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A Review On Kidney Stone Detection Using Ml And DL Techniques

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***Abstract*— Numerous factors contribute to kidney disorders, which are broadly classified as either neoplastic or non-neoplastic. A well-established technique for additional data mining and a developing area of expertise, numerous factors contribute to kidney disorders, which are broadly classified as either neoplastic or non-neoplastic. A well-established technique for additional data mining and a developing area of expertise, medical imaging driven by deep learning provides the opportunity for effective renal disease management. In order to support disease diagnosis and treatment, imaging-centric deep learning has recently found extensive application in various clinical situations related to kidney disorders, such as organ segmentation, lesion detection, discriminational diagnosis, surgical planning, and prognostic ratiocination. This study will discuss the introductory methodology of imaging-based deep learning and its present clinical uses in kidney diseases, encompassing both neoplastic and non-neoplastic conditions. We also discuss its present issues and future possibilities and come to the conclusion that tackling diversity and attaining data balance are important. An overview of the development of kidney disease categorization through the use of deep learning and medical imaging techniques is provided in this article. There is an urgent need for precise and automated individual instruments due to the rising prevalence of kidney-related conditions such nephrolithiasis, renal malignancies, and chronic kidney disease (CKD). This study thoroughly reviews the literature on a variety of deep learning models, such as hybrid architectures used for renal disease categorization, recurrent neural networks (RNNs), and convolutional neural networks (CNNs). The study also investigated the usage of three datasets: the Kidney Lesion Image Collection from The Cancer Imaging Archive, the Chronic Kidney Disease Dataset from the UCI Machine Learning Repository, and the KiTS (Kidney Tumor Segmentation). This review examines the assessment criteria, model infrastructures, and pre-processing methods.**

Detecting kidney stones is an important health concern, as complications can be prevented with precise and timely diagnosis. Additionally, the increasing prevalence of kidney stones and the increasing need for efficient, non-invasive diagnostic methods highlights the significance of this research.

Using medical imaging data to enhance individualized care, machine learning (ML) and deep learning (DL) approaches show promise. However, their full potential is hindered by constraints such as high processing costs and dependence on large databases. This article concludes with an assessment of the most recent developments in order-gravestone discovery using ML and DL techniques. It is best to contrast current approaches, highlight their advantages and disadvantages, and offer new lines of inquiry, especially when incorporating transfer literacy and optimizing performance.

***Keywords*— Kidney Stone Detection, Machine Learning, Deep Learning, Medical Imaging, Transfer Learning, Fine Tuning, CT Scans.**

I. INTRODUCTION

This study centers on the growing incidence of kidney stones and the demand for improved, non-invasive diagnostic methods. Machine learning (ML) and deep learning (DL) approaches, which use medical imaging data, offer significant potential. Despite challenges such as high processing costs and reliance on large databases, these techniques remain promising. This article assesses recent progress in kidney stone identification employing ML and DL. Evaluating existing techniques, recognizing their advantages and limitations, and investigating novel research pathways in transfer learning and performance enhancement are crucial to maximize their advantages. The building, training, and deployment of deep learning models for clinical practise rely on several essential methods in the context of renal disease. Essential elements of this deep learning strategy encompass data retrieval, pre-processing, model choice, training, validation, testing, and the evaluation and interpretation of the model's results. This section will offer a detailed summary of every step in this procedure.

a) Data Acquisition:

Gathering data serves as an essential initial phase in creating deep learning models for kidney conditions.

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To create an effective model, it is essential to compile a comprehensive dataset of high-quality medical images. The precision and generalizability of the algorithm are greatly influenced by the caliber of this training material. Utilizing multi-source data, which includes various imaging modalities, machines, and parameters, can significantly reduce biases that may arise during the data collection process. However, it is important to acknowledge that this diversity might also impact the model's flexibility. Thus, it is essential for developers to possess a clear comprehension of the model's intended use, and to gather as much relevant information as possible within that context. This preliminary phase is crucial for creating a solid base for the next stages of the deep learning process, ultimately aiding improvements in the diagnosis and management of kidney conditions.

b) Data Preprocessing

The second stage of the process, data preparation, includes cleaning and structuring the dataset for deep learning models. This phase is crucial for improving data quality and confirming that the algorithm functions properly. Data preparation includes several techniques, such as image normalization, image registration, and noise reduction. Additionally, data augmentation is a crucial aspect of this phase. In order to minimize overfitting during model training, data addition creates a number of significantly altered copies of the original data using techniques including rotation, scaling, and cropping. It's important to note that generative adversarial networks show significant promise in data augmentation by inducing new synthetic pictures with high authenticity using various contrasts and imaging procedures. The labels, which vary in form according on the sort of learning activity, are what we expect the model to produce. For example, data labeling in renal tumor classification entails giving each picture in the collection a class or category. Furthermore, in renal tumor segmentation, labels that indicate the target area are often matrices or tensors. However, the generative model, which is a component of self-supervised learning, does not require a new label.

c) Creation of a deep learning model

Establishing the deep learning model is the next stage, which includes choosing the model architecture, training the model, and adjusting the hyper parameters through model validation. Medical image analysis may be done with a variety of deep learning architectures, the most of which are based on CNN.

The CNN is a significant variant of the Multilayer Perceptron, the most basic deep neural network, and is primarily intended for image processing. Additionally, the process of selecting the best deep learning architecture for the various learning tasks is known as model framework selection. For instance, residual networks (ResNet) and its variations are typically utilized for classification tasks, whereas U-Net and its 3D counterparts are commonly employed for segmentation tasks. This involves providing the deep learning model with preprocessed training data and modifying the model's weights to minimize the difference between the predicted yield and the real output. The main elements of the algorithm, such as learning rate, time span, batch size, and layer count, are referred to as hyper parameters, which are variables that control the model's behaviour. To enhance the performance of the training model post-training, the hyper parameters must be adjusted by model confirmation. By means of ongoing model training and hyper parameter accommodation, the ideal model, which includes the ideal weights and hyper parameters is determined through comparison.

d) Segmentation

The accurate segmentation of areas of interest is fundamental to quantitative image analysis and an essential aspect of imaging-focused deep learning studies. Manual segmentation takes a lot of time and effort. Furthermore, the complexity of the pictures and the annotator's experience have a significant impact on the delicateness and repeatability of manual or automated segmentation. As a result, much research is focused on creating automatic segmentation algorithms with the goal of providing end-to-end segmentation techniques that significantly reduce process costs. Yang et al. [20] proposed a 3D Multi-Scale Residual Fully Convolutional Neural Network aimed at segmenting kidney tumors larger than 7 cm. Achieving a Dice score of 0.9390 for the Kidney and Kidney Tumor Segmentation Challenge dataset and 0.8575 for the in-house sanitarium dataset, the method employs a multi-scale strategy to gather global contextual information, demonstrating enhanced precision compared to the leading system. The research indicates that large kidney tumors can be promptly segmented and assessed with the proposed network in medical image processing.

Precisely delineating renal tumors and kidney structures is essential, alongside the simple segmentation of tumor edges. The Meta Greyscale Adaptive Network was proposed for segmenting 3D integrated renal structures in CT angiography (CTA) data.

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The proposed model tackled problems such as minimal variance and network representation preferences caused by grayscale distribution differences among images by segmenting the kidneys, renal tumors, ducts, and veins in one outcome. Involving 123 patients, the study reported an average Dice coefficient of 87.9 for renal structures, suggesting positive results for renal cancer treatment.

e) Differential diagnosis

A practical method for accurately identifying renal mass imaging characteristics in order to distinguish and diagnose them is deep learning. A deep learning model was recently used by Zabihollahy et al. [21] to distinguish renal cell carcinoma (RCC) from benign solid renal masses (fat-poor renal angiomyolipoma and renal oncocytomas) using discrepancy-enhanced computed tomography (CECT) images from 155 cases. The model was validated using CECT images from 160 cases. With the help of this semi-automated approach, the suggested CNN algorithm achieved delicacy, perfection, and recall rates of 83.75, 89.05, and 91.73, respectively. Due to their similar radiological and immune-histochemical characteristics, it is difficult to differentiate between oncocytoma and chromophobe RCC (ChRCC). Baghdadi & Co.To distinguish between the two kinds of cancers, Pedersen et al. [20] have suggested a deep learning method that makes use of over 20,000 2D CT pictures. Additionally, the model was evaluated on three separate datasets, achieving scores of 90.0 to 97.7 delicacy when judged image by image and over 100 delicacy when calculated by 51 maturity votes of distinct picture groupings for each case. These investigations on the diagnosis of kidney tumors also imply that deep learning has the implicit ability to break a similar challenge from various bounds; hence, its potential for clinical operation has to be investigated. When it comes to the discrimination diagnosis, it is very useful to know that the bracket findings at the patient position are based on those at the two-dimensional position.

f) Tumor staging/Grading

Assessing the stage and grade of kidney tumors, especially malignant varieties, is crucial for tracking the patient's condition and developing personalized treatment strategies. In a recent retrospective study, Xu et al. [22] developed four unique deep learning models for grading clear cell renal cell carcinoma (ccRCC) by analyzing CT images, with each model demonstrating adequate performance in external validation.

Xu et al. also proposed a new weight calculation method to assess the outputs of the four models and subsequently combine them to achieve the final grade assessment. In order to make the decision more accurate and reliable, this gesture was similar to an expert discussion in which a number of experts examined the circumstances of the case and integrated their view points. Ultimately, the ensemble model enhanced the predictive performance, achieving an AUROC of 0.882 and bolstered the network design ability. The study is important for investigations involving marker noise and category imbalance, and it avoids the challenge of a weak link between image contents during the pre-training and development phases in deep learning research.

g) Surgical planning

At present, diagnosing and treating renal tumors rely significantly on the accurate segmentation of renal arteries in abdominal CTA scans and the careful assessment of vascular structures, especially small vessels. These methods are essential for preoperative preparation in both open and minimally invasive surgeries. Wang et al. introduced an innovative approach for precisely forecasting the dominant renal vascular area through Voronoi visualization. This approach merges tensor-based graph-cut methods for segmenting kidneys and renal arteries with a neural network. In 27 cases, the kidney segmentation delicacy achieved a Dice score of 95, whereas in 8 cases, the renal artery segmentation delicacy achieved a centerline imbrication ratio of 80. With a Bones measure of 80, the final dominant-region estimating delicacy was successful. Even though order segmentation yields positive results, the performance is still negatively impacted by the various patterns of renal disease and the thickness of the picture slices. Furthermore, He et al.'s innovative 3D semi-supervised model for precise renal highway segmentation yielded results that were similar (Dice score: 88.4).

h) Chronic Kidney Diseases

Employing deep learning in kidney disorders enhances data mining of kidney images, and feature alterations are additionally used to further refine the precision of chronic kidney disease diagnosis. Lee et al. recently conducted a multi-task study involving 909 patients, of whom 385 had CKD and 524 did not. The kidney ultrasound images were examined to characterize chronic kidney disease (CKD). While employing the Mask native convolutional neural network model for kidney and liver segmentation, measurable traits such as kidney length and the kidney-to-liver echogenicity rate were eliminated.

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Simultaneously, CKD insight was gathered utilizing the ResNet-18. It was significant that three models were released. By utilizing only the US image data for assessment, the initial model's average AUROC attained a score of 0.81 (sensitivity 78.2, specificity 71.5, and delicacy 74.4). The average AUROC increased to 0.88 once the alternative model integrated the extra measurable attributes derived from the original model (sensitivity 86.1, specificity 77.5, and accuracy 81.2). The final model achieved an average AUROC of 0.91 (sensitivity 89.4, specificity 82.9, and precision 85.9) following the incorporation of clinical data (including diabetes history).

i) Autosomal Dominant Polycystic Kidney Disease

Additionally, as excretions enlarge over time in autosomal dominant polycystic kidney disease (ADPKD), the total kidney volume (TKV) increases. Consequently, the assessment of TKV is vital for determining the rigidity of ADPKD, its progression, and how it responds to therapy. Improvements in deep learning further augment this process. Kline and associates[26] created an entirely automated approach that randomly selected 2000 cases with their MRI data for training and validation, using 400 cases excluded from training for testing, and they established a reference standard TKV based on their earlier research. In the test dataset, the model achieved impressive results, with a Dice coefficient of 0.97 ± 0.01 and a Jaccard coefficient of 0.94 ± 0.03 (sensitivity = 0.97 ± 0.02, specificity = 0.99 ± 0.01, and accuracy = 0.98 ± 0.02). Moreover, van Gastel et al. enhanced the network's architecture informed by Kline et al.'s research and achieved superior outcomes in the TKV dimension compared to the conventional handcrafted dimension. These studies offered another time-saving approach for evaluating complaints in patients with ADPKD, highlighting the capabilities of deep learning in TKV measurement. Kuo et al. [27] proposed a deep learning approach for independently evaluating eGFR and CKD status using kidney ultrasound images. A neural network was developed utilizing 4505 kidney ultrasound images to forecast renal function through transfer learning and kidney length reflections. The model achieved a total classification score of 85.6 for CKD status and a Pearson correlation coefficient of 0.741. To develop the equations for calculating creatinine product and achieve optimal results, Pieters et al. [28] also offered a completely automated method that linked clinical factors with body-composition measurements obtained from abdominal CT scans. Deep learning shows strong performance in both kidney volume measurement and evaluation of renal function, as evidenced by this research.

II. Literature Review

Sohaib Asif et al [1] proposed two ensemble models for detecting kidney stones in CT scans. The initial model, named Stacked Ensemble Net, is a dual-level deep stack ensemble that effectively combines predictions from four foundational models: InceptionV3, InceptionResNetV2, MobileNet, and Xception. The second model, PSO Weighted Avg Net, utilizes the Particle Swarm Optimization (PSO) method to establish the best weights for a weighted average ensemble. This ensemble approach improves performance by efficiently merging the predictions of the models and allocating suitable weights in the ensembling process.In their study, CHAKI JYOTISMITA et al. [2] propose an ensemble Deep Neural Network (DNN) method that employs inductive transfer to autonomously identify kidney stone images from Computed Tomography (CT) scans. They utilize pre-trained DNN models to generate three datasets for extracting features from kidney CT images. By merging features from various pre-trained DNNs, including DarkNet19, they create an integrated ensemble deep feature vector. The Iterative ReliefF feature selection method is utilized to select the most informative ensemble deep feature vectors for identifying kidney stones. The chosen feature vectors are subsequently input into a K Nearest Neighbor classifier, which is optimized using a Bayesian approach and assessed using a 10-fold cross-validation method. The suggested approach attains remarkable accuracies of 99.8% with high-quality datasets and 96.7% with noisy datasets, exceeding current DNN-based and conventional image detection techniques. This automated method can help urologists confirm their physical assessments of kidney stones, thereby minimizing the likelihood of potentially deadly mistakes

Gulhane Monali and colleagues [3] carried out an extensive study that presented various advanced models such as the Gradient Boosting Classifier, LightGBM, CatBoost, Random Forest, Support Vector Classifier (SVC), Logistic Regression, XGBoost, Deep Neural Network (DNN), and an Improved DNN. The Enhanced DNN demonstrated outstanding performance metrics, reaching a precision of 90%, an accuracy of 89%, a recall of 90%, and an F1-Score of 89.5%. This combined approach aids in recognizing complex patterns in datasets by merging deep neural networks with conventional machine learning methods. The model's data-driven characteristics guarantee its flexibility in adapting to changing healthcare contexts by consistently updating its internal parameters.

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This research represents a significant step forward in developing a thorough and customized instrument for identifying kidney stones. Through the use of a comprehensive method that combines advanced classification algorithms, the research sought to improve the efficiency of kidney stone identification, thereby effectively showcasing the advantages of this approach. The Enhanced DNN surpassed the traditional DNN, achieving an F1-Score of 89.5%, a precision of 90%, an accuracy of 89%, and a recall of 90%. To tackle the inherent difficulties linked to traditional detection techniques, a variety of models—such as Gradient Boosting Classifier, LightGBM, CatBoost, SVC, Random Forest, Logistic Regression, XGBoost, and Enhanced DNN—were employed in the research. This comprehensive approach successfully interprets intricate patterns in datasets by merging the advantages of deep neural networks with traditional machine learning techniques. Utilizing data-driven methods to consistently adjust internal parameters guarantees the model's flexibility to altering healthcare conditions. This research represents a significant progress in creating a more advanced and tailored diagnostic instrument for identifying kidney stones, potentially enhancing patient care and clinical results.

Francisco Lopez et al [4] demonstrate the implicit interest in using AI techniques to automatically identify the lithogenesis (cause) of kidney stone production. However, in order to fully utilize an automated detection process in clinical settings, further tests need be performed to detect various kinds of kidney stones with mixed composition. The database should be expanded to include more kidney stone varieties with distinct biochemical compositions, such as cystine and struvite. Moreover, most workshops in the literature, including this one, rely on still images, which could limit the adaptability of the proposed computer vision systems (the video sequences displayed during defenses may suffer from motion blur, and kidney stones could be hidden by blood or debris). The design, performance, and results of the kidney stone classifiers (both shallow machine learning and deep learning methods) are also discussed. In fact, if the InceptionV3 architecture achieved the neat results (weighted delicacy, perfection, recall, and F1- Score of 97 ± 03,97 ± 03,98 ± 04, and 98 ± 03, respectively), it also demonstrates that a shallow machine learning method can approach nearly the performances of the most promising deep-learning methods by selecting an appropriate color space and texture features (the XGBoost classifier produced weighted delicacy, perfection, recall, and F1- Score values of 96 ± 14).

Manoranjitham R. et al [5] proposed the Guided Bilateral Feature Detector to identify and reward characteristics for diagnosing kidney stones in CT scans. The Guided Bilateral Filter Detector utilized a companion weight to prevent halo artifacts and maintain image edges, unlike traditional filters like Gaussian and bilateral filters. The SVM method was utilized alongside the extracted features to accurately identify kidney stones on CT images. Unlike the Global Features (GF) and Binary Features (BF), the traits obtained through the Generalized Bag of Feature Descriptors (GBFD) demonstrated significant robustness against noise. In assessing the effectiveness of the suggested GBFD Support Vector Machine (SVM) model, it exhibited impressive outcomes regarding accuracy (Acc), recall (Rec), precision (Pre), and F1 scores. To enhance the validation of its effectiveness in recognizing and diagnosing kidney stones in CT images, six machine learning methods were utilized, comprising SIFT SVM, SURF SVM, Principal Component Analysis (PCA) K-Nearest Neighbors (KNN), EANet, Inception v3, VGG16, and ResNet50. Additionally, the confusion matrix obtained from the GBFD SVM was divided into normal and stone categories according to the assessed performance metrics: accuracy, recall, precision, and F1 score. The systematic experimental results showed that the proposed GBFD SVM reached an impressive accuracy of 98.56%, comparable to other deep neural network (DNN) models while also keeping a lower computational cost. In the future, the use of the GBFD SVM could be expanded to other imaging techniques to create multiple disease detection systems. In a similar study, Ahmed Fahad et al. [6] concentrated on identifying kidney stones in KUB X-ray images utilizing an improved VGG16 model. The results indicated that the altered VGG16 model successfully detected kidney stones in KUB X-ray images, attaining a sensitivity rate of 97.41%. Nevertheless, a major drawback of their study is the lack of high-quality and unique medical imaging data from KUB X-rays concerning kidney stones. The dataset's quality and variety play vital roles in kidney stone research.

N. Manjunatha et al.[7] employed techniques such as dilatation and Canny edge detection to enhance the visibility and prominence of kidney stones on CT imaging. These methods improved the neural network's accuracy and reliability in finding stones by highlighting important information and eliminating distractions. Our experiments demonstrated the ability to detect kidney stones in CT images using CNNs, a sort of artificial intelligence. Our CNN model found and guided kidney stones in CT images more accurately than conventional methods.

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This demonstrates how significant deep learning may be in the medical field. Our CNN-based method can help physicians identify kidney stones more quickly and easily, which might improve patient care in clinical settings. Betgeri, Santushti et al.[8] Progress in deep learning has greatly enhanced diagnostic capabilities in medical imaging across various domains. However, the requirement for extensive datasets and regulations governing data sharing continue to pose challenges. Federated Learning (FL), which facilitates decentralized training of models while keeping data private, offers a potential solution. Nonetheless, FL models are susceptible to data corruption, which can adversely affect their performance. This research introduces a robust FL framework aimed at improving the diagnosis of kidney stones through the application of pre-trained models. This paper outlines a strong framework for advancing kidney stone diagnostics by leveraging pre-trained models. Our experimental configuration utilizes two separate kidney stone image datasets, each classified into six different quality levels. The process includes two key components: Federated Robustness Validation (FRV) and Learning Parameter Optimization (LPO). After conducting seven epochs and ten rounds, we achieved a maximum delicacy of 84.1 during the LPO phase and 77.2 in the FRV phase, indicating enhancements in diagnostic delicacy and resistance to image degradation. This improvement contributes to better patient care and fosters greater trust in FL-based medical systems, while also highlighting the potential for integrating pre-trained models with FL to address challenges and improve performance in medical diagnostics.

R. Satya Prasad and colleagues[9] carried out an extensive study on the effectiveness of Random Forest (RF) algorithms and Convolutional Neural Networks (CNNs) for identifying kidney stones in MRI scans. The results showed that CNNs demonstrated a notably greater sensitivity of 96% compared to the 40% sensitivity shown by Random Forest algorithms. This highlights the enhanced ability of CNNs in the field of medical image processing, particularly regarding kidney stone identification. However, each approach has its own fundamental constraints. Although CNNs show higher sensitivity, they typically have lower interpretability and necessitate more extensive training datasets.Conversely, Random Forest models, although showing less sensitivity, provide faster training durations and greater clarity. The research indicates that while CNNs can successfully detect kidney stones, additional exploration is needed. Possible paths for enhancement involve optimizing hyperparameters, investigating advanced CNN architectures, and employing larger and more varied datasets.

Moreover, improving the interpretability of CNNs could lead to greater transparency and trust in their use. In conclusion, this study underscores the capabilities of CNNs in detecting kidney stones; nevertheless, further research is necessary to improve and advance these models for effective clinical use.

Tahir, Fouad Shaker et al[10] introduced a convolutional neural network-based methodology that employs the Dual-Tree Complex Wavelet Transform (DFCWT) to enhance medical images, particularly those of kidneys compromised by stones, for the purpose of facilitating kidney stone detection. This approach involves initially eliminating noise from the medical images and subsequently compressing them, thereby improving the quality of the compressed images while also reducing the storage requirements for the image data. In order to identify the objects, the convolutional neural network was trained using separate wavelets with the assistance of Alex Net network and the algorithm DFCWTCNN to reach the delicacy of the value of good 98.84 with 4 × 4 Epoch and 2 minutes. The image quality norms were measured by PSNR, MSE, CR, and BPP, and by selecting the quadrant that contains the approach portions that raised the noise and pressure.Gonzalez, Jorge, et al [11] underpins the suggested Guided Deep Metric Learning technique was created to learn data representations in a sophisticated manner.The outcome uses a teacher-student method and was influenced by Few-Shot Learning (FSL). Using a Knowledge Distillation method, the teacher model (GEMINI) collaborates with a student model (ResNet50) to create a condensed hypothesis space grounded in existing knowledge from the labeled data. Initially, thorough testing was performed on two datasets that were used independently for recognition: a compilation of images of the fragment sections and a group of pictures acquired of the kidney stone fragment shells. In comparison to DL-methods and other DML-approaches independently, the proposed DML-approach enhanced the identification accuracy by 10 and 12, respectively. Moreover, a multi-view approach was employed to arrange the model embeddings from the two types of datasets to simultaneously leverage the data from both face and section fragments. When testing with an effective mixed model, the identification accuracy is enhanced by at least three to thirty percent when compared to DL models and shallow machine learning methods

Jin Qiangguo et al.[12] developing successful treatment plans for urinary stones depends on a clear diagnosis. However, the modest difference between stones and girding tissues and the variation in stone positions between instances sometimes confuse the diagnostic process.

To address this issue, we propose an innovative location embedding based pairwise distance learning network (LEPD-Net), which utilizes position data and low-potential abdominal X-ray imaging for a detailed assessment of urinary stones With our novel fine-granulated pairwise distance learning, LEPDNet recognizes fine-granulated objects, integrates critical position knowledge through stone position embedding, and improves the representation of stone-related features through environment-apprehensive region improvement. To show the efficacy of our suggested strategy, we have also created an internal dataset on urinary tract monuments. Extensive experiments on this dataset show that our framework performs noticeably better than state-of-the-art techniques.

Kavitha, B. C. et al. [13] Besides interpreting lung CT images without hesitation, it progresses to the image organization phase and employs effective image management techniques. The proposed method includes advancements such as image accession, pre-processing, binarization, thresholding, division, feature extraction, and neural organization identification. The feature extraction method eliminates particular essential plots from the segmented images, whereas the binarization technique modifies similar images and contrasts them with edge views. The retrieved properties contribute to shaping the brain structure, and the framework is also analyzed for images that could be benign or malignant.

Khandelwal Neha et al [14] By preprocessing the ultrasound picture, the suggested technology has been used to detect kidney stones. Segmentation came next, and then the performing image was subjected to morphological analysis. The precise location of the kidney stone was determined with the aid of the final imaging. Proceeding with the edge finding system, which connected the kidney's stone formation's shape and structure. Rathika et al [15] Many deep learning methods have been employed to detect kidney stones with encouraging results. U-net has been employed to directly identify kidney stones from ultrasound images, X-rays, or CT scans, considering their size, shape, and position. Moreover, algorithms for detecting kidney stones have been improved through the use of ensemble learning techniques. Overall, these deep learning algorithms demonstrate potential in enhancing the sensitivity and accuracy of kidney stone detection, which could ultimately assist in better diagnosis and treatment strategies for kidney stone patients.

Chamak, Jaber Qezelbash et al [16] Systematized methods are used for content-based picture indexing and reclamation. The process of content-based picture reclamation is broken down into smaller steps, and a variety of colourful techniques are used.

Musa Genemo et al [17] This study uses deep learning techniques to categorize ill and healthy individuals based on endoscopic pictures gathered from several hospitals. Using these techniques, a 3D CNN is proposed in a shorter amount of time that allows the diagnosis of images that the specialist doctor finds difficult to diagnose. We used five 3D CNNs, with the last two models, each with six layers, classified as kidney stones and health order, and the first three models used for kidney stone detection. The creation of fresh datasets and the use of a novel model may be summed up as the study's primary benefits. Similarly, the outcomes of the models may lessen the strain on the physician and the likelihood of a false positive. Additionally, improving the present medical therapy and early consultation might change the complaint's trajectory and prolong the patient's life.

Alghamdi Hanan et al [18] showed that training a group of classifiers improves the performance of all algorithms, overcomes data inconsistency, and helps identify intricate patterns. For example, the DT classifier used MICE and ROS to reach 0.62 delicacy, whereas RF obtained 0.99 delicacy. Notably, single classifiers outperformed ensemble models with RUS by a little margin. However, neither model demonstrated strong performance, likely due to the ensemble models overfitting on the very small training set. As a result, a large dataset is necessary. Moreover, the RF and ETree ensemble models employing ROS demonstrate a recall or sensitivity of over 0.95, signifying their capacity to accurately represent positive instances. All predictors demonstrated a significant enhancement in learning when the training set experienced oversampling. For instance, with an AUC of 0.53, the GB classifier utilizing undersampling and KNN inference slightly surpassed random guessing. Utilizing the same insinuation approach but through oversampling, the GB classifier achieved an AUC of 0.88 in difference. This illustrates the importance of having a large dataset of laboratory test results to enhance the effectiveness of machine learning algorithms and aid urologists and other healthcare providers in making early diagnoses, reducing costs, and avoiding additional complications.

Nofal Samer et al [19] developed a classification model to predict a case of kidney stones using Decision Tree J48 and Nañve Bayes. In order to assess each model's delicacy, the following assessment methods were used: training and testing data sets, percentage split with 66, and 10-fold crossvalidation. The model correctly identified 469 out of 500 examples when decision tree J48 with 10-fold cross-validation was used. The model's delicacy was 93.8. The model correctly categorized 152 examples out of 170 with 89.4118 delicacy when the percentage split was used.

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The method proposed by Ehwa Yang et al [20] is analyzed in this study using both the internal hospital data and the public KiTS dataset. Our model, 3D-MS-RFCNN, demonstrated superior accuracy (0.9390 dice score for KiTS dataset and 0.8575 dice score for the external dataset) in segmenting large kidney tumors compared to the leading method, Res3D U-Net. The proposed network significantly improves the segmentation performance of extremely large targets. This work can bring advantages to the domain of medical image analysis.

Zabihollahy Fatemeh et al [21] Achieved precise differentiation of RCC from benign tumors within solid renal masses on CECT through a semi-automated majority vote CNN-based algorithm. Utilizing 160 test cases, the semi-automated majority voting CNN algorithm successfully identified RCC and benign solid masses, achieving accuracy, precision, and recall rates of 83.75%, 89.05%, and 91.73%, respectively. Employing the identical test cases, a completely automated pipeline yielded accuracy, precision, and recall values of 77.36%, 85.92%, and 87.22%, respectively. With 160 test cases, the 3D CNN reported accuracy, precision, and recall rates of 79.24%, 90.32%, and 84.21%, respectively. Xu Lifeng et al [22] proposed a deep learning model in this research that effectively differentiates among different grades of ccRCC patients. The new self-supervised pre-training method gives unique meanings to the images, allowing the same images to be utilized in both pre-training and development tasks. This prevents the separation of the pre-training task from the development task and allows the network to acquire specific feature extraction abilities before development. Moreover, we mitigated the impact of label noise and class imbalance challenges commonly found in the dataset and improved the model's accuracy using our proposed self-supervised pre-training approach. Ablation experiments illustrate the requirement and effectiveness of the proposed approach. Higher quality, cleaner specimens and sufficient development could establish the model as a standard therapeutic instrument to reduce the psychological and physical impact that biopsy inflicts on patients.

Wang Chenglong et al[23] introduced a new unsupervised blood vessel segmentation technique based on a graph-cut tensor. both suggested strategy outperforms existing reference approaches in terms of segmentation, as demonstrated by both clinical and virtual studies. We concentrated on renal artery segmentation in this investigation. Particularly on small blood veins, our clinical testing results demonstrate the robustness and superiority of our tensor-cut procedure over the other reference methods. Vascular topology that is accurate.

Guanyu Yang and He Y et al [(24] successful semi-supervised framework for 3D fine renal artery segmentation, DPA-DenseBiasNet, was suggested and verified in this research. DPA-DenseBiasNet delivers strong generalization ability by combining the benefits of DenseBiasNet, deep priori anatomy, and hard region adaptation loss. We show our DenseBiasNet, a dense biased connection approach that fuses multi-receptive field and multi-resolution features to handle intra-scale changing problems.

Employing a multi-modal smartphone imaging system that delivers both RGB and fluorescence images, Kyungsu Lee et al [25] developed a supplementary deep learning network termed the fluorescence-aided amplification network (FAA-Net) for the detection of skin disorders. To tackle problems that may occur due to the system's insufficient photo acquisition, FAA-Net is equipped with a meta-learning-driven algorithm. Additionally, we created an innovative attention-based module and incorporated it into FAA-Net, enabling it to autonomously pinpoint the areas of skin conditions and emphasize potential disease regions. To evaluate the performance of FAA-Net and compare various assessment metrics of our developed model with other advanced models for detecting skin conditions through our multi-modal system, we conducted a clinical study at a hospital. Based on experimental results, our developed model surpassed more advanced models in mean accuracy and area under the curve for skin disease classification by 8.61% and 9.83%, respectively. Timothy L. Kline et al [26] able to better understand and treat ADPKD if we investigate other cutting-edge imaging modalities like contrast-enhanced ultrasound (CEUS), dual-energy CT (DECT), 3D phase-contrast MRI (also known as 4D Flow), and molecular imaging modalities like positron emission tomography (PET). Particularly for individuals with renal impairment, CEUS may be a safer option than contrast-enhanced CT and/or MRI. Furthermore, CEUS may be useful in evaluating renal blood flow and identifying cyst-related problems such infections or tumors. However, in contrast to normal CT, DECT may offer more precise information regarding tissue composition. Identification of calcifications and/or characterization of stone composition may be beneficial in ADPKD. Using the 4D flow MRI methodology might help minimize interoperator variability (e.g., as shown in 2D phase contrast techniques) and evaluate changes in renal blood flow (and perhaps automate/standardize the results). Finally, PET may be used to investigate metabolic alterations in kidney tissues, which might reveal information about the causes and course of the illness.

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Kuo et al.[27] developed a deep learning approach that utilizes renal ultrasound images to automatically determine the estimated glomerular filtration rate (eGFR) and assess chronic kidney disease (CKD) status. They utilized transfer learning by integrating the ResNet model, pretrained on the ImageNet dataset, into their neural network architecture 4,505 renal ultrasonography pictures tagged with eGFR values obtained from serum creatinine levels were used to train this model. They used bootstrap aggregation and data augmentation approaches to boost generalization and avoid overfitting in order to improve the model's performance. Between AI-predicted and creatinine-based eGFR estimates, the model's Pearson correlation value was 0.741. Furthermore, it outperformed seasoned nephrologists, whose accuracy varied from 60.3% to 80.1%, with an overall CKD state classification accuracy of 85.6%.Using deep learning techniques. Pieters et al.[28], created a completely automated system that extracts body composition information from abdominal CT images. In both sick and healthy persons, their approach provides a valid estimate of creatinine generation by precisely quantifying muscle and fat regions at the third lumbar vertebra (L3) level.

A sample reweighting technique was presented by Junnan Xu et al.[29], who used a multi-task learning framework to improve machine reading comprehension (MRC) in a variety of tasks and domains. Their method, which takes inspiration from machine translation data selection strategies, gives each training sample's loss function a unique weight. By prioritizing more informative data, this technique enhances the model's capacity for generalization. On a number of MRC benchmark datasets, empirical research showed that incorporating this reweighting strategy with pre-existing MRC models produced state-of-the-art results, particularly when paired with contextual representations from pre-trained language models like ELMo. An adaptive method that directly learns an explicit weighting function from data was proposed by Junnan Xu [29]. This function operates as a universal approximator for continuous functions and is parameterized as a multi-layer perceptron (MLP) with a single hidden layer. The parameters of this weighting function are adjusted in tandem with the classifier's learning process, guided by a limited amount of objective meta-data. Our approach successfully learns suitable weighting functions in class imbalance and noisy label scenarios, which is consistent with conventional settings and extendable to more complicated circumstances, according to empirical assessments on both synthetic and real-world datasets. This flexibility results in increased accuracy as compared to cutting-edge techniques.

N. A. El-Hag, et.al.[30], report recent advancements in deep learning have significantly improved the diagnosis of kidney diseases using medical imaging. Several studies have explored pre-trained convolutional neural networks such as VGG16, ResNet50, and DenseNet121 for accurate classification of renal pathologies. However, limitations in image quality, particularly due to specular reflections and poor contrast, have often affected diagnostic performance. To address this, recent research emphasizes the importance of advanced image preprocessing techniques to enhance feature visibility and preserve critical diagnostic details. In this context, the Modified Specular-Free (MSF) method has been introduced to improve luminance balance and restore essential image information. The integration of MSF with the EfficientNet-B2 architecture enables superior feature extraction and classification accuracy. Overall, these combined approaches demonstrate a robust and scalable framework for improving kidney disease detection, achieving higher accuracy compared to traditional deep learning models.

C. Girija et.al [31] define kidney disease, technically known as nephropathy, as an expansive term that includes several disorders impacting the structure and functionality of the kidneys. Even slight changes in kidney function and structural metrics are linked to a heightened risk of mortality, often occurring more frequently than kidney failure itself. In the early stages, the patient's condition may not appear severe, but recovery becomes increasingly difficult as the disease progresses. Therefore, early diagnosis is crucial for preserving patient life. Automated models for disease prediction frequently employ machine learning algorithms; nevertheless, attaining high accuracy with minimal error rates is difficult because of insufficient training data, subpar image quality, and incorrect segmentation. A hybrid deep learning system is suggested for identifying kidney diseases through CT scans to tackle these problems. The input images, such as kidney stones, cysts, normal, and tumor instances, are pre-processed through a modified GenAI-based super-resolution technique to fix distorted pixels. Then, a CLAHE algorithm based on Dandelion is utilized to improve image contrast. Ultimately, a hybrid NASNet-BiLSTM model is employed to categorize the kidney condition into normal, stone, cyst, or tumor classifications. The suggested approach attains 94% precision, 93% specificity, and 96% accuracy, enabling early detection and prompt intervention to lower death rates.

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G. Luijten et al [32] emphasize that ultrasound (US) imaging is readily available and free from radiation, yet it poses difficulties due to its dynamic characteristics and non-standard imaging angles, along with the necessity for clinicians to often alternate their attention between the screen and the patient. To address these limitations, the research utilizes deep learning (DL)-driven semantic segmentation for real-time automated kidney volume measurements, which are vital for clinical evaluation yet are typically time-intensive and susceptible to operator fatigue.This automation allows clinicians to concentrate more on interpreting images instead of performing manual measurements. Moreover, augmented reality (AR) is integrated to improve usability by projecting the ultrasound interface directly into the clinician's sightline, thus enhancing ergonomics and lowering cognitive strain. The study proposes two AR-DL-assisted ultrasound pipelines implemented on HoloLens-2: one utilizing a wireless streaming approach via an application programming interface, and another supporting any ultrasound device with video output for broader applicability. The system is assessed for real-time practicality and precision by utilizing the Open Kidney Dataset alongside open-source segmentation models like nnU-Net, Segmenter, YOLO integrated with MedSAM and LiteMedSAM. The suggested open-source pipeline, comprising model implementations, measurement algorithms, and Wi-Fi-enabled streaming, greatly improves the efficiency of ultrasound training and diagnostics, especially in point-of-care environments.

A. G. Raman et al [33] evaluate the performance and generalizability of a deep learning-based nnU-Net segmentation model across different datasets and institutional settings. The study involves training the nnU-NetV2 3D model on CT scans from the KiTS19 dataset and testing it on both the KiTS19 and an independent institutional (INST) dataset, while a similar model trained on the INST dataset is also evaluated on both datasets. The results demonstrate that the KiTS-trained model achieved a Dice score of 0.85 on its native test set but dropped to 0.66 on the external dataset, whereas the INST-trained model scored 0.74 on its own dataset and 0.60 on the KiTS dataset. These findings indicate that models generally perform better on the datasets they were trained on, with consistent performance across subgroups such as tumor size, ethnicity, and gender. The study emphasizes that despite strong internal performance, a noticeable decline in accuracy on external datasets highlights limitations in generalizability.

Therefore, the authors conclude that medical AI models must be evaluated on diverse datasets and require more inclusive training strategies or adaptive algorithms to ensure robust and reliable clinical application across varied populations.A. Seraj et al [34] suggest a completely automated framework based on deep learning to tackle the difficulties related to the manual choice of ideal frames from kidney ultrasound videos, which can frequently be time-intensive and subjective. The research employs a carefully selected dataset.Out of 1,203 frames gathered from 211 patients, classified by clinical specialists into three types: Positive, Negative, and None. Different convolutional neural network architectures, encompassing InceptionV3, ResNet34/50, EfficientNet, VGG16, YOLOv8x-cls, and YOLO11x-cls were developed and evaluated for frame classification. Among these models, the YOLO11x-cls variant exhibited outstanding performance, attaining an ideal F1-score of 100% for the Good classroom. It also achieved the highest average cross-validation accuracy of 90% with little variability among folds, demonstrating high reliability and consistency. The findings highlight the efficiency of the suggested YOLO-based process in automating the choice of diagnostically significant frameworks, thus minimizing manual labor and improving precision, reliability and effectiveness of kidney ultrasound evaluation in medical practice.

O. Al-Salman [35] introduces the Functionally Guided CKD U-Net (FG-CKD-UNet), a novel multitask deep learning architecture designed to simultaneously address kidney segmentation and functional assessment for chronic kidney disease (CKD). Unlike traditional approaches that treat segmentation and eGFR prediction separately, this model integrates both tasks through a dual-headed framework with a structure–function consistency loss. The model incorporates a morphological biomarker extractor to derive clinically relevant features such as cortical thickness, kidney volume, and cortex–medulla ratios, enabling a direct link between anatomical structure and physiological function. Experimental results on T2-weighted MRI and colorized CT datasets demonstrate superior performance, achieving a Dice score of 0.94 and an HD95 of 9.8 mm for segmentation. For functional prediction, the model attains an MAE of 0.039, RMSE of 0.058, and a Pearson correlation of 0.92, outperforming baseline models such as CNN, MLP, and ResNet. Additionally, the structure–function consistency mechanism significantly reduces error, indicating improved physiological coherence. Overall, the proposed FG-CKD-UNet offers a reliable, interpretable, and comprehensive framework for accurate CKD assessment.

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M. Zhang et al [36] provide an extensive overview of deep learning uses in kidney diseases, which can be generally divided into neoplastic and non-neoplastic types. The research emphasizes that deep learning using imaging has become an effective approach for deriving significant insights from medical data, facilitating accurate diagnosis and treatment of kidney diseases. It covers a broad spectrum of clinical uses, such as organ segmentation, lesion identification, differential diagnosis, surgical planning, and prognosis forecasting. The authors also outline the fundamental methodologies involved in deep learning for medical imaging and emphasize its growing role in supporting clinical decision-making. Nevertheless, the review highlights various issues, including data imbalance, heterogeneity, and small dataset sizes, that may affect model performance Additionally, concerns related to algorithm interpretability, ethical risks, and bias assessment are addressed as critical factors for future research. Overall, the study underscores the significant potential of imaging-based deep learning in clinical practice while advocating for improvements to enhance reliability, transparency, and applicability across diverse medical settings.

T. Dipta et al [37] emphasize that the risk of kidney tumors increases with age, making early diagnosis particularly important in elderly populations. The research emphasizes the increasing importance of medical imaging when paired with deep learning methods in effectively detecting kidney tumors, particularly considering the difficulties in segmenting soft tissues like the kidneys and prostate.To address these challenges, the authors propose a model that integrates the strengths of multiple deep learning architectures, incorporating advancements in both encoder and decoder stages. Four models—MobileNetV2, ResNet50, VGG16, and VGG19—were implemented and evaluated for kidney and tumor detection. The results demonstrate high performance, with training accuracies of 99.56%, 98.53%, 98.21%, and 98.41%, and validation accuracies of 99.04%, 98.07%, 98.15%, and 98.47%, respectively. These findings indicate that the proposed approach is highly effective and adaptable, offering a reliable tool for clinicians in diagnosing kidney and renal tumors, and contributing to improved analysis of soft tissue-related diseases.

J. Guo et al [38] investigate the feasibility of kidney segmentation using deep learning models in scenarios with limited annotated data, addressing the common challenge of scarce ground truth in medical imaging. The study employs a few-shot learning approach with 3D data augmentation, utilizing MRI datasets from two cohorts comprising a total of 60 subjects.

Cascaded convolutional neural networks (CNNs) were trained using images from one, three, and six subjects, and evaluated using Dice and Jaccard coefficients. The findings indicate that the suggested method performs well even with limited training data, reaching a Dice coefficient of 0.85 with one subject and 0.91 with six subjects. Furthermore, the cascaded CNN architecture significantly outperforms a single U-Net model across multiple training scenarios and datasets. These findings highlight the effectiveness of few-shot learning combined with cascaded networks in improving segmentation accuracy. Overall, the study presents a promising and practical solution for kidney segmentation in medical imaging, particularly in cases where annotated data is limited. A. Buriboev et al [39] propose an enhanced approach to kidney segmentation by incorporating a modified CLAHE preprocessing technique to improve image quality and CNN performance on the KiTS19 dataset. The study evaluates image quality using the BRISQUE metric, demonstrating a significant improvement as the score decreases from 28.8 in the original dataset to 21.1 with the modified CLAHE method. In addition to improved visual quality, the proposed preprocessing approach leads to a notable increase in segmentation accuracy, rising from 0.951 with the original dataset to 0.996, surpassing the performance of standard CLAHE preprocessing, which achieved 0.969 accuracy. These findings highlight the effectiveness of adaptive preprocessing techniques in enhancing deep learning-based segmentation outcomes. Overall, the study emphasizes that optimizing image preprocessing plays a crucial role in improving the reliability and accuracy of kidney segmentation, thereby supporting more precise and dependable clinical diagnosis.

H. Heller et al [40] present the challenge report for the 2021 Kidney and Kidney Tumor Segmentation Challenge (KiTS21), conducted in conjunction with the International Conference on Medical Image Computing and Computer Assisted Interventions (MICCAI). As an extension of the earlier KiTS19 challenge, KiTS21 introduces several innovations, including a larger dataset and a novel annotation strategy involving multiple annotations per region of interest in a transparent, web-based environment. The test dataset was collected from an external institution to evaluate the generalizability of developed models across diverse populations. The study reports that top-performing models significantly outperformed previous benchmarks from 2019, achieving results approaching human-level performance. Additionally, a comprehensive meta-analysis was conducted to examine the methods used by participants, their performance on the leaderboard, and the factors influencing model success across different cases.

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Overall, KiTS21 contributed substantially to advancements in kidney tumor segmentation and provided valuable insights for improving semantic segmentation techniques in medical imaging.F. Isensee et al [41] examine the impact of the nnU-Net framework on 3D medical image segmentation and critically evaluate recent claims of superior performance by newer architectures. The study highlights that while many approaches propose novel models, their reported improvements often fail under rigorous validation due to issues such as inadequate baselines, limited datasets, and overlooked computational factors. To address these shortcomings, the authors conduct a comprehensive benchmarking study comparing CNN-based, Transformer-based, and Mamba-based segmentation methods. The findings reveal that state-of-the-art performance is consistently achieved by well-configured CNN-based U-Net models, particularly when integrated with the nnU-Net framework and scaled using modern computational resources. Contrary to prevailing trends, the study suggests that newer architectures do not necessarily outperform established methods when evaluated properly. Overall, the work emphasizes the presence of innovation bias in the field and calls for more rigorous and standardized validation practices to ensure genuine scientific advancement in medical image segmentation.

X. Zhou et al [42] focus on improving kidney tumor segmentation in CT images, which is essential for accurate surgical planning in procedures such as partial nephrectomy aimed at preserving kidney function. The study highlights the challenges of segmentation due to variations in tumor size, location, and similarity in intensity with surrounding tissues. To address these issues, the authors propose two hybrid deep learning approaches that combine convolutional neural networks (CNNs) with transformer-based architectures. The sequential hybrid method extracts features using a CNN and passes them to a transformer network, while the parallel hybrid method employs a dual encoder structure that simultaneously captures local details and global contextual information. The models are evaluated using metrics such as balanced accuracy, Dice Similarity Coefficient, precision, and recall. The results demonstrate that the parallel hybrid approach significantly outperforms the sequential method, particularly for small tumors, with notable improvements in balanced accuracy, Dice score, and recall. Overall, the study confirms that integrating CNN and transformer-based techniques enhances segmentation accuracy and reliability in kidney tumor detection from CT images.

K. He et al [43] address the critical challenge of early and accurate diagnosis of renal carcinoma by proposing a comprehensive deep learning-based approach for tumor detection and classification using 3D CT scans. The study highlights the limitations of existing models, such as U-Net variants, transformer-based methods, and GAN-based approaches, which often struggle with edge segmentation, require large labeled datasets, and exhibit training instability. To overcome these issues, the authors introduce a multi-stage framework that begins with preprocessing techniques, including normalization and denoising, applied to the KiTS19 dataset to enhance image quality. Tumor segmentation is performed using a 3D SegCaps model, which effectively captures spatial relationships and improves boundary detection in volumetric data. The segmentation output is further refined using Dense Conditional Random Fields (DenseCRF) to enhance accuracy. Finally, the refined tumor regions are identified using the YOLOv5 detection model for precise localization. The proposed approach attains better results with a Dice Similarity Coefficient of 0.94, IoU of 0.95, precision of 0.98, and recall of 0.97, surpassing various leading-edge methods. In summary, the method shows significant promise for enhancing diagnostic precision and facilitating individualized treatment choices in the management of renal cancer.

M. N. Hossain et al [44] present an effective automated deep learning-driven diagnostic system for the detection and classification of kidney disease, tackling the shortcomings of conventional methods that tend to be time-intensive and susceptible to human error. The research highlights the significance of early identification in lowering death rates and enhancing treatment results. The proposed framework combines DenseNet121 and EfficientNetB0 for deep feature extraction, followed by the integration of machine learning classifiers such as Support Vector Machine (SVM), Random Forest, and XGBoost using a soft voting strategy. The model is evaluated on a large dataset of 12,446 CT images covering four classes: cyst, stone, tumor, and normal. Experimental results demonstrate exceptional performance, achieving an accuracy of 99.24% and an F1-score of 99%. These findings indicate that the proposed hybrid approach is highly effective in accurately diagnosing kidney diseases and holds significant potential for supporting early detection and clinical decision-making, particularly in resource-limited healthcare environments.

R. Ahmed et al [45] propose a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) for the early prediction of Chronic Kidney Disease (CKD) using patient medical data. The study emphasizes the importance of early diagnosis to prevent kidney failure and improve patient outcomes. The proposed system is deployed on cloud infrastructure to ensure scalable storage, efficient processing, and secure data management with HIPAA-compliant encryption. Performance comparisons with existing cloud-based approaches demonstrate significant improvements, including reduced latency, increased throughput, and faster processing time. Additionally, the system achieves high reliability with 100% fault tolerance and 99% data retention. The hybrid CNN-RNN model also delivers strong predictive performance, achieving an accuracy of 99%, precision of 95%, recall of 96%, and an F1-score of 94%. Overall, the study highlights the effectiveness of integrating deep learning with cloud computing to develop a robust, efficient, and secure solution for accurate CKD diagnosis.

P. Sharma et al [46] develop a multimodal ultrasound-based deep learning fusion model to automatically classify early fibrosis in patients with chronic kidney disease (CKD). The study utilizes multiple ultrasound modalities, including gray-scale imaging, superb microvascular imaging, and strain elastography, to capture complementary structural and functional information. Patients are categorized based on pathological fibrosis severity, and the dataset is divided into training and testing sets for model evaluation. The proposed deep learning model integrates features from all three imaging modes, significantly improving predictive performance compared to single-modality approaches. The results show that the multimodal model achieves an AUC of 0.86, outperforming gray-scale, microvascular, and elastography-based models individually. Additionally, the model demonstrates strong diagnostic performance with accuracy of 0.779, specificity of 0.767, and sensitivity of 0.796. These findings indicate that combining multiple ultrasound modalities enhances the accuracy and reliability of early fibrosis detection, making the proposed approach a valuable tool for improved diagnosis and clinical decision-making in CKD management. M. Liu et al [47] investigate the application of deep learning techniques for segmenting kidney layer structures, including the cortex, outer stripe, inner stripe, and inner medulla, in whole slide images (WSI) used in renal pathology. The study highlights the limitations of manual segmentation, which is labor-intensive and impractical for large-scale digital pathology data.

To address this challenge, the authors evaluate the feasibility of using advanced deep learning models, including both convolutional neural networks (CNNs) and transformer-based architectures such as Swin-Unet, Medical-Transformer, TransUNet, U-Net, PSPNet, and DeepLabv3+. The models are quantitatively assessed on renal cortex segmentation tasks using mice kidney WSI datasets, with performance measured using the Mean Intersection over Union (mIoU) metric. The results indicate that transformer-based models generally outperform traditional CNN-based approaches in capturing complex structural features. Overall, the study demonstrates that deep learning methods hold significant promise for improving the accuracy and efficiency of kidney layer segmentation, thereby supporting more precise and informed analysis in digital renal pathology.

Y. Su et al [48] propose a deep learning-based framework for automated kidney disease detection to address challenges related to limited specialist availability and delayed diagnosis. The study evaluates multiple pre-trained models and identifies ResNet50 and VGG19 as highly effective for feature extraction due to their strong representation capabilities. The proposed approach incorporates feature fusion with an inception block to capture diverse spatial features while handling dataset imbalance. To further enhance learning, a ConvLSTM module is integrated to model sequential dependencies and capture temporal patterns in disease progression. An additional inception block is applied after ConvLSTM to refine hierarchical feature extraction. The model is trained and validated on a newly introduced Multiple Hospital Collected (MHC-CT) dataset, consisting of annotated tumor and normal kidney CT scans, achieving an impressive accuracy of 99.60% for binary classification. Furthermore, the model demonstrates strong generalization capability by achieving 91.31% accuracy on a public multiclass dataset. Overall, the study highlights that combining feature fusion with sequential learning significantly improves diagnostic performance, offering a robust and efficient solution for automated kidney disease detection in clinical applications.D. Karimi et al [49] propose a novel semi-supervised deep learning framework for improving kidney structure segmentation in ultrasound imaging, particularly for chronic kidney disease (CKD) cases where image quality degrades in advanced stages. The study integrates Pseudo-Label Guided Contrastive Loss (PLGCL) with the ST++ learning strategy to effectively utilize both labeled and unlabeled data, enhancing model performance in data-limited scenarios.

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The results demonstrate that the proposed method significantly outperforms existing state-of-the-art techniques, achieving higher Dice coefficients across all CKD stages, with notable improvements in late-stage conditions such as G4 and G5. By combining contrastive learning with pseudo-labeling, the framework effectively addresses challenges in complex ultrasound segmentation tasks. Overall, the approach improves the accuracy of renal structure delineation, supports better assessment of disease progression, and contributes to more informed clinical decision-making and treatment planning.

Beyond segmentation and classification tasks, a substantial body of work has focused specifically on kidney stone detection, characterization, and composition prediction using deep learning across multiple imaging modalities. Elton et al. [50] developed an automated deep learning system for kidney stone detection and volumetric segmentation on noncontrast CT scans, establishing an end-to-end pipeline for stone localization and volume estimation. Black et al. [51] extended this line of work toward treatment planning by applying a deep learning computer vision algorithm to predict kidney stone composition directly from CT images, a factor critical to selecting appropriate intervention. Parakh et al. [52] evaluated deep convolutional neural networks for urinary stone detection on CT, with particular attention to model performance and generalization across imaging protocols. Building on composition prediction, Kim et al. [53] used deep learning to classify the composition of urinary stones, aiming to reduce dependence on invasive stone analysis. Moving beyond CT, Kobayashi et al. [54] proposed a computer-aided diagnosis system using a convolutional neural network for automated detection of urinary tract stones on plain X-ray, offering a lower-cost alternative diagnostic pathway. Cui et al. [55] then returned to CT-based analysis, presenting an automated machine learning approach for the segmentation and measurement of urinary stones. Situating these technical contributions within clinical practice, Tailly and Ghani [56] reviewed the broader role of artificial intelligence in the diagnosis, treatment, and prevention of urinary stones, while Stone [57] offered a complementary commentary on the use of deep learning for assessing kidney stone composition. Turning to endoscopic and in vivo imaging, Lopez-Tiro et al. [58] examined the in vivo recognition of kidney stones using machine learning, and Lopez et al. [59] assessed several deep learning methods for identifying kidney stones in endoscopic images.

Finally, Flores-Araiza et al. [60] advanced this endoscopic line of research by introducing an interpretable deep learning classifier based on prototypical parts, improving the transparency and clinical trustworthiness of stone image classification. Collectively, these studies illustrate a progression from CT-based detection and volumetric segmentation toward composition prediction, alternative imaging modalities such as X-ray, and increasingly interpretable endoscopic classification approaches, reflecting the field's movement toward more clinically actionable and trustworthy AI-assisted stone diagnosis.

Further advancing kidney stone detection through deep learning, Villalvazo-Avila et al. [61] compared multiple feature fusion strategies to improve deep learning-based kidney stone identification, examining how combining complementary image features affects classification robustness. Caglayan et al. [62] demonstrated deep learning model-assisted detection of kidney stones on computed tomography, reporting improved diagnostic support for radiologists interpreting CT studies. Li et al. [63] proposed deep segmentation networks capable of jointly segmenting kidneys and detecting kidney stones in unenhanced abdominal CT images, addressing the added difficulty of stone identification without contrast enhancement. Moving into interventional settings, Setia et al. [64] introduced a computer vision-enabled approach for segmenting kidney stones during ureteroscopy and laser lithotripsy, extending stone-detection research from diagnostic imaging into real-time surgical guidance. Babajide et al. [65] presented an automated machine learning pipeline for the segmentation and measurement of urinary stones on CT scans, reinforcing the value of automated volumetric quantification for treatment planning. Viswanath et al. [66] proposed a deep learning reaction–diffusion level set segmentation approach specifically designed for automatic kidney stone detection in clinical healthcare settings. Bayram et al. [67] contributed a detection and prediction model for kidney diseases that incorporated explainable artificial intelligence, aiming to make deep learning-based stone diagnosis more interpretable for clinicians. Returning to in vivo and endoscopic imaging, Lopez-Tiro et al. [68] examined the recognition of kidney stones in vivo using machine learning techniques, while Villalvazo-Avila et al. [69] again explored feature fusion strategies for kidney stone identification, complementing their earlier comparative study.

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Finally, Flores-Araiza et al. [70] developed an interpretable deep learning classifier based on the detection of prototypical parts within kidney stone images, further advancing the goal of transparent, trustworthy stone classification. Together, these studies reflect a growing emphasis within the field on combining accurate stone detection and segmentation across diagnostic and interventional imaging with model interpretability and explainability, positioning deep learning as an increasingly integral component of both the diagnostic and surgical management of urolithiasis.

Complementing algorithmic advances, several studies have examined real-time and clinically deployable applications of deep learning for kidney stone composition analysis and detection, alongside supporting evidence from the broader stone-imaging literature. Peta et al. [71] reported initial experience with real-time detection of kidney stone composition using artificial intelligence, machine learning, and smartphone technology, demonstrating the feasibility of point-of-care composition analysis outside traditional imaging workflows. Kolli et al. [72] developed a supervised learning algorithm for kidney stone prediction, contributing an efficient classical machine learning approach to complement deep learning-based methods. Returning to endoscopic video, Setia et al. [73] proposed a deep learning approach for segmenting kidney stones directly within endoscopic video streams, extending earlier still-image segmentation work into a temporal, procedure-based setting, while Lopez et al. [74] assessed multiple deep learning methods for identifying kidney stones in endoscopic images, reinforcing the growing interest in optical-domain stone characterization. To contextualize these AI-driven approaches, Brisbane et al. [75] provided a foundational overview of kidney stone imaging techniques, and Xiang et al. [76] conducted a systematic review and meta-analysis establishing the diagnostic accuracy of low-dose CT of the kidneys, ureters, and bladder for urolithiasis, together forming the clinical imaging baseline against which deep learning methods are typically benchmarked. Building on this foundation, Parakh et al. [77] evaluated deep convolutional neural networks for urinary stone detection on CT images with attention to model generalization, Black et al. [78] applied deep learning computer vision to detect kidney stone composition from CT, Elton et al. [79] developed an automated deep learning system for kidney stone detection and volumetric segmentation on noncontrast CT scans, and Kim et al. [80] used deep learning to predict urinary stone composition.

Taken together, this cluster of references traces a trajectory from established, non-AI diagnostic imaging standards toward increasingly automated, real-time, and even smartphone-based deep learning tools for stone detection, segmentation, and composition prediction across CT, endoscopic, and point-of-care modalities.

Extending this thread of stone-detection research across imaging modalities and hardware platforms, Kobayashi et al. [81] applied a convolutional neural network-based computer-aided diagnosis system for the automated detection of urinary tract stones on plain X-ray, offering a low-cost screening alternative, while Babajide et al. [82] presented an automated machine learning pipeline for segmenting and measuring urinary stones on CT scans. Contextualizing these technical developments, Tailly and Ghani [83] reviewed the clinical role of artificial intelligence in the diagnosis, treatment, and prevention of urinary stones, providing a urological perspective on the field's trajectory. Building on CT-based detection, Caglayan et al. [84] demonstrated deep learning model-assisted detection of kidney stones on computed tomography, and Li et al. [85] proposed deep segmentation networks capable of jointly segmenting kidneys and detecting stones in unenhanced abdominal CT images. Viswanath et al. [86] contributed a reaction–diffusion level set segmentation approach for automatic kidney stone detection, while Setia et al. [87] advanced stone segmentation into the endoscopic video domain using deep learning. Looking further back to earlier imaging-based approaches, Malalla et al. [88] conducted a preliminary study on C-arm imaging techniques for detecting nephrolithiasis and kidney stones, illustrating an alternative fluoroscopic modality explored prior to the deep learning era. Finally, a series of earlier works by Viswanath and Gunasundari [89], [90] examined hardware-accelerated implementations of kidney stone detection, including a reaction-diffusion level set segmentation approach implemented on FPGA using Xilinx System Generator [89] and a VLSI implementation combining level set segmentation with artificial neural network classification [90], both aimed at enabling real-time, embedded stone-detection systems. Collectively, this cluster of references illustrates the field's evolution from early hardware-accelerated and alternative-modality detection methods toward modern deep learning-based segmentation and classification across X-ray, CT, and endoscopic video, underscoring a sustained multi-decade interest in automating kidney stone diagnosis through both algorithmic and system-level innovation.

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Prior to the widespread adoption of deep learning, earlier work laid important groundwork for automated kidney stone classification and imaging-based diagnosis. Serrat et al. [91] introduced myStone, an early system for automatic kidney stone classification based on image analysis, while Kazemi and Mirroshandel [92] proposed an ensemble learning method for predicting kidney stone type from patient data. On the imaging side, Ibrahim et al. [93] compared ultrashort echo time MRI against reference-standard CT for detecting different kidney stone types, evaluating MRI as a radiation-free alternative for stone characterization. Black et al. [94] presented early findings on a deep learning computer vision algorithm for detecting kidney stone composition, framing this work as a step toward a fully automated composition-analysis pipeline, while Brisbane et al. [95] provided a broader overview of kidney stone imaging techniques that contextualized these emerging AI-based approaches within established diagnostic modalities. Situating stone-specific research within the wider trajectory of medical imaging AI, Litjens et al. [96] conducted a comprehensive survey of deep learning applications across medical image analysis, Greenspan et al. [97] offered an editorial overview of deep learning's promise for medical imaging more broadly, Chartrand et al. [98] provided a primer introducing deep learning concepts specifically for radiologists, and Yan et al. [99] introduced DeepLesion, a large-scale automatically mined lesion annotation dataset that enabled universal lesion detection with deep learning, a resource with direct relevance to renal and urinary lesion detection tasks. Finally, Yang et al. [100] revisited the clinical role of artificial intelligence in the diagnosis, treatment, and prevention of urinary stones, reinforcing the field's continued interest in translating these technical advances into urological practice. Together, this cluster of references establishes the foundational imaging, dataset, and survey literature that preceded and informed the more specialized deep learning-based kidney stone detection and classification methods discussed in subsequent studies.

III. Challenges And Future Scope

Deep learning applied to medical imaging has developed as a promising method to enhance the diagnosis and treatment of kidney conditions, encompassing non-neoplastic renal issues and renal tumor diseases, as numerous studies have indicated in recent years. Nonetheless, there are several challenges that must be addressed to enhance its prospects. One of the main barriers to deep learning in kidney diseases using medical imaging is the shortage of extensive, varied datasets.

To enable deep learning algorithms to produce accurate predictions, a large amount of data needs to be processed. Transporting large, high-quality medical image databases can be challenging due to the need for collaboration among various organizations and healthcare providers. At the same time, it's essential to consider dataset balance to avoid implicit bias during data collection. For example, in renal tumor segmentation tasks, the size of the tumor ranges from small to large. The model reliably generates improved segmentation outcomes for some large tumors compared to small and medium-sized tumors, likely because of the unbalanced dataset. Nonetheless, the sample reweighting method proposed by Xu et al. [29] may aid future studies on class imbalance by effectively balancing the input of types with differing volume distributions to the loss function. Moreover, a challenge lies in the differences in medical images due to differing imaging techniques and processes. Additionally, ensemble learning, which integrates the results from multiple distinct models, along with transfer literacy, which employs existing model parameters to initialize and train new models on novel data, could possibly address this challenge.

Despite their significant achievements in various clinical applications, explaining how these models arrived at a particular prognosis in clinical practice remains challenging. This is due to the ambiguous nature of the deep learning process, which makes it challenging to pinpoint the unproductive connection between input and outcome. Consequently, moral dilemmas emerge. When doctors utilize deep learning algorithms for clinical assessments, misunderstandings may arise, making it challenging to determine who is responsible due to the algorithm's interpretability concerns and applicable laws. To validate the developed model on a larger scale in external facilities, multiple studies are currently underway. If the same satisfactory results as the internal findings can be achieved, the effects of limited interpretability on doctors can be somewhat alleviated. Moreover, certain advanced methods are working to imitate the delicate connections between neighboring pixels to create an understandable framework for deep learning. A newer framework known as topological data analysis (TDA) can dismantle the opaque nature of conventional deep learning models by emphasizing the shape of data and integrating it with a method called persistent homology to convert data into visually insightful representations. The understanding of the pathophysiological factors, origins, and outcomes of various diseases, including cancer, asthma, and chronic lung conditions, has improved considerably due to TDA utilization.

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Further discussion is essential to enhance the interpretability of deep literacy and to establish normative reporting guidelines and a vital tool for bias risk assessment. Deep learning applied to medical imaging in kidney disease continues to hold great promise, even with its current challenges

IV. Conclusion

It has been widely used in the field of renal disorders, and recent studies have confirmed that imaging-based deep learning has enormous potential in data mining and analysis. Promising results have been shown using both renal tumor clinical scripts and non-tumor illness clinical scripts. The poor interpretability and repetition of deep learning, which are also connected to the fact that existing studies on deep learning tend to focus on certain clinical scenarios, continue to be obstacles to the development of deep learning in clinical practice. Thus, many things need to be addressed before deep learning may be used in therapeutic settings.

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