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Advances in Kidney Disease Classification: Medical Imaging, Deep Learning, and Performance Comparison and Challenges

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Abstract

This study presents an overview of the progress of kidney disease classification using deep learning and medical imaging techniques. Given the increasing prevalence of kidney-related ailments such as chronic kidney disease (CKD), renal tumors, and nephrolithiasis, there is a critical need for accurate and automated diagnostic tools. This work systematically examines existing literature focusing on various deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid architectures applied to kidney disease classification. The study further explored the use of 3 datasets like the KiTS (Kidney Tumor Segmentation), the Chronic Kidney Disease Dataset from the UCI Machine Learning Repository, and the Kidney Lesion Image Collection from The Cancer Imaging Archive. The review explores into the preprocessing techniques, model architectures, and evaluation metrics used across different studies, highlighting the advances in image segmentation, feature extraction, and classification accuracy. Key challenges, such as the heterogeneity of kidney diseases, the need for good and generalizable models, and the impact of limited labeled datasets, are highlighted. The review concludes by presenting Performance Analysis of Deep Learning models in recent years, emphasizing the significance of deep learning in enhancing kidney disease diagnosis, achieving high accuracy rates in the classification of complex kidney conditions, and ultimately improving patient outcomes.

1. Introduction

Medical imaging has fundamentally transformed the landscape of healthcare, offering non-invasive techniques for diagnosing, monitoring, and guiding the treatment of a wide array of diseases. Technologies such as Magnetic Resonance Imaging (MRI) [1] [2], Computed Tomography (CT) [3][4], Ultrasound [5], X-rays [6], and Positron Emission Tomography (PET) [7] [8] have become indispensable tools in clinical practice. They provide detailed anatomical and functional insights that enable healthcare professionals to detect abnormalities, and track disease progression. In the current era, integrating artificial intelligence (AI) and deep learning (DL) into medical imaging has opened new avenues for automated and accurate classification of diseases. This integration holds significant promise, particularly for conditions that benefit from early detection and classification, such as kidney diseases.

Medical imaging is playing an important role in the classification of numerous diseases, ranging from cardiovascular and neurological disorders to pulmonary diseases and cancers. For example, in oncology, imaging modalities like CT and MRI are widely used for tumor detection, characterization, and staging, helping to distinguish between benign and malignant lesions. In the field of neurology, MRI scans are instrumental in identifying and classifying conditions such as Alzheimer's disease, brain tumors, and multiple sclerosis by capturing subtle changes in brain structures [9]. In cardiology, echocardiography and CT angiography are utilized to classify cardiovascular diseases by evaluating the morphology and functionality of the heart and blood vessels. Pulmonary diseases, including pneumonia, tuberculosis, and chronic obstructive pulmonary disease (COPD), are often diagnosed and classified using chest X-rays and CT scans, which reveal characteristic patterns and abnormalities within the lungs. Beyond these areas, medical imaging is also crucial in dermatology, where dermoscopic images help classify skin lesions and melanoma, and in ophthalmology, where retinal imaging aids in the diagnosis and classification of diabetic retinopathy and age-related macular degeneration.

In nephrology, medical imaging is increasingly recognized as a valuable tool for the diagnosis and classification of kidney diseases, particularly Chronic Kidney Disease (CKD). CKD represents a significant global health challenge, often leading to end-stage renal failure if not detected and managed early. Traditional diagnostic methods for kidney diseases involve a combination of laboratory tests, clinical evaluations, and histopathological analysis of kidney biopsies. However, these methods come with limitations. They are often invasive, subject to inter-observer variability, and may not fully capture the complex morphological changes associated with different kidney pathologies. Medical imaging offers a non-invasive alternative, providing visual insights into kidney structure and function that can aid in early disease detection and classification. Ultrasound is commonly used to assess kidney size, structure, and the presence of cysts or tumors. CT and MRI offer detailed cross-sectional images that help detect structural abnormalities, renal masses, and vascular changes. Additionally, functional imaging techniques like nuclear medicine scans can evaluate renal perfusion, filtration, and overall function.

Despite the utility of medical imaging in nephrology, the interpretation of these images requires significant expertise and is often subjective, leading to variability in diagnostic outcomes. This is where deep learning, a subset of AI and machine learning, has begun to make a transformative impact. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in analyzing medical images and classifying various diseases with high accuracy. CNNs are uniquely suited for medical imaging tasks as they can learn hierarchical features directly from raw imaging data without the need for manual feature engineering. This capability is particularly advantageous for complex imaging modalities like CT and MRI, where intricate patterns and subtle changes must be detected to differentiate between normal and pathological states.

In the domain of kidney disease classification, deep learning algorithms have demonstrated potential in automating the examination of medical images, thereby reducing the reliance on human expertise and minimizing inter-observer variability [10]. For example, CNNs have been applied to ultrasound images to classify kidney abnormalities, such as differentiating between normal kidneys, CKD, and renal cysts. Additionally, deep learning models have been utilized to analyze CT and MRI images for the classification of renal tumors, kidney stones, and vascular pathologies. These models have demonstrated the ability to identify clear patterns and morphological changes that may indicate various stages or types of kidney diseases, thereby facilitating early detection and accurate classification. This capability is particularly crucial in CKD, where early diagnosis can significantly impact patient outcomes by enabling timely therapeutic interventions.

Recent advancements in deep learning have further enhanced its application in medical imaging for kidney disease classification. Sophisticated architectures such as U-Net for image segmentation, ResNet for improved feature extraction, and transfer learning techniques that leverage pre-trained models have all contributed to higher classification performance. Multi-modal deep learning approaches, which combine imaging data with clinical and genetic information, are also being explored to provide a more comprehensive understanding of kidney diseases. Despite these advancements, several challenges persist. Kidney diseases exhibit considerable heterogeneity, and variations in imaging protocols across different healthcare settings can affect the generalizability of deep learning models. Moreover, the limited availability of large, annotated datasets poses a significant challenge for training robust models. Another concern is the DL model's nature, which raises issues related to interpretability and reliability in clinical decision-making.

To overcome these challenges, continuous research and innovation are required. Research is underway to create explainable AI models that provide insight into how deep learning systems make decisions. Incorporating domain knowledge into model design and utilizing federated learning to harness distributed datasets while preserving patient privacy are other promising avenues. Kidney disease classification is uniquely poised to benefit from these integrative, multi-omics approaches. In routine clinical care, kidney biopsies, blood, and urine samples are frequently collected, providing ample data for generating molecular insights. By integrating this data with imaging findings using deep learning models, it is possible to reclassify patients into molecularly defined subgroups that better reflect the underlying disease mechanisms.

The integration of medical imaging and deep learning models presents a good approach to the classification of kidney diseases. By automating the analysis of medical images and identifying disease-specific patterns, these technologies can enhance diagnostic accuracy, support early intervention, and ultimately improve patient outcomes. As research continues to address current challenges, Nephrology patients may receive more personalised and accurate care in the future due to the potential of deep learning to transform kidney disease detection and classification.

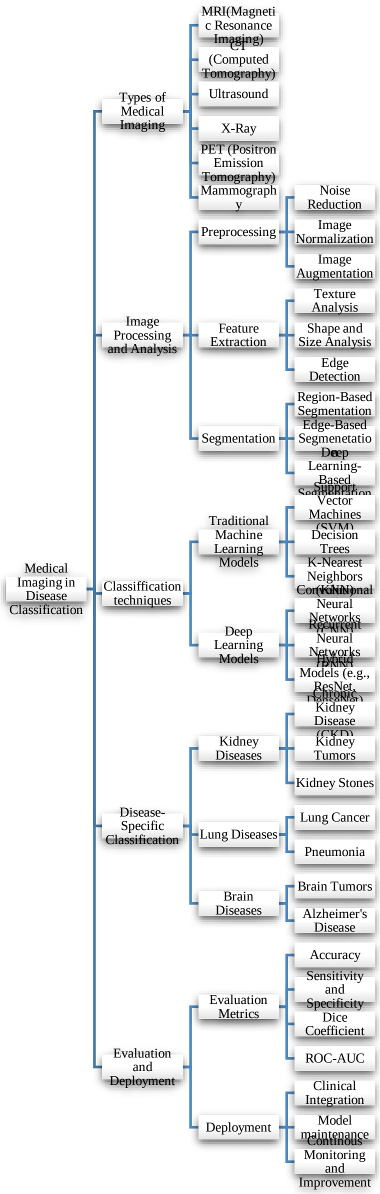

Figure 1. Medical Imaging in Disease Classification

1.1. Medical Imaging in Disease Classification

Medical imaging is pivotal in classifying various diseases, ranging from cardiovascular disorders, neurological conditions, pulmonary diseases, and cancers to renal pathologies [11]. For instance, in oncology, medical images like CT and MRI scans are extensively used to detect and classify tumors, and distinguish between benign and malignant growths, and stage cancer. In neurology, MRI scans are used to identify and classify conditions such as Alzheimer's disease, brain tumors, and multiple sclerosis by analyzing changes in brain structures. Similarly, in cardiology, echocardiography and CT angiography are utilized for classifying cardiovascular diseases by assessing the structure and function of the heart and blood vessels.

In the context of pulmonary diseases, chest X-rays and CT scans are widely used for the classification of conditions such as pneumonia, tuberculosis, and chronic obstructive pulmonary disease (COPD). These imaging modalities aid in identifying characteristic patterns within the lungs, facilitating early diagnosis and treatment planning. The application of medical imaging extends to various other fields, such as dermatology, where dermoscopic images are used to classify skin lesions and melanoma, and ophthalmology, where retinal imaging is employed to diagnose and classify diabetic retinopathy and age-related macular degeneration.

1.2. Kidney Disease and Medical Imaging

Kidney diseases, particularly CKD, pose a significant global health burden [12]. Early and accurate classification of kidney diseases is necessary for starting adequate therapeutic interventions and stopping the disease from progression to end-stage renal failure. Traditional methods for diagnosing and classifying kidney diseases involve laboratory tests, clinical evaluation, and histopathological analysis of kidney biopsies. However, these methods often have limitations, such as invasiveness, variability in interpretation, and limited capability to capture the complex morphological changes associated with kidney pathologies.

Medical imaging offers a non-invasive alternative for kidney disease diagnosis and classification. Ultrasound is commonly used for assessing kidney size, structure, and the presence of cysts or tumors. CT and MRI provide detailed cross-sectional images of the kidneys, enabling the detection of structural abnormalities, renal masses, and vascular changes. Functional imaging, such as nuclear medicine techniques, can assess renal perfusion, filtration, and function. However, interpreting these images requires considerable expertise and is often subjective, leading to variability in diagnostic accuracy.

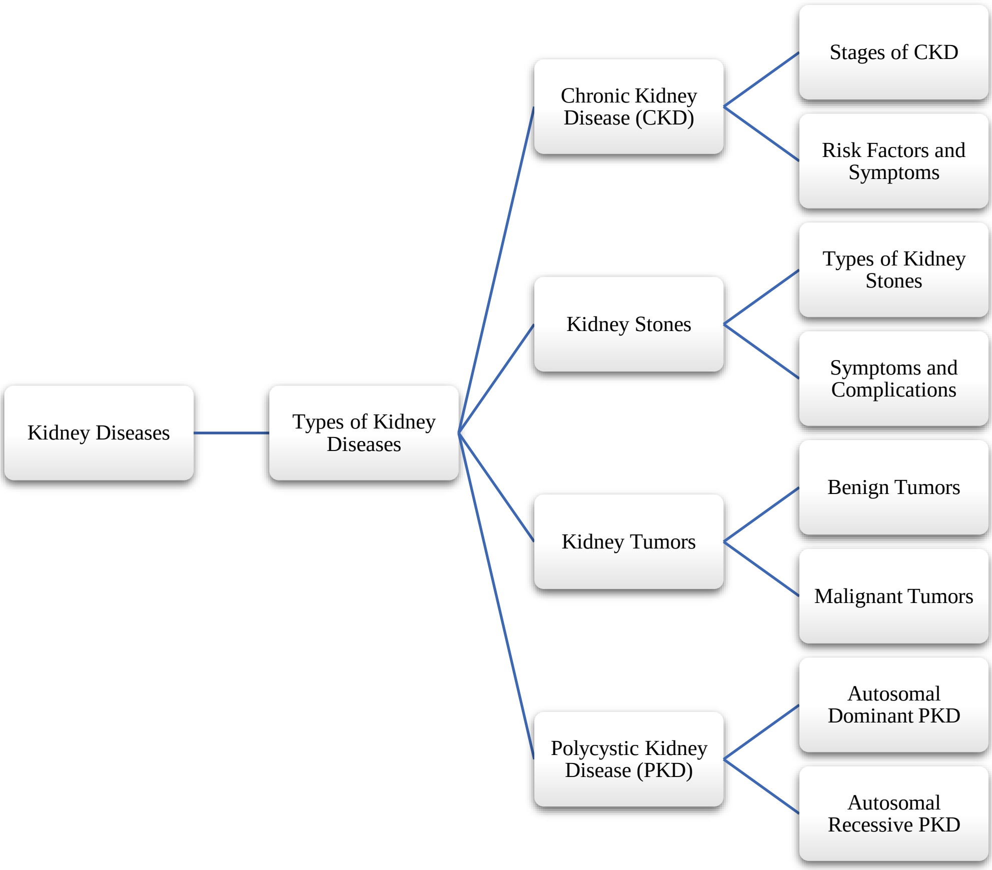

Figure 2. Types of Kidney Diseases

1.3. The Role of Deep Learning in Kidney Disease Classification

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Medical imaging analysis has proven excellent applications for deep learning, an area of AI and machine learning. A type of deep learning model called Convolutional Neural Networks (CNNs) was developed primarily for image processing, and it has shown exceptional performance in automatically extracting information from medical pictures and accurately classifying a wide range of ailments. Innovations in banking, retail, healthcare, and other industries have all improved through deep learning [13]. CNNs are especially well-suited for difficult medical imaging applications because, in contrast to standard image processing techniques, they can learn hierarchical features directly from basic image information without the requirement for human feature engineering.

In kidney disease classification, deep learning models have shown promise in automating the analysis of medical images, thereby reducing the dependence on human expertise and minimizing variability in diagnosis. For instance, CNNs have been applied to ultrasound images to classify kidney abnormalities, such as distinguishing between normal kidneys, CKD, and renal cysts. Similarly, deep learning models have been used to analyze CT and MRI images for the classification of renal tumors, kidney stones, and vascular pathologies. These models can identify subtle patterns and morphological changes that may be indicative of different stages or types of kidney diseases, enhancing the early detection and accurate classification of renal pathologies.

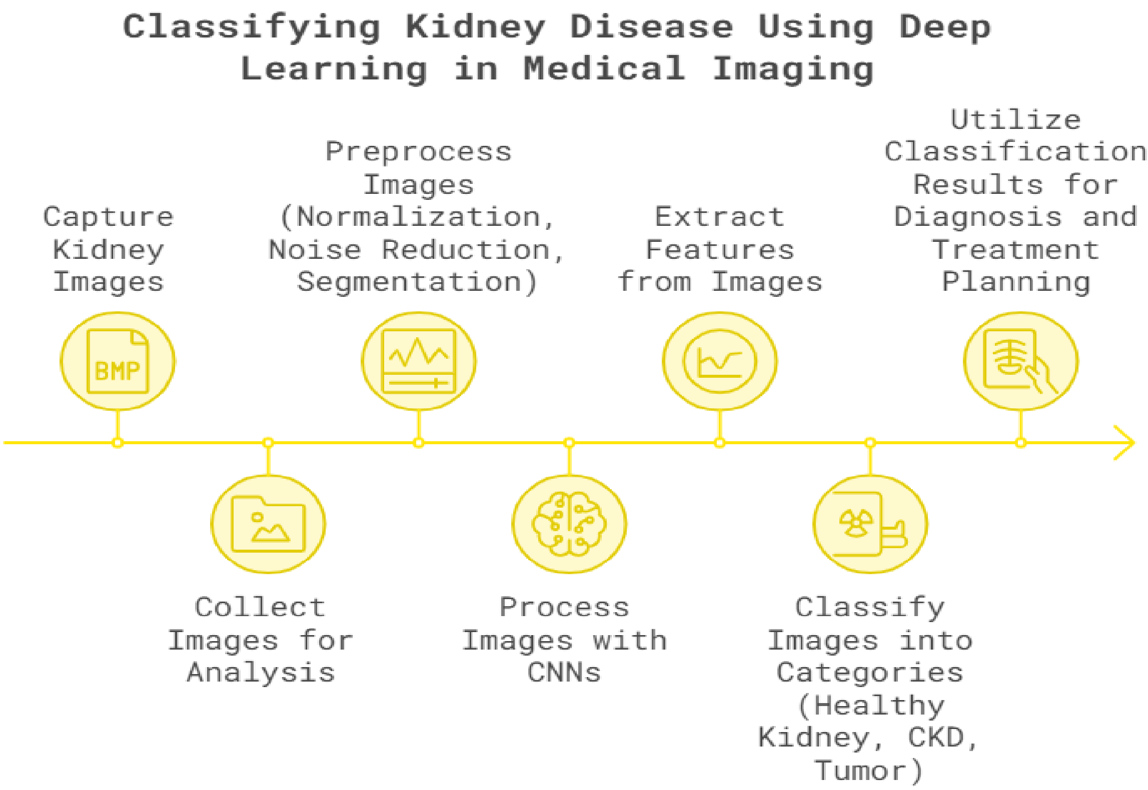


Figure 3. Flow of Kidney Disease Classification in Deep Learning

CKD is classified into different stages based on the Glomerular Filtration Rate (GFR), a key indicator of kidney function. Patients can be categorized as "at increased risk for CKD" when they have a GFR of 90 mL/min or higher along with certain risk factors, such as diabetes or hypertension, but without evident kidney damage. The first stage of CKD involves kidney damage with a normal or increased GFR of 90 mL/min or more, indicating that the kidneys are still functioning well despite some signs of damage. In the second stage, there is a mild decrease in GFR, ranging from 60 to 89 mL/min, suggesting a reduction in kidney function. Stage three is characterized by a moderate decrease in GFR, with values between 30 and 59 mL/min, indicating more significant impairment of kidney function. By the fourth stage, the GFR drops further to between 15 and 29 mL/min, reflecting a severe decline in kidney performance. Identifying and monitoring these stages is crucial for early intervention and management of CKD to prevent progression to kidney failure [14].

2. Literature Survey

The literature survey section focuses exclusively on research papers that explore medical imaging techniques related to kidney diseases. This includes a review of various studies that have utilized medical imaging modalities like ultrasound, CT scans, MRI, and others for the diagnosis, classification, and treatment planning of kidney-related conditions. The survey encompasses papers that discuss the application of advanced image processing and deep learning algorithms in kidney disease classification, such as differentiating between CKD stages, detecting kidney stones, and identifying renal tumors. The survey aims to provide insight into the recent advanced techniques, their effectiveness, and potential areas for future exploration in the domain of kidney disease diagnosis and management using medical imaging.

Almustafa [15] built a useful technique for CKD early diagnosis by using a CKD dataset and various kinds of classification algorithms. Random Tree, Decision Tree (DT), K-Nearest Neighbour (K-NN), J48 (a decision tree technique), Stochastic Gradient Descent (SGD), and Naïve Bayes were among the classifiers they used. The authors proposed a feature selection-based methodology to enhance classification performance by finding the most significant characteristics for diagnosing CKD, hence increasing the efficiency of CKD prediction. The experimental findings showed that the J48 and Decision Table classifiers performed the best, obtaining 99% accuracies with ROC values of 0.999 and 0.992, Mean Absolute Errors (MAEs) of 0.0225 and 0.1815, and Root Mean Square Errors (RMSEs) of 0.0807 and 0.2507, respectively. To evaluate the effect of parameter modifications on classifier performance, sensitivity analysis was carried out. Feature selection techniques were applied, and the results showed that choosing the most relevant characteristics was essential as the Naïve Bayes and Decision Tree classifiers' classification accuracy increased to 99.75%, 98.25%, and 99.25%.

Eddy et al [16] highlighted the challenges and limitations of current CKD classification methods, which are primarily based on clinical features, associated comorbidities, and biopsy results. These traditional classifications often fail to account for the significant variation in disease presentation, progression, and response to treatment among patients, indicating heterogeneity in the underlying biological mechanisms of CKD. To address this issue, the authors proposed using technological advances that enable the collection and analysis of large-scale datasets, including DNA and RNA sequencing, proteomics, and metabolomics data, from patients along the genotype-phenotype continuum of CKD. By integrating these high-dimensional datasets through computational approaches such as machine learning, the authors aim to re-classify patients into molecularly defined subgroups that more accurately reflect the underlying disease mechanisms. This molecular reclassification could provide a more precise framework for diagnosis, risk stratification, and the development of targeted disease-specific therapies. Since kidney biopsies, blood, and urine samples, which are essential for generating molecular data, are commonly obtained during routine clinical care, CKD patients are particularly well-suited for these integrative, multi-omics approaches. The ultimate goal of this integrated molecular classification is to enhance patient care by improving diagnostic accuracy, enabling better risk projection, and informing the selection of personalized treatments.

Poonia et al [17] developed a precise prediction model for renal illness early detection. They examined a dataset of healthy and renal disease patients that was made available to the public using machine learning techniques. They conducted experiments using a variety of methods, including naive Bayes, support vector machines, artificial neural networks, and k-nearest neighbours. They used strategies like Chi-Square testing and Recursive Feature Elimination to choose the most pertinent characteristics for the prediction model. They discovered through the study that the model with the best accuracy, 98.75%, was a logistic regression-based model with features chosen using the Chi-Square test. The model was shown to have several important characteristics, such as the following: White blood cell count, blood glucose random, blood urea, serum creatinine, packed cell volume, albumin, haemoglobin, age, sugar, blood pressure, hypertension, and diabetes mellitus.

Aswathy et al [18] proposed a novel IoT and cloud-based model for diagnosing CKD. Their model, called FPA-DNN, uses IoT devices to collect patient health data, preprocesses the data, applies Oppositional Crow Search for feature selection, and utilizes the Flower Pollination Algorithm to tune the parameters of a Deep Neural Network for classification. The model was evaluated on a benchmark CKD dataset and achieved superior performance compared to other methods, demonstrating high sensitivity, specificity, accuracy, F-score, and kappa values.

Kim, Dong-Hyun, and Soo-Young Ye [19] Investigated the potential of ultrasound image analysis to diagnose chronic kidney disease (CKD) at different stages. They extracted 58 parameters from ultrasound images using the GLCM algorithm, including information on kidney size and internal echo characteristics. These parameters were then used to train an artificial neural network (ANN) model to classify CKD severity. The results showed that the ANN model achieved a classification rate of 95.4%, showing reliability for diagnosing CKD based on ultrasound images.

Khamparia et al [20] proposed a novel deep-learning framework for early-stage detection of CKD using multimedia data. Their model, based on a stacked autoencoder and softmax classifier, extracted useful features from a dataset of 400 CKD patients and achieved a classification accuracy of 100%. This outperformed conventional machine learning models, showing the capability of their approach for improving the diagnosis and treatment of CKD.

Jerlin and Eswaran [21] introduced an innovative approach that uses the fruit fly optimisation algorithm (FFOA) to optimise a multi-kernel support vector machine (MKSVM) for the classification of CKD. The medical dataset's optimum characteristics were chosen using FFOA, processed, and supplied into the MKSVM for classification. The proposed method was assessed using four benchmark CKD datasets, and it outperformed other approaches in terms of classification precision, indicating that it is efficient in diagnosing CKD.

Mohammed and Dana. [22] developed a unique AI-based method for renal disease diagnosis that combines a Random Forest classifier with a pre-trained Densenet-201 model for feature extraction. Their approach outperformed earlier models with an accuracy rate of 99.719% after being trained on a dataset of 12,446 CT urogram and total abdominal images. This work has implications for enhancing healthcare outcomes and advances the development of AI-based systems for renal disease diagnostics.

Abdullah et al [23] carried out an extensive study to create a machine-learning model for the precise and early identification of chronic kidney disease. They started by studying several feature selection methods, such as forward selection, backward selection, forward exhaustive selection, Random Forest feature selection, and forward selection. By utilising these methods to extract the most important features from the dataset, the model's efficiency was increased and its computational complexity was minimised. The authors used several types of machine learning classifiers, including Random Forest, Linear and Radial SVM, Naïve Bayes, and Logistic Regression, after deciding on the best features. In order to identify patterns and relationships between the chosen characteristics and the existence or absence of CKD, these classifiers were trained on the preprocessed dataset. Each machine learning model's performance was assessed using measures including AUC score, sensitivity, specificity, and accuracy. These metrics offer a thorough evaluation of the model's capacity to accurately categorise patients with CKD and separate them from healthy ones. The results of the research showed that the Random Forest classifier when combined with Random Forest feature selection, performed best overall across all assessment measures. This combination performed better than other classifiers, showing that it is an effective option for CKD early detection. The model can accurately detect patients with CKD, even in the early stages, due to its excellent Performance.

Singh et al [24] presented a deep learning model to predict and identify CKD early. When they evaluated the performance of their model with other machine learning methods, they showed that the deep neural network yielded 100% accurate results. This implies that nephrologists may find the proposed approach useful in the diagnosis of chronic kidney disease. Haemoglobin, specific gravity, serum creatinine, red blood cell count, albumin, packed cell volume, and hypertension were the main characteristics of the model that were found.

Alshakrani et al [25] studied the prediction of CKD using machine learning techniques. Gaussian Naive Bayes, Decision Tree, K-Nearest Neighbour, Random Forest, Logistic Regression, AdaBoost, and Gradient Boosting were among the seven methods they examined. The results indicated that Gaussian Naive Bayes and Random Forest had the best accuracy of 100%, indicating that these techniques could be useful for CKD early detection and prediction. This work advances the creation of AI-based strategies to enhance renal function and lessen the impact of chronic kidney disease.

Gudeti et al [26] undertook research to examine the performance of several machine learning algorithms for predicting CKD in India. They analysed a dataset of patients with and without CKD using an R-based methodology. Finding the best machine learning method to classify cases of CKD was the aim. This study advances the creation of AI-based tools for the early diagnosis and treatment of CKD, a serious public health concern in India.

Singh and Divya [27] presented a unique hybrid method for CKD diagnosis that uses an SVM classifier that has been optimised using a hybridised dimensionality reduction methodology. The method consists of two steps: Principal Component Analysis (PCA) is used for feature extraction, and ReliefF is used for filter-based feature selection. Outperforming previous techniques, the authors' model attained an optimal prediction accuracy of 92.5% on a clinical CKD dataset and 98.5% on a benchmark CKD dataset. Additionally, the Friedman test is used to validate the proposed approach, and statistical significance is obtained.

Salau et al [28] carried out research utilising an imbalanced data set to examine the effect of resampling methods on the identification of CKD. A comparison was made between the effectiveness of several classification methods, such as decision tree, random forest, K-nearest neighbour, adaptive boosting, and support vector machine, and the synthetic minority oversampling and near-miss undersampling approaches. It was demonstrated by the results that the optimal class distribution is reliant upon several parameters, such as dataset features, performance measures, and the classification method.

Patil and Savita [29] presented a unique ultrasound-based CKD detection methodology. The model consists of phases for feature extraction, segmentation, classification, and pre-processing. Pre-processing and segmentation are carried out using enhanced Gaussian filtering and watershed-based segmentation. Extracted features include projected Local Vector Pattern, ROI, and mean intensity. The classification process then employs an optimised neural network and long short-term memory, with weights modified by self-updated cat swarm optimisation. Averaging the outcomes from both classifiers yields the final output. The authors demonstrate that the proposed framework outperforms existing techniques for detecting CKD.

Rahman et al [30] Developed a precise framework for identifying CKD using machine learning approaches. To address missing values and class imbalance, they preprocessed the data using MICE imputation and borderline SVMSMOTE. They also employed ensemble learning techniques, such as LightGBM. The most important features were chosen using the boruta technique and recursive feature removal, and the classifiers' performance was then maximised by hyperparameter adjustment. When compared to other approaches, the proposed approach had an overall average accuracy of 99.75%, indicating that it is effective in CKD detection.

Sahab Uddin et al [31] presented a deep learning framework called "KidneyMultiNet" for predicting kidney disease based on kidney CT scan images. KidneyMultiNet combines two pre-trained convolutional neural networks, Densenet201 and Xception, using transfer learning. The model was trained and tested on a publicly available kidney CT scan dataset and achieved a maximum performance of 99.92% in predicting kidney disease. This suggests that KidneyMultiNet is a promising tool for accurate diagnosis of kidney disease.

3. Deep Learning Models used in Kidney Disease Classification

This section presents some Deep-learning models used for kidney disease classification. These models are employed to automatically analyze medical images, detect abnormalities, and classify kidney-related conditions. Their ability to learn complex patterns from large datasets allows for accurate segmentation of kidney lesions, tumors, and other anomalies. By using pre-trained models and transfer learning, researchers enhance performance, often achieving classification accuracies of more than 90%.

3.1. DenseNet201 model

This study focused on classifying kidney diseases using machine learning and deep learning models. The objective was to differentiate between various kidney-related conditions, including CKD stages, polycystic kidney disease (PKD) [32], kidney stones, renal tumors, and transplant rejection. Emphasized the importance of accurately classifying kidney diseases to improve diagnosis, treatment planning, and the overall quality of life for patients.

The methodology included training models on labeled datasets of kidney images and patient data to identify and categorize these conditions. Specifically, the study targeted classifying kidney tumors into different subtypes like renal cell carcinoma (RCC) [33], angiomyolipoma (AML) [34], and oncocytoma [35], which is crucial for determining appropriate treatment strategies.

For kidney disease classification, a deep learning approach, particularly focusing on X-ray classification. They employed the DenseNet201 model [36] shown in Figure 4, a deep convolutional neural network known for its ability to learn complex features from medical images. The model was trained on kidney X-ray images to detect and classify various kidney diseases automatically. The study's results demonstrated a high classification accuracy, with the DenseNet201 model achieving a 97% accuracy rate in diagnosing kidney diseases.

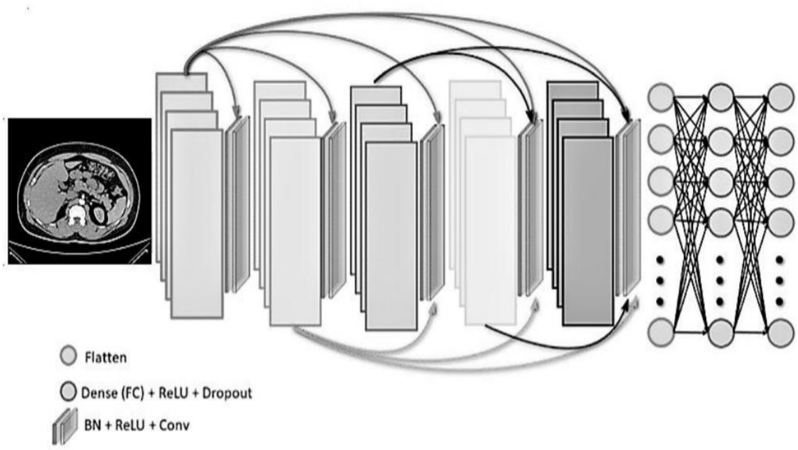
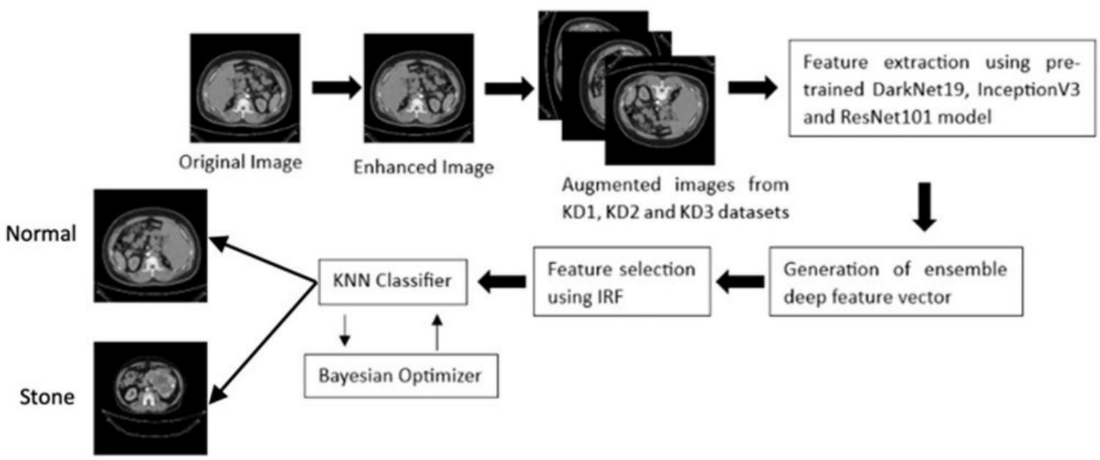


Figure 4. DenseNet201 Model Architecture [37]

3.2. FINDWELL

an automated method for detecting kidney stones using CT images was developed. Recognizing the importance of early detection, especially since kidney stones can often be asymptomatic, utilized an inductive transfer-based ensemble Deep Neural Network (DNN) to analyze the CT images as shown in Figure 5. The methodology involved creating three different datasets from the CT kidney images for feature extraction using pre-trained DNN models. Assembled an ensemble of several pre-trained networks, including DarkNet19 [38], InceptionV3 [39], and ResNet101 [40], to extract deep features from the images. By using feature concatenation, they created a comprehensive deep feature vector that captures the essential characteristics of the kidney images.

Figure 5. Block Diagram of FINDWELL model [41]



To further refine the feature set, an Iterative ReliefF feature selection method was employed, which identifies the most informative features in the ensemble deep feature vector. These selected features were then fed into a KNN classifier [42], which was optimized using a Bayesian optimizer [43]. The classifier's performance was evaluated using a 10-fold cross-validation approach, enhancing the model's reliability in detecting kidney stones. The results were impressive, with the proposed method achieving 99.8% accuracy on high-quality image datasets and 96.7% on noisy image datasets. These results outperformed other DNN-based and traditional image detection approaches, highlighting the method's robustness and effectiveness. By providing an automated approach to detect kidney stones, this method can assist urologists in confirming their diagnoses and reducing the risk of human error.

3.3. VGG16 model

Developed an automated system for detecting kidney stones using deep learning models, specifically focusing on CT image datasets. Experimented with various deep learning architectures to identify the most efficient model for kidney stone detection. Among the models tested, the VGG series, particularly the VGG16 architecture [44], demonstrated the highest accuracy, achieving 99% in classifying the presence of kidney stones. To ensure the robustness of the model, a stratified K-fold cross-validation was employed, a technique that divides the dataset into multiple folds to validate the model's performance comprehensively. In addition to detecting kidney stones, also used Gradient-weighted Class Activation Mapping (Grad-CAM) to identify the exact area of the kidney stone within the CT images. Grad-CAM helps visualize which regions in the image contributed most to the model's decision, providing a heatmap to indicate the areas of interest. This two-step process involved first classifying the CT images using the VGG16 model and then using Grad-CAM to highlight the kidney stone's location. The final step involved a domain expert verifying the results to ensure the system's accuracy and reliability as shown in Figure 6. This methodology not only achieved high accuracy in kidney stone detection but also provided an interpretable mechanism for locating the stones, assisting healthcare professionals in making informed decisions.

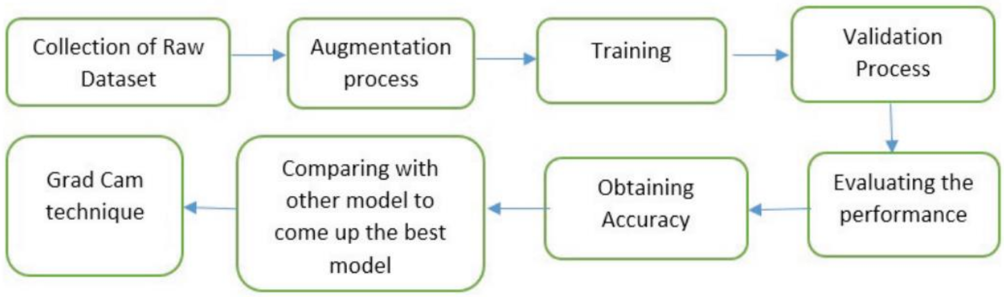


Figure 6. Block diagram of [45]

3.4. DeepLabv3+ 2.5D model

A significant challenge of kidney tumor segmentation in medical imaging was tackled, which plays a critical role in diagnosing and planning treatment for kidney cancer, a major public health concern. The task of accurately segmenting kidney tumors is complex due to the heterogeneous nature of these tumors. Manual segmentation by specialists is not only time-consuming but also prone to variability. While convolutional neural networks (CNNs) have emerged as powerful tools for automatic medical image segmentation, they come with their own set of challenges. Three-dimensional (3D) CNNs, though effective in capturing the spatial features of medical images, are computationally expensive and resource-intensive. On the other hand, two-dimensional (2D) networks are more memory-efficient but fall short in leveraging the full 3D context of the images. To address these issues, the authors proposed a novel 2.5D network that strikes a balance between memory consumption and model complexity. The 2.5D approach aims to incorporate some of the 3D contextual information while maintaining the lower computational cost of 2D networks. This method is designed to assist radiologists in diagnosing kidney tumors more efficiently, particularly in computed tomography (CT) imaging. The proposed method consists of three major steps: (1) preprocessing of the KiTS19 dataset to prepare the images for analysis, (2) initial segmentation using the DeepLabv3+ 2.5D model with a DPN-131 encoder, and (3) reduction of false positives through image processing techniques. It was evaluated on 210 CT scans from the KiTS19 dataset [46], which is a widely recognized dataset for kidney tumor segmentation. The method demonstrated impressive performance, achieving an accuracy of 99.71%, sensitivity of 84.24%, and specificity of 99.82%. It also achieved a Dice coefficient of 85.17% and a Jaccard index of 75.62%, which are metrics commonly used to measure the overlap between the predicted segmentation and the ground truth. Additionally, the method showed a Hausdorff distance of 18.39 mm and an average surface distance of 3.36 mm, indicating a precise delineation of tumor boundaries. These results are noteworthy as they suggest that the 2.5D network can provide segmentation results comparable to those of high-performance 3D networks but with reduced computational demands.

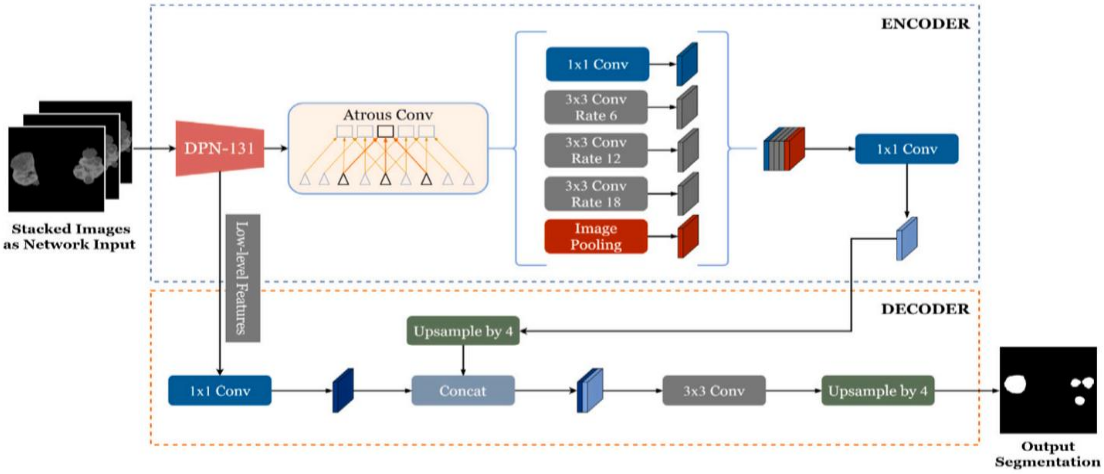


Figure 7. Architecture of DeepLabv3+ 2.5D model [47]

3.5. Hybrid V-Net-Based Model

This model addressed the challenge of kidney tumor segmentation in medical imaging, particularly for soft tissue organs like the kidneys. Kidney tumors are more prevalent in older individuals, making accurate diagnosis crucial in later stages of life. While medical imaging combined with deep learning has shown promise in this area, successful segmentation of soft tissues remains challenging due to their complex nature. To tackle this, the authors proposed a novel hybrid model based on V-Net, a deep learning architecture commonly used for segmentation tasks. The proposed hybrid V-Net model builds on the strengths of existing V-Net models while introducing

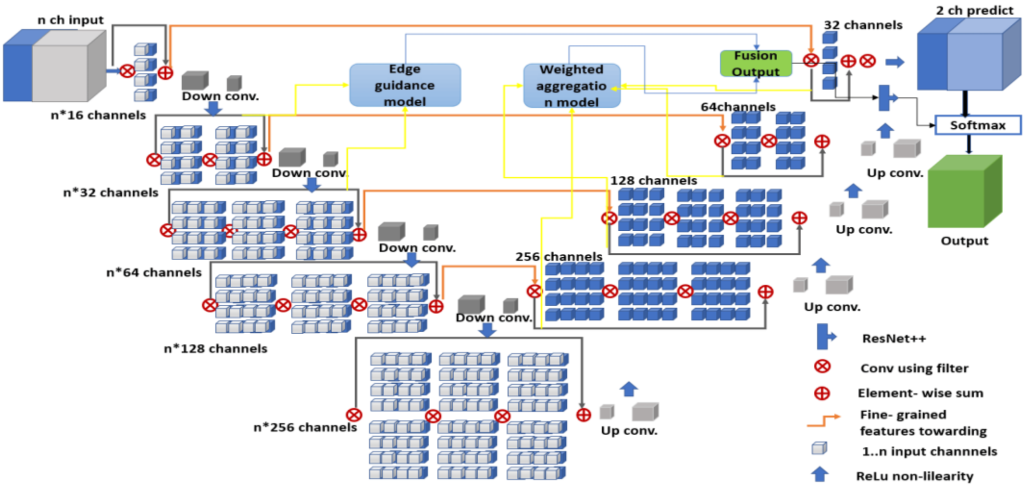


Figure 8. Architecture of Hybrid V-Net-Based Model [47]

enhancements in both the encoder and decoder phases. These improvements were designed to address the difficulties associated with segmenting soft tissue organs, which have proven challenging for many existing systems. By refining the V-Net architecture, the authors aimed to create a more effective segmentation tool that can aid physicians, particularly in accurately identifying and delineating kidney tumors.

The key achievement of the authors was the development of this enhanced V-Net model, which demonstrated superior performance in kidney and tumor segmentation tasks. They reported that their hybrid V-Net model achieved an average Dice coefficient of 97.7% for kidney segmentation and 86.5% for tumor segmentation. The Dice coefficient is a standard metric for evaluating the accuracy of image segmentation, and these high scores indicate a significant improvement over existing imaging models.

4. Datasets for kidney Disease Classification

In this section, we explored into three datasets frequently employed for kidney disease classification in medical imaging research. These datasets are essential resources that provide a wealth of labeled images and associated metadata, enabling the training and evaluation of machine learning and deep learning models specifically for kidney disease detection and classification. The selected datasets include, KiTS (Kidney Tumor Segmentation) Dataset [46], **Chronic Kidney Disease Dataset (UCI Machine Learning Repository) [49] and Kidney Lesion Image Collection (The Cancer Imaging Archive - TCIA) [50]. They** offer a variety of image modalities and diagnostic contexts, covering aspects such as kidney tumor segmentation, chronic kidney disease (CKD) staging, and lesion characterization. By focusing on these datasets, we aim to highlight their composition, structure, and unique features that make them valuable for advancing kidney disease research.

4.1. KiTS (Kidney Tumor Segmentation) Dataset

The KiTS (Kidney Tumor Segmentation) Dataset is a comprehensive collection of medical imaging data specifically curated for the task of kidney tumor segmentation. It has been widely used in research to develop and evaluate algorithms for detecting and segmenting kidney tumors, particularly in computed tomography (CT) scans. The dataset is recognized for its contribution to the development of automated tools for kidney cancer diagnosis and treatment planning. Here is a detailed explanation of the dataset and its components:

The KiTS (Kidney Tumor Segmentation) dataset is a widely used resource in medical imaging research, designed to advance kidney tumor segmentation techniques. It comprises high-resolution computed tomography (CT) scans from 210 patients, with detailed 3D annotations distinguishing between kidney and tumor regions. The dataset is organized into a structured format, with raw CT images in DICOM format and corresponding segmentation masks provided in NIfTI format. This structure facilitates easy usage for training and evaluating deep learning models. Researchers can access the dataset publicly for non-commercial research purposes via the official KiTS challenge website, enabling broad application in segmentation tasks. The dataset has been instrumental in various applications, including benchmarking segmentation algorithms and training convolutional neural networks (CNNs) for kidney and tumor detection. Evaluation metrics commonly used with the KiTS dataset include the Dice coefficient, Jaccard index, and Hausdorff distance, allowing researchers to assess the performance of their models in terms of accuracy and similarity to the ground truth. One of the primary advantages of the KiTS dataset is its detailed annotations by expert radiologists, providing a high-quality benchmark for model development. Additionally, its multiclass annotations and diverse cases present a complex challenge, fostering the development of robust segmentation algorithms. However, some limitations and considerations include the need for substantial computational resources to handle the large 3D images and the complexity of preprocessing required for optimal model performance. Despite these challenges, the KiTS dataset remains a valuable tool for advancing kidney tumor segmentation in medical imaging.

Table 1. KiTS Dataset features and Description

Feature	Description
Imaging Modality	Computed Tomography (CT)

Number of Cases	210 patient cases
Number of Images	Thousands of CT slices (varies per case)
Annotations	3D segmentation masks for kidneys and tumors
Tumor Types	Various, including benign and malignant
Format	DICOM for raw images, NIfTI for segmentation masks
Resolution	Varies, typically high-resolution (512x512 pixels per slice)
Preprocessing	Some cases may include pre-processed versions (e.g., resampled images)
Clinical Information	Basic demographic data, surgical outcomes, tumor size
Dataset Splits	Training and test sets provided for model validation
Ground Truth	Manual annotations by expert radiologists
License	Publicly accessible for non-commercial research use
Challenges	Used in the KiTS Challenge (2019, 2021) for benchmarking segmentation algorithms

4.2. Chronic Kidney Disease Dataset (UCI Machine Learning Repository)

The Chronic Kidney Disease (CKD) dataset from the UCI Machine Learning Repository is a well-known resource used for research in medical diagnosis and disease prediction. It consists of 400 instances with 24 attributes, including both numerical and categorical features like age, blood pressure, blood glucose levels, and kidney function indicators. This structure allows researchers to explore various aspects of CKD diagnosis, making it suitable for tasks like classification, regression, and feature analysis. The dataset is structured in a CSV format, with some missing values requiring preprocessing for effective model training. The CKD dataset is publicly accessible and widely used in academic research and educational purposes to develop and evaluate machine learning models. It has been employed in numerous applications, including the development of diagnostic tools using algorithms like decision trees, support vector machines, and neural networks. Common evaluation metrics for models trained on this dataset include accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). One of the key advantages of the CKD dataset is its simplicity and diverse set of attributes, enabling a comprehensive analysis of factors influencing kidney disease. It provides an excellent benchmark for both beginners and advanced researchers in machine learning and medical informatics. However, the dataset has some limitations, including its relatively small size and the presence of missing values, which require careful handling to avoid biased results. Despite these considerations, the CKD dataset remains an essential tool for advancing research in early detection and diagnosis of chronic kidney disease.

Table 2. Overview of the Chronic Kidney Disease Dataset

Aspect	**Details**
Purpose	Classification of chronic kidney disease (CKD) using various medical indicators.
Number of Instances	400
Number of Attributes	24 (11 numeric, 13 nominal)
Target Variable	Class (ckd, notckd)
Missing Values	Yes, present in several attributes.
Source	UCI Machine Learning Repository
Attribute Types	Numeric, Nominal

Table 3. Attributes in CKD Dataset

Attribute Name	Type	Description	Possible Values/Range
Age	Numeric	Age of the patient in years	Integer (e.g., 25, 50, etc.)
Blood Pressure (bp)	Numeric	Blood pressure in mm/Hg	Continuous (e.g., 70-180)
Specific Gravity (sg)	Nominal	Measure of urine concentration	1.005, 1.010, 1.015, etc.
Albumin (al)	Nominal	Presence of albumin in urine	0, 1, 2, 3, 4, 5
Sugar (su)	Nominal	Presence of sugar in urine	0, 1, 2, 3, 4, 5
Red Blood Cells (rbc)	Nominal	Count of red blood cells in urine	normal, abnormal
Pus Cell (pc)	Nominal	Presence of pus cells in urine	normal, abnormal
Pus Cell Clumps (pcc)	Nominal	Presence of pus cell clumps in urine	present, not present
Bacteria (ba)	Nominal	Presence of bacteria in urine	present, not present
Blood Glucose Random (bgr)	Numeric	Random blood glucose level in mgs/dl	Continuous (e.g., 70-300)
Blood Urea (bu)	Numeric	Level of urea in blood in mgs/dl	Continuous (e.g., 10-200)
Serum Creatinine (sc)	Numeric	Level of creatinine in blood in mgs/dl	Continuous (e.g., 0.5-15)
Sodium (sod)	Numeric	Sodium level in blood in mEq/L	Continuous (e.g., 120-150)
Potassium (pot)	Numeric	Potassium level in blood in mEq/L	Continuous (e.g., 3-7)
Hemoglobin (hemo)	Numeric	Hemoglobin level in gms	Continuous (e.g., 5-17)
Packed Cell Volume (pcv)	Numeric	Percentage of red blood cells	Integer (e.g., 20-60)
White Blood Cell Count (wc)	Numeric	Number of white blood cells per cubic mm	Continuous (e.g., 3000-20000)
Red Blood Cell Count (rc)	Numeric	Number of red blood cells per cubic mm	Continuous (e.g., 2.5-6)
Hypertension (htn)	Nominal	Presence of hypertension	yes, no
Diabetes Mellitus (dm)	Nominal	Presence of diabetes mellitus	yes, no
Coronary Artery Disease (cad)	Nominal	Presence of coronary artery disease	yes, no
Appetite	Nominal	Appetite status	good, poor
Pedal Edema (pe)	Nominal	Presence of pedal edema	yes, no
Anemia	Nominal	Presence of anemia	yes, no

Class	Nominal	Presence of chronic kidney disease	ckd, notckd

4.3. Kidney Lesion Image Collection (The Cancer Imaging Archive - TCIA)

The Kidney Lesion Image Collection from The Cancer Imaging Archive (TCIA) is a valuable dataset designed to support research in kidney lesion detection and characterization. It comprises a diverse set of CT scans, each containing detailed annotations of kidney lesions, including information on tumor size, shape, and location. The dataset is structured to include both the original CT images and corresponding segmentation masks, allowing for a comprehensive analysis of kidney lesions. Available in standard imaging formats like DICOM, the dataset is organized to facilitate various tasks such as segmentation, classification, and lesion characterization. Researchers can access the dataset through TCIA's online platform, following the data usage policies set by the archive, making it widely accessible for non-commercial research purposes. This dataset has been extensively used in applications and benchmarks focused on developing and validating deep learning models for kidney lesion segmentation and classification. Common evaluation metrics employed with this dataset include the Dice coefficient, Jaccard index, and sensitivity and specificity, which help assess the accuracy of segmentation models. One of the primary advantages of the Kidney Lesion Image Collection is its comprehensive annotations provided by medical experts, offering a high-quality benchmark for algorithm development. Additionally, the dataset's inclusion of various lesion types adds to its robustness, aiding the development of models capable of generalizing across different clinical scenarios. However, limitations include the complexity of the data, which may require significant preprocessing and computational resources, and the inherent challenges associated with imaging data, such as variability in image quality and patient anatomy. Despite these considerations, the Kidney Lesion Image Collection remains an essential resource for advancing research in kidney lesion detection and segmentation.

Table 4. Summary of the Kidney Lesion Image Collection

Aspect	**Details**
Source	The Cancer Imaging Archive (TCIA)
Imaging Modality	Computed Tomography (CT)
Number of Patients	Varies (check specific collection details)
Number of Images	Thousands of CT slices
Annotations	Available (Lesions, Tumors, Cysts)
Format	DICOM (Digital Imaging and Communications in Medicine)
Clinical Information	May include demographic and clinical details
License	Publicly accessible under TCIA's data usage policies
Use Cases	Segmentation, Classification, Detection of Kidney Lesions

Dataset Description and Structure

The dataset consists of CT imaging data organized into a structured format suitable for analysis. It is designed for tasks like lesion segmentation, tumor classification, and radiomics. Each patient case typically includes:

- CT Scans: High-resolution CT images in DICOM format, which provide detailed anatomical information about the kidney.
- Annotations: Ground truth annotations for lesions, including masks or labels identifying regions of interest such as tumors and cysts.
- Metadata: Relevant clinical information, including patient demographics, lesion characteristics, and imaging acquisition parameters.

Table 5. Attributes and Annotations

Attribute	Description	Type
Patient ID	Unique identifier for each patient case	Alphanumeric
CT Images	Series of CT slices of the kidney	DICOM format
Lesion Annotations	Ground truth segmentation masks for lesions	Binary masks, Region labels
Lesion Type	Classification of lesions (e.g., tumor, cyst)	Categorical
Tumor Size	Size of the lesion in mm	Numeric
Imaging Protocol	Details about CT imaging parameters	Descriptive
Clinical Data	Patient demographic and clinical information	Age, Sex, Diagnosis, etc.

5. Performance Analysis of Recent (2020-2024) Deep Learning Models in Kidney Disease Classification

Table 6. Performance Comparison of recent DL-based models for Kidney Disease Classification

Year	Models	Accuracy
2020	ANN [51]	99%
	Ensemble [52]	95%
	Genetic Algorithm [53]	99%
2021	CNN [54]	99%
	CNN [55]	89%
	RNN [56]	95%
	ANN [57]	80%
2022	VGG19 [58]	99.25%
	FPA-DNN [18]	98.75%
	DNN [59]	98.8%
	Optimized CNN [60]	98.75%
2023	MobileNetV3 [61]	97%
	EfficientNetB5 [62]	93.5%
	DenseNet201 [37]	97%
	EfficinetNetB3 [63]	95.77%
	XResNet50 [64]	97%
	DenseAUXNet201 [65]	98.02%
2024	EfficientNet_B1 [66]	94.38%
	DL model [67]	92%
	Ensemble model [68]	98%
	HDKN [69]	97%

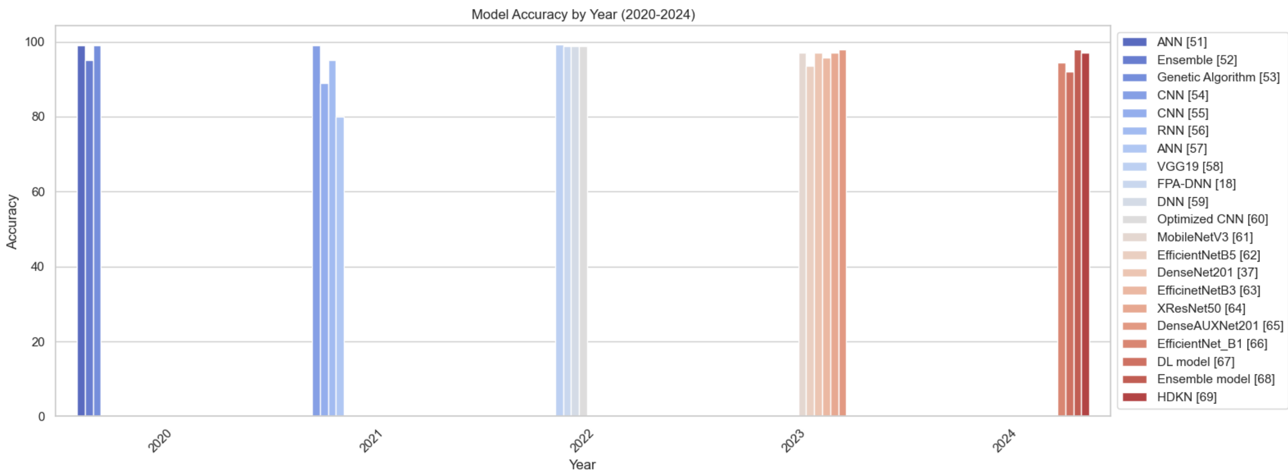


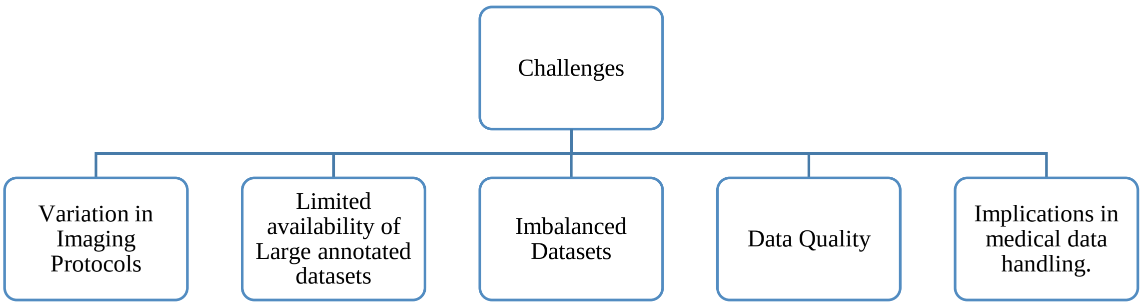
Figure 9. Performance Comparison of recent DL-based models for Kidney Disease Classification

6. Advancements and Challenges

Recent advancements in deep learning have led to the development of more sophisticated architectures, such as U-Net for image segmentation [70], ResNet for enhanced feature extraction [71], and transfer learning techniques that leverage pre-trained models to improve classification performance. These advancements have further improved the accuracy of kidney disease classification using medical images. Additionally, multi-modal deep learning approaches that combine imaging data with clinical and genetic information have been explored to provide a more comprehensive assessment of kidney diseases.

Despite these advancements, several challenges remain. The heterogeneity of kidney diseases, variations in imaging protocols, limited availability of large annotated datasets, imbalanced datasets, data quality and Implications in medical data handling that pose significant hurdles for training robust and generalizable deep learning models. The nature of deep learning models raises concerns about interpretability and reliabiliy in clinical decision-making. To address these challenges, ongoing research is focusing on developing explainable AI models, incorporating domain knowledge into model design, and utilizing federated learning to leverage distributed datasets while preserving patient privacy.

Figure 10. Challenges in Kidney Disease Classiffication



7. Conclusion

In this review, we have systematically analyzed and synthesized the current advancements in kidney disease classification using medical imaging and deep learning techniques. By exploring a variety of models, including CNNs, RNNs, and ensemble learning methods, we identified significant strides in automated kidney disease diagnosis, particularly in segmenting and classifying various kidney conditions such as CKD, renal tumors, and kidney stones. The use of prominent datasets like the KiTS, Chronic Kidney Disease Dataset (UCI), and the Kidney Lesion Image Collection (TCIA) has been instrumental in driving the research in this domain, offering a foundation for developing and benchmarking advanced deep learning models.

Through this review, we observed that techniques such as VGG19, DenseNet201, and hybrid models have achieved remarkable accuracy rates, some exceeding 99%, showcasing their potential in clinical settings. However, the challenges such as the complexity of kidney tissue segmentation, limited availability of annotated datasets, and the need for models capable of real-time processing remain significant. Our work underscores the importance of further research into more generalized and robust models, leveraging multi-modal data, and adopting advanced optimization techniques to overcome these challenges.

In conclusion, this review highlights the transformative impact of deep learning in kidney disease classification. It not only demonstrates the feasibility of using AI-driven tools for enhanced diagnostic accuracy but also sets the stage for future innovations aimed at early detection and personalized treatment strategies. By advancing the field of automated kidney disease classification, we move closer to more efficient, accurate, and accessible diagnostic tools, ultimately contributing to better patient care and outcomes.

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