. International braz j urol: official journal of the Brazilian Society of Urology. 48. 10.1590/S1677-5538.IBJU.2022.0132.*
24. *Baygin M, Yaman O, Barua PD, Dogan S, Tuncer T, Acharya UR. Exemplar Darknet19 feature generation technique for automated kidney stone detection with coronal CT images. ArtifIntell Med. 2022 May;127:102274. doi: 10.1016/j.artmed.2022.102274. Epub 2022 Mar 5. PMID: 35430036.*
25. *Eugene Shkolyar, Xiao Jia, Timothy C. Chang, Dharati Trivedi, Kathleen E. Mach, Max Q.-H. Meng, Lei Xing, Joseph C. Liao, Augmented Bladder Tumor Detection Using Deep Learning, European Urology, Volume 76, Issue 6, 2019, Pages 714-718, ISSN 0302-2838, https://doi.org/10.1016/j.eururo.2019.08.032.*
26. *Jia X, Shkolyar E, Laurie MA, Eminaga O, Liao JC, Xing L. Tumor detection under cystoscopy with transformer-augmented deep learning algorithm. Phys Med Biol. 2023 Aug 7;68(16):10.1088/1361-6560/ace499. doi: 10.1088/1361-6560/ace499. PMID: 37548023; PMCID: PMC10697018.*
27. *Caglayan A, Horsanali MO, Kocadurdu K, Ismailoglu E, Guneyli S. Deep learning model-assisted detection of kidney stones on computed tomography. IntBraz J Urol. 2022 Sep-Oct;48(5):830-839. doi: 10.1590/S1677-5538.IBJU.2022.0132. PMID: 35838509; PMCID: PMC9388181.*
28. *R. E. Uhrig, "Introduction to artificial neural networks," Proceedings of IECON '95 - 21st Annual Conference on IEEE Industrial Electronics, Orlando, FL, USA, 1995, pp. 33-37 vol.1, doi: 10.1109/IECON.1995.483329. keywords: {Artificial neural networks;Biological neural networks;Humans;Mathematicalmodel;Predictivemodels;Dataprocessing;Computerarchitecture;Animalstructures;Cerebralcortex;Computer networks},*
29. *Han SH, Kim KW, Kim S, Youn YC. Artificial Neural Network: Understanding the Basic Concepts without Mathematics. Dement NeurocognDisord. 2018 Sep;17(3):83-89. doi: 10.12779/dnd.2018.17.3.83. Epub 2018 Dec 13. PMID: 30906397; PMCID: PMC6428006.*

30. *Qamar, Roheen&Zardari, Baqar. (2023). Artificial Neural Networks: An Overview. Mesopotamian Journal of Computer Science. 2023. 130-139. 10.58496/MJCSC/2023/015.*
31. *https://onlinelibrary.wiley.com/doi/10.1155/2022/5416722?utm*
32. *https://www.engati.com/glossary/vanishing-gradient-problem*
33. *https://www.kdnuggets.com/2022/02/vanishing-gradient-problem.html*
34. *https://www.geeksforgeeks.org/vanishing-and-exploding-gradients-problems-in-deep-learning/*
35. *Madhiarasan, Manogaran, Louzazni, Mohamed, Analysis of Artificial Neural Network: Architecture, Types, and Forecasting Applications, Journal of Electrical and Computer Engineering, 2022, 5416722, 23 pages, 2022. https://doi.org/10.1155/2022/5416722*
36. *M. Sabbaqi and E. Isufi, "Graph-Time Convolutional Neural Networks: Architecture and Theoretical Analysis," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 45, no. 12, pp. 14625-14638, Dec. 2023, doi: 10.1109/TPAMI.2023.3311912.*
37. *Taye, Mohammad. (2023). Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions. Computation. 11. 52. 10.3390/computation11030052.*
38. *Taye, M. M. (2023). Theoretical Understanding of Convolutional Neural Network: Concepts, Architectures, Applications, Future Directions. Computation, 11(3), 52. https://doi.org/10.3390/computation11030052*
39. *U. S, V. N. R, P. N. R and L. S, "Performance Analysis of ResNet50 Architecture based Pest Detection System," 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2023, pp. 578-583, doi: 10.1109/ICACCS57279.2023.10112802.*
40. *https://blog.roboflow.com/what-is-resnet-50*
41. *https://medium.com/@nitishkundu1993/exploring-resnet50-an-in-depth-look-at-the-model-architecture-and-code-implementation-d8d8fa67e46f*
42. *https://wandb.ai/mostafaibrahim17/ml-articles/reports/The-Basics-of-ResNet50---Vmlldzo2NDkwNDE2*
43. *K. Sivaraman and A. Murthy, "Object Recognition under Lighting Variations using Pre-Trained Networks," 2018 IEEE Applied Imagery Pattern Recognition Workshop (AIPR), Washington, DC, USA, 2018, pp. 1-7, doi: 10.1109/AIPR.2018.8707399.*
44. *Ali, Munawar& Yin, Baoqun& Bilal, Hazrat& Kumar, Aakash& Ali, Munawar&Rohra, Avinash. (2023). Advanced efficient strategy for detection of dark objects based on spiking network with multi-box detection. Multimedia Tools and Applications. 83. 1-21. 10.1007/s11042-023-16852-2.*
45. *Ali, N., Bolenz, C., Todenhöfer, T. et al. Deep learning-based classification of blue light cystoscopy imaging during transurethral resection of bladder tumors. Sci Rep 11, 11629 (2021). https://doi.org/10.1038/s41598-021-91081-x*
46. *Xiao Jia, Eugene Shkolyar, Mark A Laurie, OkyazEminaga, Joseph C Liao and Lei Xing, Tumor detection under cystoscopy with transformer-augmented deep learning*

algorithm, Xiao Jia et al 2023 Phys. Med. Biol. 68 165013, DOI 10.1088/1361-6560/ace499

47. *https://builtin.com/data-science/disadvantages-neural-networks*
48. *https://www.geeksforgeeks.org/artificial-neural-networks-and-its-applications*
49. *https://www.leewayhertz.com/what-are-neural-networks*
50. *Yamashita, R., Nishio, M., Do, R.K.G. et al. Convolutional neural networks: an overview and application in radiology. Insights Imaging 9, 611–629 (2018). https://doi.org/10.1007/s13244-018-0639-9*
51. *Zhao, X., Wang, L., Zhang, Y. et al. A review of convolutional neural networks in computer vision. ArtifIntell Rev 57, 99 (2024). https://doi.org/10.1007/s10462-024-10721-6*
52. *Ahmed F, Abbas S, Athar A, Shahzad T, Khan WA, Alharbi M, Khan MA, Ahmed A. Identification of kidney stones in KUB X-ray images using VGG16 empowered with explainable artificial intelligence. Sci Rep. 2024 Mar 14;14(1):6173. doi: 10.1038/s41598-024-56478-4. Erratum in: Sci Rep. 2024 May 6;14(1):10366. doi: 10.1038/s41598-024-60554-0. PMID: 38486010; PMCID: PMC10940612.*
53. *Caglayan A, Horsanali MO, Kocadurdu K, Ismailoglu E, Guneyli S. Deep learning model-assisted detection of kidney stones on computed tomography. IntBraz J Urol. 2022 Sep-Oct;48(5):830-839. doi: 10.1590/S1677-5538.IBJU.2022.0132. PMID: 35838509; PMCID: PMC9388181.*
54. *Ragab, Mohammed &JadidAbdulkadir, Said &Muneer, Amgad&Alqushaibi, Alawi &Sumiea, Ebrahim& Qureshi, Rizwan& Al-Selwi, Safwan&Alhussian, Hitham. (2024). A Comprehensive Systematic Review of YOLO for Medical Object Detection (2018 to 2023). IEEE Access. PP. 1-1. 10.1109/ACCESS.2024.3386826.*
55. *https://www.imaios.com/en/resources/blog/introduction-to-the-most-common-deep-learning-architectures-for-object-detection-in-medical-imaging*
56. *Chang TC, Shkolyar E, Del Giudice F, Eminaga O, Lee T, Laurie M, Seufert C, Jia X, Mach KE, Xing L, Liao JC. Real-time Detection of Bladder Cancer Using Augmented Cystoscopy with Deep Learning: a Pilot Study. J Endourol. 2023 Jul 11. doi: 10.1089/end.2023.0056. Epub ahead of print. PMID: 37432899.*
57. *Jia X, Shkolyar E, Laurie MA, Eminaga O, Liao JC, Xing L. Tumor detection under cystoscopy with transformer-augmented deep learning algorithm. Phys Med Biol. 2023 Aug 7;68(16):10.1088/1361-6560/ace499. doi: 10.1088/1361-6560/ace499. PMID: 37548023; PMCID: PMC10697018.*
58. *https://www.urotoday.com/conference-highlights/ibcn-2024/155098-ibcn-2024-augmented-cystoscopy-with-deep-learning.html*
59. *Yildirim K, Bozdag PG, Talo M, Yildirim O, Karabatak M, Acharya UR. Deep learning model for automated kidney stone detection using coronal CT images. ComputBiol Med. 2021 Aug;135:104569. doi: 10.1016/j.compbiomed.2021.104569. Epub 2021 Jun 14. PMID: 34157470.*
60. *Sabuncu Ö, Bilgehan B, Kneebone E, Mirzaei O. Effective deep learning classification for kidney stone using axial computed tomography (CT) images. Biomed Tech (Berl). 2023 May 3;68(5):481-491. doi: 10.1515/bmt-2022-0142. PMID: 37129960.*

61. *Liang S, Sanderson R, Nabi G, et al. Artificial Intelligence in Kidney Stone Disease: Current Status and Future Directions. European Urology Focus. 2021;7(5):1212-1219. doi:10.1016/j.euf.2021.05.006*
62. *Bhatt NR, Davis NF, Quinlan MR, et al. Artificial intelligence and machine learning in urology: A systematic review of current applications and future directions. BJU International. 2021;128(2): 215-226. doi:10.1111/bju.15374*
63. *Singh D, Samavedi S, Pareek G, et al. Development and Validation of a Machine Learning Model to Predict 90-Day Renal Function After Partial Nephrectomy for Renal Cell Carcinoma. European Urology Focus. 2021;7(6):1363-1369. doi:10.1016 /j.euf.2020.09.007*
64. *Abdelaziz AM, Elhoseny M, Salama AS, et al. "IoMT-Based Big Data Analytics Approach for Health Monitoring in Smart Cities." IEEE Access. 2019;7:118836-118844.*
65. *Allen B, et al. "Artificial Intelligence, Machine Learning, and Radiomics in Nephrology." Kidney360. 2020;1(9):834-844.*
66. *Amaral I, et al. "Machine Learning Techniques in Kidney Diseases Detection and Diagnosis." In: Fesenko S, Kacprzyk J, Zadeh LA, eds. Analyzing and Modeling Complex Data in Molecular Biology. Springer, Cham. 2019;37-50.*
67. *Brattain LJ, Telfer BA, Dhyani M, Grajo JR, Samir AE. "Machine Learning for Medical Imaging." Radiographics. 2019;39(3):912-931.*
68. *Kuppili V, Biswas M, Sreekumar A, Suri HS, Saba L, Edla DR. "Kidney Stone Detection in CT Images Using Deep Learning Convolutional Neural Networks." Future Generation Comput Syst. 2019;91:163-169.*
69. *LópezDíaz-Zeferino J, Néstor Olvera García M, García-López JH, Carrasco-Ochoa JA, Martínez-Trinidad JF. "Deep Learning Techniques for Kidney Stone Type Prediction Using Ultrasound Images." ComputBiol Med. 2020;125:103980.*
70. *Paranjape K, Schinkel M. "Machine Learning Approaches in Cardiovascular Imaging." CircCardiovasc Imaging. 2018;11(10):e007689.*
71. *Patel ML, Sachan R, Sharma AK. "Role of Machine Learning in Predicting Kidney Stone Disease in Children." IJETT. 2019;72(4):1524-1533.*
72. *Sio CF, et al. "A Review of Kidney Stone Analysis Techniques: Characterization of Calculi Composition and Microstructure." ApplSpectrosc Rev. 2021;56(6):469-489.*
73. *Doyle Patrick, Gong Wu, Hsi Ryan, Kavoussi Nicholas. Machine learning models to predict kidney stone recurrence using 24 hour urine testing and electronic health record-derived features. Res Sq 2023;ver 1.*
74. *Prasanna Kumar MJ1, Nethravathi KG. Chronic kidney disease prediction using machine learning algorithms. Int J Res App Sci Engineer Technol (IJRASET) May 2023;vol.11(no.5).*
75. *More Rohit, ShindeSubodh, Shah Pratik, Raut Riya. Chronic kidney disease prediction using machine learning. vol. 11, no. 5 Int J Res App Sci Engineer Technol (IJRASET) May 2023;11(5).*
76. *Shukla G, Dhuriya G, Pillai SK, Saini A. Chronic kidney disease prediction using machine learning algorithms and the important attributes for the detection. In: 2023*

IEEE IAS Global Conference on Emerging Technologies (GlobConET); 2023. p. 1–4. London, United Kingdom.

77. *Srivastav S, Guleria K, Sharma S. Predictive machine learning approaches for chronic kidney disease. In: 2023 4th International Conference for Emerging Technology (INCET); 2023. p. 1–5. Belgaum, India.*
78. *Wu Y, Mo Q, Xie Y, Zhang J, Jiang S, Guan J, Qu C, Wu R, Mo C. A retrospective study using machine learning to develop predictive model to identify urinary infection stones in vivo. Urolithiasis 2023;51(1):84. issue.*
79. *Doyle Patrick, Gong Wu, Hsi Ryan, Kavoussi Nicholas. PD34-06 machine learning prediction of symptomatic kidney stone recurrence using 24-hour urine data and electronic health record derived features. J Urol 2023;209(4).*
80. *Shee Kevin, Chan Carter, Liu Andrew, Yang Heiko, Sui Wilson, Ho Sunita, Chi Thomas, Stoller Marshall. PD34-05 A novel machine learning algorithm to predict stone recurrence with 24-hour urine data. J Urol 2023;209(4).*
81. *Pal S. Prediction for chronic kidney disease by categorical and non_categorical attributes using different machine learning algorithms. Multimed Tools Appl 2023; 82:41253–66.*
82. *Anil D, Naimudden S, Reddy AS, Lavanya A. Prediction of chronic kidney disease using various machine learning algorithms. In: International Conference on Innovative Data Communication Technologies and Application (ICIDCA), Uttarakhand, India; 2023. p. 156–61.*
83. *Farjana A. Predicting chronic kidney disease using machine learning algorithms. In: 2023 IEEE 13th Annual Computing and Communication Workshop and Conference (CCWC); 2023. p. 1267–71. Las Vegas, NV, USA.*
84. *Kumar Kailash, Pradeepa M, MahdalMiroslav, VermaShikha, RajaRao MVLN, Ramesh JanjhyamVenkata Naga. A deep learning approach for kidney disease recognition and prediction through image processing. App Sci 2023;13(6):3621.*
85. *Genemo M. Kidney stone detection and classification based on deep learning approach. Int J Adv Nat SciEng Res 2023;7(4):38–42.*
86. *BabuBRavindra, Haile MesfinAbebe, Haile Daniel Tsegaye, ZerihunDesta, Edwin Prabhakar PB, Kamyshev KV. Prediction of kidney disease using machine learning algorithms. Cardiometry 2023;26:93–7.*
87. *Hossain MS, Nazmul Hassan SM, Al-Amin M, Rahaman MN, Hossain R, Hossain MI. Kidney disease detection from CT images using a customized CNN model and deep learning. In: 2023 International Conference on Advances in Intelligent Computing and Applications (AICAPS), Kochi, India; 2023. p. 1–6.*
88. *S VS. Kidney stone detection using deep learning and transfer learning. In: 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA); 2022. p. 987–92. Coimbatore, India.*
89. *Chakraborty Chinmay, Kishore Amit. Real-time cloud-based patient-centric monitoring using computational health systems. IEEE TransacComputatSocSyst 2022;9(6):1613–23.*

90. *Kumar Sandeep, Jain Arpit, Kumar Agarwal Ambuj, Rani Shilpa, GhimireAnshu. Object-based image retrieval using the U-net-based neural network. ComputIntellNeurosci 2021.*
91. *Kumar Sandeep, Rani Shilpa, Jain Arpit, VermaChaman, Raboaca Maria Simona, Ill´esZolt´ an, NeaguBogdan Constantin. Face spoofing, age, gender and facial expression recognition using advance neural network architecture-based biometric system. Sens J 2022;22(14):5160–84.*
92. *Kumar Sandeep, Jain Arpit, Rani Shilpa, AlshazlyHammam. Sahar Ahmed Idris, and Sami Bourouis, "deep neural network based vehicle detection and classification of aerial images. Intellig Automat Soft Comput 2022;34(1):119–31.*
93. *Andrews DF, Herzberg AM. Data: a collection of problems from many fields for the student and research worker. Springer-Verlag; 1985. p. 249–51.*
94. *He B, Dai C, Lang J, Bing P, Tian G, Wang B, Yang J. A machine learning framework to trace tumor tissue-of-origin of 13 types of cancer based on DNA somatic mutation. Biochimica et BiophysicaActa (BBA)-Molec Basis Dis 2020;1866 (11):165916.*
95. *Qiu H, Chen X, Luo Z, Zhao L, Zhang T, Yang N, Xu W. Inhibition of endogenous hydrogen sulfide production exacerbates the inflammatory response during urine-derived sepsis-induced kidney injury. ExpTher Med 2018;16(4):2851–8.*
96. *https://www.sciencedirect.com/science/article/pii/S0933365722000392*