



Automatic Kidney Lesion Detection using Deep Learning - A Survey

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Abstract— Detecting kidney damage is an important step in the diagnosis and treatment of kidney disease. Deep learning methods have shown the potential to improve the accuracy and efficiency of kidney injury detection. Using medical imaging modalities such as ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and X-rays, we discuss recent research on the application of algorithms to deep learning to diagnosing kidney damage. We investigate the effectiveness of various deep learning architectures and algorithms, and the issues and limitations associated with using deep learning to identify kidney damage. Our study demonstrates that diagnosis of kidney damage using multiple imaging methods can be performed with high accuracy and efficiency using deep learning algorithms. However, there are a number of important limitations to overcome, including the need for large labelled data sets and the potential for bias. We also describe future goals of deep learning research for detecting kidney damage, such as creating understandable deep learning models and combining deep learning with other clinical data. Overall, this study highlights the potential of deep learning algorithms for better recognition of renal lesions and their contribution to improving the diagnosis and treatment of renal diseases.

Keywords— Kidney Lesion Detection, Deep Learning, Medical Imaging, Magnetic Resonance Imaging, Computed Tomography, Convolutional Neural Network, Segmentation.

I. INTRODUCTION

The kidneys are vital organs of the human body, responsible for filtering waste and excess fluid from the blood to maintain balance in the body. Abnormal growths or masses on the kidneys are called nephropathy, also known as nephropathy. Early detection is critical to the successful treatment of these lesions, which can be benign or malignant. A medical procedure called nephropathy recognition involves detecting and evaluating the presence and severity of kidney damage. The testing processes typically uses medical imaging techniques, including ultrasound, computed tomography (CT), magnetic resonance imaging (MR) and X-rays. With these methods, a medical professional can view the kidney and note any abnormalities, such as tumours or cysts.

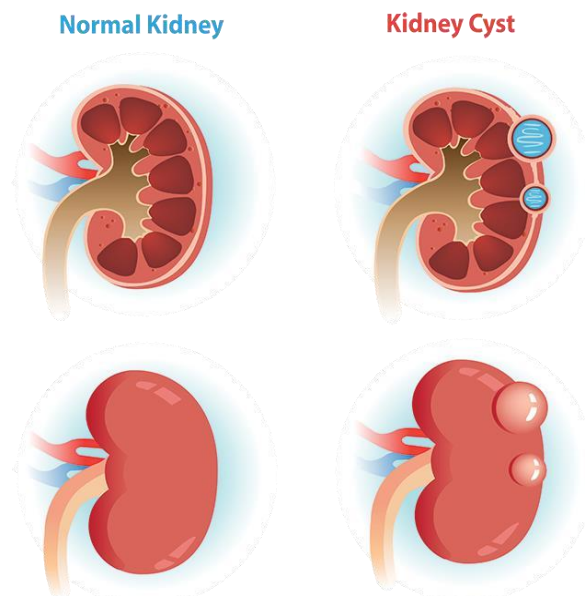


Figure-1: Normal kidney vs Kidney with cyst



To prevent benign kidney damage from turning into malignant damage, early detection and treatment of kidney damage is crucial. Early detection also allows healthcare professionals to choose the best course of action, which may involve surgery, chemotherapy or radiation therapy, depending on the nature and severity of the injury.

Kidney damage can take many different forms such as cysts, tumours and abscesses. Cysts are fluid filled sacs that can form outside or inside the kidney.

They're usually benign and don't need treatment, but if they get too big or start to hurt, they need to be surgically removed or drained. Identifying kidney damage is a crucial step in the diagnosis and management of kidney disease. Using medical imaging methods including ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and X-rays, the detection phase involves detecting and evaluating the presence and severity of kidney damage. However, manual analysis of medical photos can be time-consuming and error-prone. To improve the accuracy and efficiency of diagnosing kidney damage, researchers investigated the use of deep learning algorithms.

There are several advantages to using deep learning algorithms to find kidney damage. Secondly, deep learning algorithms can quickly and reliably process huge sets of medical image data, saving time and reducing the risk of human error. Second, deep learning algorithms can gain accuracy and generalization by learning from large medical image datasets. Finally, the sensitivity and specificity of identifying kidney damage can be improved by training deep learning algorithms to recognize subtle signs and patterns that humans may struggle to notice.

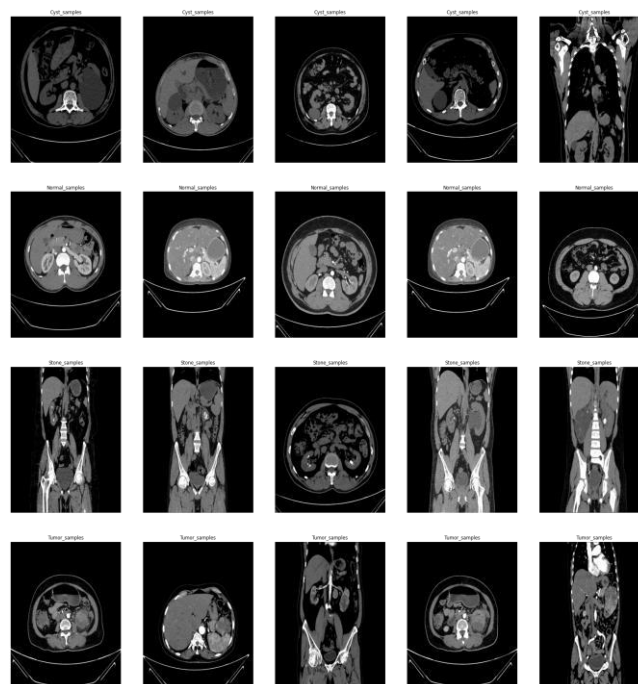


Figure - 2: A few samples of Kidney tumour, cyst, normal or stone findings.

The token bucket provides a mechanism to allow the desired level of bursting in a stream by limiting its average rate as well as the maximum burst size. It can be viewed as an abstraction of the transmission rate expressed as the relationship between the CBS confirmed burst size, the CIR information rate, and the time interval T. It is based on the token generated after a specific time limit and resides in the bucket. By using the token bucket algorithm, network congestion can be avoided because it deals with more traffic and it is also one of the flexible algorithms, so that data is not lost in the network.

II. BACKGROUND AND RELATED WORK

In this paper[1], we propose an end-to-end multiscale 3D supervised U-Net to simultaneously segment kidneys and renal tumours from raw-scale CT images. By extending the original U-3D network architecture, we combine the multiscale supervised method with exponential logarithmic loss. This allows U-Net architecture to further optimize the, by extending its possibilities for even better performance. Compared to the current trend of deep neural networks with complex



architectures and multiple different submodules, we take a more general approach and still achieve state-of-the-art comparable results. Simpler architectures have the advantage of higher reproducibility and wider generalization of results, contrast with potentially very bloated models, and lower reproducibility of more complex architectures.

[2] This study's goal was to Early prediction of chronic diseases using soft computing technology improves the reliability of healthcare systems. It also reduces the time-consuming process of diagnostic testing and helps physicians make the best decisions about treatment. Here they propose a early prediction system for CKD disease, which is important for the early diagnosis of stage because it damages the renal system. Therefore, a model based on the ANFIS technique was developed and an accuracy of 94% of was achieved in the proposed model. The ANFIS model incorporates two fuzzy logic and neural network techniques, both of which are robust mathematical estimators. In future work, we can compare this system with other techniques such as deep neural networks and convolutional neural networks.

In this paper[3], they have analyzed a dataset of medical records of 491 patients with CKD and cardiovascular disease risk from the United Arab Emirates and develop a machine learning possibility. Then used machine learning to detect the most significant variables included in the dataset, first excluding and then including components indicating the year of CRF onset or time of onset. patient's last visit. Our results confirm the effectiveness of our method. As for the limitations, we should point out that they only performed the analysis on one dataset. They searched for alternative public datasets to use as validation cohorts, but unfortunately did not find any with the same clinical characteristics.

Researchers have published an article [4] on deep learning-based heterogeneous modified artificial neural network (HMANN) approach for detection of chronic kidney disease. There is some noise and complexity in the image segmentation. Therefore, it requires an algorithm to handle missing and noisy values with the ability to classify the proposed HMANN method reduces noise and helps segment the kidney image so that the location of kidney stones can be clearly identified. To find a good solution to this problem, tested three classifiers: Support Vector Machines, Artificial Neural Networks, and Multilayer Perceptrons. In this paper, feature reductions were performed using the significant results from these studies to reduce overfitting and identify the most important predictive features of CKD. Additionally, the new factor discovery classifier has been used to detect CKD more accurately than modern formulas.

In this paper[5], they have proposed to estimate CKD using an efficient feature extraction technique under the framework of graph embedding. Figure integrations are able to distinguish CKD stages by preserving local intrinsic features. The experimental results show that the proposed method performs well in classifying CKD stages. The combination of graph merging and embedding overcomes the limitation of the unbalanced class frequency problem and shows excellent classification accuracy. The system can be generalized to other medical problems. It can be used in clinics and hospitals to analyse heart and kidney function at different stages of patient care.

This article[6] is based on Chronic kidney disease (CKD) describes a significant loss of kidney function and is also known as chronic kidney disease. The kidneys filter waste and excess blood from the blood and excrete it in the urine. When chronic kidney disease 4044 reaches an advanced stage, dangerous levels of fluid, 4044 electrolytes and waste products can build up in the body. CKD increases the risk of end-stage renal disease (ESRD) and cardiovascular disease and other cardiac risk factors, such as high blood lipids, are also present in people with CKD. Of the individuals with CKD, the most common cause of death was cardiovascular disease rather than kidney failure. Kidney or chronic disease kidney disease is no small problem for a person's health. It will be the cause of a person's death, so everyone should take care of their health to prevent it early in life. In this article, use various machine learning classifiers to find the best accuracy, ROC, accuracy, recall, and measure. However, Random Forest gave 99% accuracy and it also had the highest ROC value.

A group of researchers [7] has devised an intelligent system that can predict the deep learning framework developed in this study overcomes the CKD problem which is a high-profile issue. In the frame, they were integrated the time intervals of the air pollution data and the CKD patient data, and extracted the features of the time series of the air pollution data. Then extract time signature information from these features using a LSTM model to obtain an accurate staging of CKD patients. Finally, they used actual CKD data from Taiwan and air pollution data in our experiments to verify the effectiveness of the method proposed by to predict the CKD stage of patients.

Pedro Moreno-Sanchez (2021) [8] commented on the importance of features to improve the readability of early diagnosis of chronic kidney disease. The incidence, prevalence and high economic burden on healthcare systems of chronic kidney disease (CKD) make it a global public health problem. With CRI having killed 1.2 million people since 1990, the death rate for all age groups rose to 41.5% in 2017.



The main goal of treatment for CKD is to slow the progression of kidney damage, usually by addressing the underlying cause. The classifier model was created using the CRISP-DM technique. The scikitlearn GridSearchCV package is used to train and validate classifiers using fivefold cross-validation. The Apollo Hospital in Karaikudi, India provided the dataset used in this study over a period of approximately two months in 2015, with a total of 400 samples. Of the 400 samples, 250 were from the CKD group and 150 from the nonCKD group. As noted in the authors' conclusion, GridSearchCV "achieved 100% accuracy, precision, sensitivity, specificity, and f1-score results." A study by Van Eyck et al. is the most accurate result to date compared to previous related results.

1. No	Title	Author	Methodology	Limitation
1	MSS U-Net: 3D segmentation of kidneys and tumours from CT images with a multi-scale supervised U-Net.	Wenshual Zhao, Dihong Jiang, Jorge Pena Queralt, Tomi Westerlund Year: 2020	In this model CNN(U-Net) method is used.	In this model it will not perform well on complex images.
2	Adaptive Neuro Fuzzy Inference System based Prediction of Chronic Kidney Disease.	Komal Damodara, Anitha Thakur. Year: 2021	We have analysed and classified Artificial Neural Network (ANN) and Adaptive Neuro Fuzzy Inference System (ANFIS).	Reduces time consuming diagnosis test process.
3	A Machine Learning Analysis of Health Records of Patients With Chronic Kidney Disease at Risk of Cardiovascular Disease.	Davide Chicco, Christopher A. Lovejoy, Luca Oneto. Year: 2021	The classification techniques that is, Random Forest, SVM, Decision Tree and Artificial Neural Network (ANN) are used.	Used dataset is a imbalance dataset.
4	Detection and Diagnosis of Chronic Kidney Disease Using Deep Learning Based Heterogenous Modified Artificial Neural Network.	Fuzhe Ma, Tao Sun, Lingyun Liu, Hongyu Jing. Year: 2020	In this model, Heterogenous Modified Artificial Neural Network(HMANN) has been proposed for the early detection, segmentation, and diagnosis of chronic renal failure on the Internet of Medical Things (IoMT) platform and Back Propagation Algorithm is also used for error detection.	The method could be rather sensitive to noisy data and irregularity since it uses back propagation.
5	Automated Detection of CKD Using Image Fusion and Graph Embedding Techniques with Ultrasound Images.	Anjan Gudigar , U Raghavendraa, Jyothi Samanth , Mokshagna Rohit Gangavarapu , Abhilash Kudva , Ganesh Paramasivam , Krishnananda Nayak , RuSan Tan , Filippo	Computer Aided Diagnosis (CAD) technology is used in this project.	The limitation is of the unbalanced class frequency problem and shows excellent classification accuracy.



		Molinari, Edward J. Ciaccio , U. Rajendra Acharya. Year: 2021		
6	Performance Analysis of Chronic Kidney Disease through Machine Learning Approaches.	Minhaz Uddin Emon, Al Mahmud Imran, Rakibul Islam, Maria Sultana Keya, Raihana Zannat, Ohidujjaman. Year: 2021	The proposed model has 8 ML classifiers are used namely: LR, NB, MLP, SGD, Adaboost, Bagging, DT, RF classifier are used.	A forest is less interpretable than a single decision tree. Single trees may be visualized as a sequence of decisions.
7	Deep learning for etiology of chronic kidney disease.	Sheng-Min Chiu, FengJung Yang, Yi- Chung Chen, Chiang Lee. Year: 2020	The DLMs used in this study were long and short-term memory (LSTM) models.	DLMs take longer to train and also requires more memory.
8	Features Importance to Improve Interpretability of Chronic Kidney Disease Early Diagnosis.	Pedro A. Moreno- Sanchez Year: 2020	AdaBoost is selected as the best classifier with a 100% in terms of accuracy, precision, sensitivity, and fl-score;	Noisy data and outliers have to be avoided before adopting an Adaboost algorithm.

Table-1: Relevant studies on advantages and disadvantages of approaches to detect kidney disease.

III. CONCLUSION

In conclusion, the use of deep learning algorithms for kidney injury diagnosis has shown great promise for improving the accuracy and efficiency of detection procedures. Recent research analysed in this study focused on the use of deep learning algorithms on various imaging modalities, including ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and x-rays.

The results of the study show that the use of deep learning algorithms for the identification of kidney lesions is very accurate and efficient, and gratifying results have been obtained in the segmentation of tumours and lesions .

However, the use of deep learning methods also has drawbacks, such as the need for large labelled data sets, the possibility of bias, and the lack of model interpretability. These limitations must be overcome to ensure deep learning algorithms are reliable and effective in clinical practice.

Future research will focus on creating interpretable deep learning models to clarify the decision-making process of algorithms, as well as combining deep learning with other clinical data to improve accuracy and reliability. effectiveness in the diagnosis and treatment of kidney disease.

Overall, this study highlights the potential of deep learning algorithms to improve the identification of kidney lesions and their contribution to the advancement of kidney disease diagnosis and treatment. Deep learning is an evolving field, which is why more research and development is needed to fully realize its promise of increasing kidney injury recognition and optimizing patient care.



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