Artificial intelligence in diagnostic medicine: a case study of kidney disease applications

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ABSTRACT

The rapid evolution of artificial intelligence (AI), particularly in convolutional neural networks (CNNs) and deep learning, has revolutionized numerous domains, ranging from medical imaging to creative arts and legal analytics. This research emphasizes the role of pre-trained CNN architectures in identifying kidney conditions, leveraging a dataset comprising images of healthy kidneys as well as those affected by cysts, tumors, and stones. The pretrained models known for their outstanding image recognition capabilities, were adapted for this classification task through transfer learning (TL) techniques. By refining these models and carefully calibrating key parameters like learning rate, batch size, and network depth, they demonstrated superior performance compared to traditional machine learning approaches. The findings underscore the transformative potential of pre-trained CNNs in advancing the precision of kidney disease diagnostics, with implications for broader medical applications.

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1. INTRODUCTION

Artificial intelligence (AI) plays an increasingly significant role in medical diagnosis, providing powerful tools to enhance the accuracy and efficiency of clinical processes. Using techniques such as machine learning and deep learning, AI analyzes large volumes of complex data to detect anomalies or predict diseases. For instance, convolutional neural networks (CNNs) have proven effective in interpreting medical images, such as mammograms for breast cancer screening [1], lung cancer classification from CT-scan images [2] and detecting ocular diseases like diabetic retinopathy from retinal photographs [3]. Additionally, supervised models can predict cardiovascular diseases based on clinical data [4], while systems like IBM Watson Health assist healthcare professionals by offering treatment recommendations derived from ex-tensive medical literature [5]. These advancements reduce diagnostic time and optimize patient care, although challenges remain, particularly regarding data quality, model interpretability, and adoption by clinicians. Building on these advancements, this paper focuses on exploring the application of AI in the context of kidney diseases. Kidney diseases represent a significant global health challenge, with millions of patients affected by chronic kidney disease (CKD) and acute kidney injury (AKI). Early diagnosis and precise classification are crucial for improving patient outcomes and reducing healthcare costs. Leveraging AI's capabilities, particularly in analyzing complex medical data, this work aims to address the limitations of traditional diagnostic methods and enhance the understanding, prediction, and management of kidney diseases.

Globally, in 2017, a systematic analysis from the GBD [6] project revealed 697.5 million cases of CKD at all stages for all age groups. The number of deaths related to CKD was estimated at 1.2 million in 2017 and 1.43 million in 2019 [7]. These alarming figures highlight the crucial importance of early and accurate diagnosis to improve health outcomes and patients' quality of life. Kidney diseases can vary in severity, ranging from mild to severe, including conditions such as CKD and end-stage renal disease. Early diagnosis is essential to prevent disease progression, manage symptoms, and avoid severe complications.

Diagnosing kidney diseases poses a major challenge for healthcare professionals, often requiring invasive procedures, detailed analyses, and specialized skills. The complexity of renal pathologies, combined with the need for early and accurate detection, makes this field particularly demanding. Traditionally, diagnostic methods include biopsies, laboratory analyses, and sophisticated medical imaging such as ultrasounds, computed tomography (CT) scans, and magnetic resonance imaging (MRI). However, these methods can be expensive, time-consuming, and carry risks for patients.

This document is organized in the following way: an itroduction is presented in section 1, section 2 discusses state-of-the-art research on AI in medical imaging, with a particular focus on kidney pathologies. The following section outlines the proposed pre-trained models and the dataset used. Section 4 presents the experimental results, while the final section provides conclusions and future perspectives.

2. RELATED WORK

The emergence of AI and deep learning offers innovative opportunities to improve diagnostic practices in nephrology. AI, particularly deep learning, has demonstrated its ability to analyze vast amounts of data and identify complex patterns that often escape the human eye. Pre-trained models, which are deep learning models that have been trained on large datasets before being adapted for specific tasks, represent a major advancement in this field. These technologies not only speed up the diagnostic process but also minimize the risk of human errors, enhancing the overall quality of care. Furthermore, AI supports personalized medicine by analyzing vast amounts of data to provide treatments tailored to each patient's specific needs. Its incorporation into medical diagnostics marks a significant breakthrough, enabling more effective disease management, better utilization of hospital resources, and improved clinical decision-making.

Waheed *et al.* [8], the study introduces a CNN-based approach for the early detection of melanoma, a form of skin cancer. The images are processed using a pre-trained deep learning model. Through extensive training on a large dataset, the CNN classifier effectively differentiates between malignant melanoma and benign lesions, recognizing that early diagnosis can greatly influence the patient's prognosis. Experimental results indicate that the proposed method outperforms existing techniques in terms of diagnostic accuracy.

Khanna [9], the authors examine medical brain images, the progression stages of Alzheimer's disease symptoms, and neuropsychiatric features. Their objective is to classify varying degrees of dementia, as this classification plays a key role in determining the appropriate treatment. To improve prediction on new data, ensemble learning integrates multiple decision-making systems, each employing different strategies to unify classifiers. The study combines a deep convolutional neural network (DCNN) with deep ensemble learning, specifically utilizing MobileNetV2 and long short-term memory (LSTM) on MRI data to predict dementia severity levels.

Ahmed and Mustafa [10], the authors try to develop an efficient and cost-effective method for the early diagnosis and classification of knee osteoarthritis (OA) severity using X-ray images. They explore both binary and multiclass classification, introducing two frameworks: one utilizing a pre-trained CNN for feature extraction, PCA for dimensionality reduction, and SVM for classification, and another employing transfer learning (TL) to fine-tune the CNN for different classification levels. Their experimental results indicate that binary classification achieved the highest accuracy (90.8%), with fewer multiclass labels improving performance. The study demonstrates the potential of the proposed approach in enabling early OA detection, facilitating timely intervention, and enhancing patient outcomes.

Lu *et al.* [11], the authors investigate the impact of AI in enhancing the early and accurate diagnosis of coronary atherosclerotic heart disease, a prevalent cardiovascular condition with significant health and societal implications. They review the advancements in AI-driven diagnostic models, highlighting their applications in coronary angiography, CT angiography, intravascular imaging, cardiac MRI, and functional parameter analysis. The study provides a comprehensive overview of the technical background, current research progress, and emerging challenges, offering insights into the future potential of AI in improving coronary disease diagnosis.

Verma *et al.* [12], the authors performed a bibliometric analysis using the Web of Science database, employing specific search terms related to organic systems and research methodologies. Their findings revealed that machine learning is the least utilized in nephrology, representing only 3.2% of its applications across medical subspecialties. This insight led us to focus on kidney-related diseases, where leveraging AI can play a crucial role in supporting medical teams with early diagnoses, thereby improving the effectiveness of treatment strategies.

After analyzing research on kidney-related studies, we found that the application of the pre-trained models to kidney disease classification remains relatively unexplored, although promising results have been reported in the literature [13]-[15]. Their use in the classification of kidney diseases is promising, as they have the potential to provide faster, more accurate, and non-invasive analyses, thereby reducing the reliance on traditional methods.

The three studies propose interesting approaches for applying AI in the diagnosis of CKD but present several shortcomings. The study proposed by [13] presents a deep learning-based system for automated kidney disease detection but lacks robust validation on diverse datasets, and the absence of details on data preprocessing and hyperparameters raises concerns about the reproducibility of the results. The article of [14] stands out for optimizing model parameters but neglects model interpretability, which is crucial in a medical setting, and does not sufficiently address practical implications and missing data.

Finally, the study proposed on [15] compares several classification methods but lacks in-depth comparative analysis of model performance and does not discuss the robustness of the models against data biases or poor data quality. Moreover, the explanation of the Wide & Deep Learning model is insufficient for implementation by other researchers. In summary, while these works demonstrate significant potential for AI in kidney disease diagnosis, they suffer from major limitations, particularly in terms of external validation, interpretability, and discussion of practical challenges for clinical adoption. To address these shortcomings, the present paper proposes the use of pre-trained models and highlights the potential of TL to improve the detection of kidney diseases, offering enhanced performance and generalization with limited data and providing a pathway toward more reliable and efficient clinical implementations.

3. THE PROPOSED MODEL AND THE USED DATASET

The dataset used in this paper, titled “CT Kidney Dataset: Normal-Cyst-Tumor and Stone,” was collected from the picture archiving and communication system (PACS) of various hospitals in Dhaka, Bangladesh [16]. The patients included in this collection had already been diagnosed with kidney tumors, cysts, normal kidneys, or kidney stones (4 classes, see Figure 1).

The selected images include coronal and axial slices from both contrast-enhanced and non-contrast studies, following the protocol for the whole abdomen and urography. Figure 1 shows samples from each class in the dataset. The red markings represent the discovery area or the region of interest that a radiologist uses to draw conclusions for specific diagnostic classes.

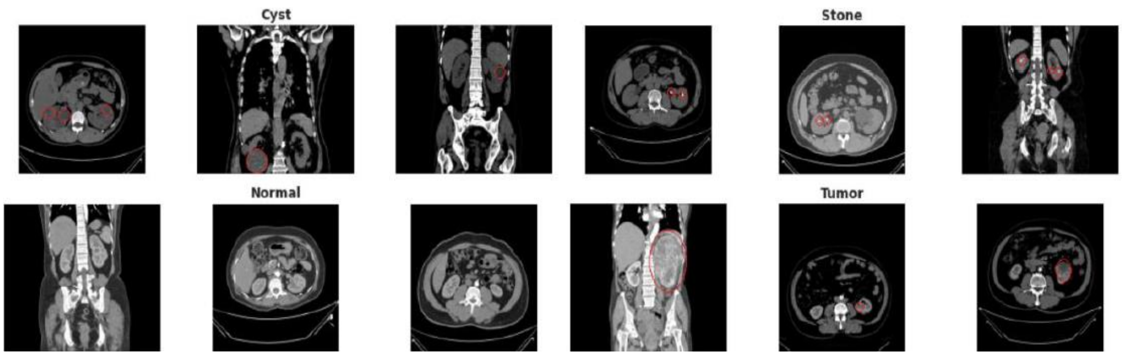

Figure 1. The used dataset [16]

Our dataset contains 12,446 entries divided into four classes, as shown in Table 1. After splitting the dataset, 80% of the images were used for training the model, while 20% were set aside for testing. Although the dataset is relatively small, the use of TL, along with the observations made in [17], supports our decision to forgo various data augmentation techniques. TL models (e.g., ResNet, VGG, Inception...) are pre-trained on large-scale datasets like ImageNet [18], allowing them to capture relevant features from the start.

Table 1. The used dataset

Classes				
Cyst	Normal	Stone	Tumor	Total
3709	5,077	1,377	2,283	12446

We opted for three pre-trained neural network architectures: ResNet18, AlexNet and InceptionV3, chosen specifically for their balance between resource efficiency, computational complexity, and parameter count. While deeper and more advanced models, such as ResNet101 [19] or enhanced Inception variants [20], offer higher performance potential, they also demand significantly greater GPU memory and computational resources during both training and inference.

To address this trade-off, our selection prioritizes a practical equilibrium between accuracy and resource utilization. In this work, we leverage TL [21] by employing deep learning models to identify kidney anomalies. These models are pre-trained CNNs, where TL is utilized to extract and fine-tune features for anomaly detection. Indeed, Figure 2 illustrates how TL enables the use of a pre-trained model on a similar task by reusing part of its layers (with “frozen” weights) for a new task, reducing the need for data and training time. AlexNet, ResNet18, and InceptionV3 are well-known pre-trained deep learning models that have demonstrated significant success in various image classification tasks, including medical image analysis.

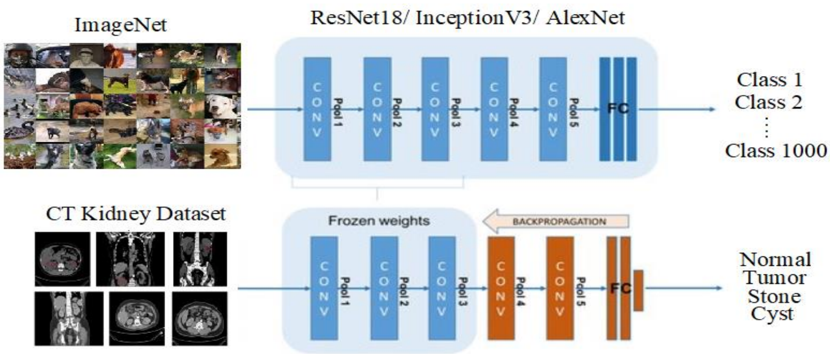

Figure 2. The proposed model

3.1. AlexNet

Introduced by [22], was one of the first deep CNNs to achieve groundbreaking performance in the ImageNet competition, revolutionizing computer vision. It consists of five convolutional layers and three fully connected layers, and its success lies in its ability to efficiently process large datasets, making it an excellent choice for medical image classification tasks such as detecting kidney abnormalities.

3.2. ResNet18

Introduced by [23], is a variant of the ResNet architecture known for its use of residual connections that help mitigate the vanishing gradient problem during training. These residual connections enable the model to learn deep-er features without the degradation problem that arises in very deep networks. Res-Net18 has been widely used in medical applications, showing robust performance in classifying diseases from medical imaging.

3.3. Inception V3

Proposed by [24], is known for its efficient use of computational resources, combining multiple convolutional filter sizes at each layer, and thus capturing features at different scales. InceptionV3 has achieved excellent performance in a variety of domains. By leveraging pre-trained models such as AlexNet, ResNet18, and InceptionV3, one can benefit from TL, which allows the use of these models for tasks involving limited training data, such as kidney disease detection, by fine-tuning them on specific datasets. The Table 2 summarizes the main characteristics of the three models used in this study. ResNet18 is the lightest and most compact, InceptionV3 offers a deeper structure with multi-scale filters, while AlexNet is the largest and most parameter-heavy. These differences illustrate the trade-off between model complexity, size, and computational efficiency.

Table 2. The obtained results

Feature	ResNet18	InceptionV3	AlexNet
Depth	18	48	8
Model size	44 MB	92 MB	240 MB
Number of parameters	11.7 M	23.9 M	60 M
Convolutional Filter Sizes	3*3, 7*7	1*1, 3*3, 5*5	11*11, 5*5, 3*3
Input image size	224*224	299*299	227*227

4. RESULTS, DISCUSSION, AND COMPARISON

TL has become a powerful technique in deep learning, particularly when working with limited data or computational resources. The key advantage of TL is that it allows models pre-trained on large, general datasets, such as ImageNet to be fine-tuned for more specific tasks, such as detecting diseases from medical images. By reusing knowledge gained from a broader domain, TL significantly reduces the need for extensive labeled data, which is often scarce in medical applications [25].

Moreover, it accelerates the training process, as the model has already learned low-level features (e.g., edges, textures) that are common to many images, requiring fewer iterations to adapt to the target task [26]. This approach has shown particularly beneficial results in medical image analysis, where high-quality labeled datasets are difficult and expensive to obtain [27].

Furthermore, TL can improve model generalization by leveraging the rich features learned from large datasets, making the model more robust to variations in input data and more effective in real-world clinical environments [28].

To evaluate the performance of our models, we used the following metrics:

$$Accuracy = TP + TN/\ TP + FN + TN + FP \quad (1)$$

$$Precision = TP/TP + FP \quad (2)$$

$$Recall = TP/TP + FN \quad (3)$$

$$F1 - score = 2\ * Precision\ * Recall/Precision + Recall \quad (4)$$

Where:
TP $(True\ Positive)$: Correctly predicted positive cases.
FP $(False\ Positive)$: Incorrectly predicted positive cases.
TN $(True\ Negative)$: Correctly predicted negative cases.
FN $(False\ Negative)$: Incorrectly predicted negative cases.

As mentioned in Table 3, the optimal parameter configuration for AlexNet, ResNet, and Inception V3 includes a learning rate of 0.001, a single training epoch, and a mini-batch size of 20. We explored several well-known optimizers as mentioned in [29], including stochastic gradient descent with momentum (SGDM), RMSProp, and Adam, to identify the one that delivers the best performance for our model.

While all three architectures achieved impressive performance with high accuracy (over than 98% for accuracy), ResNet18 demonstrated a clear superiority (99,8%). This enhanced performance can be attributed to its residual connections, which help address gradient degradation and improve deep layer learning. Compared to AlexNet, which is shallower and less complex, and Inception V3, which relies on computationally intensive modules, ResNet18 strikes an optimal balance between depth, computational efficiency, and generalization. Its lightweight design and effective gradient utilization give it a significant advantage in our classification task.

Table 3. The obtained results

Models	Hyper-parameters					Classification reports			
	Loss	Epochs	LR	LR	Optimizer	Accuracy	F1-score	Precision	Recall
ResNet 18	Binary	1	**0.001**	**0.001**	**SGDM**	**99,8%**	**99,70%**	**99,86%**	**99,55%**
	cross		0.001	0.001	Rmsprop	95,5%	95,13%	94,59%	95,67%
	entropy		0.001	0.001	Adam	96,7%	95,79%	95,30%	96,29%
Inception	Binary	1	**0.001**	**0.001**	**SGDM**	**99,0%**	**98,50%**	**98,20%**	**98,80%**
V3	cross		0.001	0.001	RmsProp	18,4%	25%	25%	25%
	entropy		0.001	0.001	Adam	53%	25%	25%	43,79%
Alexnet	Binary	1	**0.001**	**0.001**	**SGDM**	**98,5%**	**97,82%**	**98,87%**	**96,78%**
	cross		0.001	0.001	RmsProp	42,6%	25%	25%	26,55%
	entropy		0.001	0.001	Adam	29,8%	25%	25%	25%

This combination achieved an impressive classification accuracy of 99.8% (see the confusion matrix of Figure 3) for ResNet18, demonstrating rapid and efficient model convergence with precise weight adjustments for each data batch, while minimizing computation time and avoiding oscillations during training.

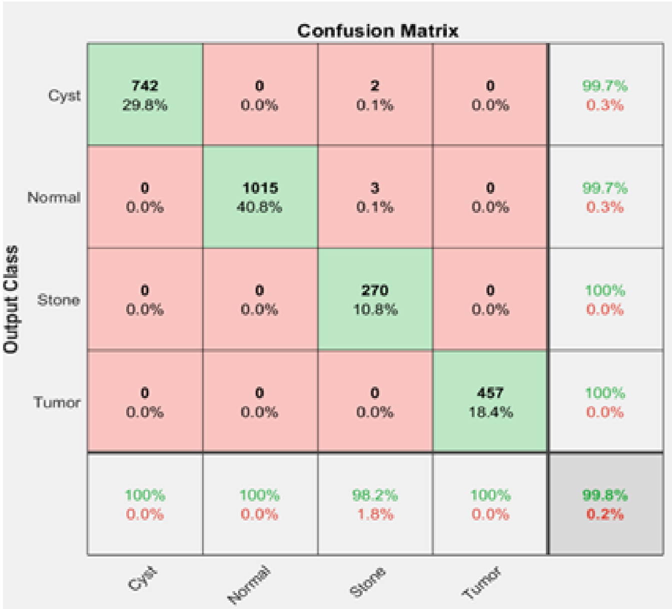

Figure 3. The confusion matrix of ResNet18

On the other hand, the results demonstrated the superiority of SGDM over the other approaches. Indeed, SGDM incorporates a momentum term that helps accelerate convergence by reducing oscillations in gradient descent, which is particularly beneficial for deep models. Unlike RMSProp, which dynamically adjusts the learning rate for each parameter but can sometimes stagnate in local minima, SGDM ensures a more stable progression toward the global optimum. Moreover, while Adam combines the advantages of Adagrad and RMSProp, it exhibited a tendency to generalize less effectively in our case, possibly due to its dynamic learning rate adjustments, making optimization less robust for certain architectures. Thus, SGDM proved to be the most effective choice, offering better stability and convergence while enhancing the model's generalization to new data.

For a fair comparison, we selected studies that used the same dataset. We observed that our ResNet18 model outperforms other models (Swin Transformer, VGG16, Custom CNN, and Digital Twin) in terms of accuracy. In addition to this superior performance, ResNet18 has the advantage of being less computationally expensive. Unlike Swin Transformer, which relies on attention mechanisms that are computationally intensive, or VGG16, whose depth results in higher memory consumption, ResNet18 offers an excellent balance between efficiency, training speed, and performance, making it a more suitable solution for resource-constrained environments. Table 4 provides an overview of the comparison.

Table 4. Comparison of our model with related work

Reference	Year	Used model	Accuracy
Islam *et al.* [16]	2022	Swin transformer	99.3%
		VGG16	98.2%
Bhandari *et al.* [30]	2023	Custom CNN	99.39%
Sasikaladeyi and Revathi [31]	2024	Digital-twin	99.71%
Our model	2025	ReseNet18	99.8%

5. CONCLUSION

AI through its advanced machine learning and deep learning techniques, plays a crucial role in the early diagnosis of diseases by enabling faster, more accurate, and cost-effective analyses. In particular, in the field of kidney dis-eases, AI offers significant potential to identify signs of renal decline at early stages, thereby improving the chances of effective treatment and reducing the risks of serious complications such as CKD. To fully harness this potential, researchers increasingly rely on pre-trained models that combine efficiency with state-of-the-art performance, bridging the gap between theoretical advancements in AI and their practical application in medical diagnostics.

The advantages of pre-trained models go far beyond their high accuracy. In addition to delivering exceptional performance, these models, thanks to TL, significantly reduce training time by leveraging knowledge acquired from extensive initial datasets. This approach allows for the transfer of learned features from one task to another, making it easier to adapt models to specific problems with minimal effort. This characteristic is particularly valuable in contexts where computational resources, such as processing power and annotated data, are limited. Furthermore, their ability to require less training data makes them an ideal solution for specialized fields like medicine or scientific research, where datasets are often expensive or difficult to obtain. By incorporating TL, these models not only optimize performance across various tasks but also capitalize on existing knowledge, thus making the learning process more efficient and faster.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This paper doesn’t talk about using people or animals.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [M.D], upon reasonable request.

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