AN EXTENSIVE REVIEW OF KIDNEY STONE SYMPTOMS, TYPES AND PREDICTION METHODS IN UP TO DATE

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***Abstract*— Kidney stone disease is a most harmful disease which leads to kidney failure and also kills patients. The imaging techniques like CT scans, ultrasonography, X-ray and MRI scans are mostly used for easy prediction. in Recent times, Machine Learning and Deep Learning are used for effective kidney stone prediction. In this article, the review of DL model-based kidney stone prediction is discussed with several details namely Methods used in literature, performance analysis, merits and challenges respectively. The symptoms and types of stones are presented to show the variation among each stone in a kidney. Therefore, the extensive review based on kidney stone prediction is discussed with an exact tabulation to provide effectiveness.**

Keywords*— *DL model, Kidney stone prediction, performance metrics, Accuracy, classification

I. INTRODUCTION

In the recent era, kidney stones are increased all over the world drastically which caused kidney failure and pain for humans. The kidney is the most essential organ that caused stone formation due to unwanted substances in urine [1-3]. Kidney stone diseases are now most common for all gender and sector peoples that too mostly in developed countries. The main reason for stone formation in kidneys is due to overweight, minimum level of water consumption, bad food diet and also regular intake of medicines and sometimes stress etc[4,5].

The prediction of Kidney stone disease is mandatory due to its harmfulness. There are imaging techniques that are used for the diagnosis of a kidney stone to increase the lifespan of the affected person [6-9]. Some of the systems used to diagnose kidney stones are blood tests, urine tests, CT scans, ultrasonography, X-ray and MRI scans etc. These imaging techniques are easy to predict the kidney stone and simple the Doctor work with automation. This can be beneficial by saving time and minimising the risk of an error [10].

To avoid false and error in prediction, Machine Learning (ML) and Deep Learning (DL) are implemented in medical imaging [11-15]. In the recent eras, ML and DL-based techniques are applied for so many fields such as Agriculture, communication, the Military, share market, education, weather forecasting and also in Medical Fields etc [16,17]. Several ML/DL methods are frequently used in medical applications for various issues such as Breast cancer, Brain tumour, Alzheimer's disease, Heart fat, Bone crack, Throat cancer, skin cancer, kidney stone and so on [18-20].

Some of the popular ML/DL methods that are often used for medical imaging are Naive Bayes (NB), Decision Tree (DT), Neural Network (NN), Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), AlexNet, GoogleNet, DenseNet, ShuffleNet, MobileNet and so on. These methods are very efficient in the prediction and also provided superior performance in segmentation and classification respectively [21-25].

The rest of the work is structured as: section 2 presented the kidney stone symptoms and the types of stones are discussed in section 3. Section 4 presented the related work with tabulation and section 5 described the performance metrics. Section 6 presented the conclusion with a future enhancement in it.

II. SYMPTOMS OF KIDNEY STONE

The kidney stones are predicted by several symptoms that are listed below [26-28]:

i) Renal colic that provided excessive cramping pain,
ii) Flank pain that caused in the backside,
iii) Hematuria which means blood in urine,
iv) Infection in the urinary tract,

v) Obstructive uropathy means the disease occurred in the urine tract,
vi) Urine blockages,
vii) Hydronephrosis that was a kidney dilation

Therefore, these affected the health and work of patients which required immediate and efficient treatment to enhance their quality of life [29,30].

III. TYPES OF KIDNEY STONE

Kidney stones are mainly caused due to a chemical abnormality in urine. There are several stones are formed in the human kidney based on various chemical compositions, sizes and shapes [31,32]. The most common type of stones is given in the following [33].

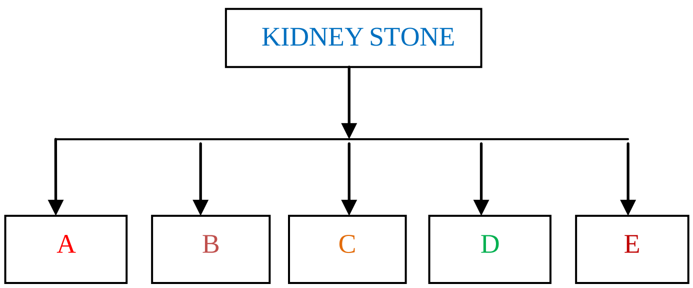

Fig 1. Classification of Kidney Stone

A. Calcium Stones

Calcium stones are the most common renal stones that are caused for many patients due to a urinary calculi abnormality. It is a mixture of Calcium Oxalate and Calcium Phosphate which is occurred in more than 60% of kidney stone patients. It has two types namely CaOx monohydrate (COM) and CaOx dihydrate (COD) where COM is frequently observed disease than COD [34].

B. Struvite Stones

Struvite stones are referred to as an infection that is caused by upto 10–15% of patients. It is an ingredient of Magnesium Ammonium Phosphatewhich seems to be a triple phosphate stone. These stones caused various diseases like Klebsiella pneumonia, Enterobacter and Pseudomonas aeruginosa [35]. These stones have mostly occurred in women than males.

C.Uric Acid Stones or Urate

It has occurred in 3–10% of patients with kidney stones which comprised a high purine of animal protein like fish and meat. This stone has a possibility to cause a low urine volume, hyperuricosuria and low urinary pH. These types of uric acid stones are commonly occurred in males than in women [36,37].

D.Cystine Stones

This type of stone is caused by a genetic disorder based on cystine and amino acid. It has occurred a 2% of kidney stone patients that provided a urinary excretion of excessive cystinuria. The cystine does not dissolve in urine and caused a cystine stone that evacuates 600 millimoles of cystine/per day[38].

E. Drug-Induced Stones

Some the drugs like triamterene, guaifenesin, atazanavir, and sulfa drugs are the reason for Drug-Induced stones [39]. It has occurred in 1% of kidney stone patients. For example, a frequent drug with a heavy dose for the disease especially for HIV would develop Drug-Induced Stones and leads to kidney failure [40].

IV. RELATED WORKS

Several methods are developed by various authors in recent decades for kidney stone prediction that is discussed in the following and tabulated in Table 1.

Black et al [41] presented the CNN and ResNet-101 model for a multi-class kidney stone classification. It can be diagnosed through automatic imaging based on cross-validation. This system has achieved a weighted recall of 94.12%, specificity of 97.83% and precision of 94.12% with an efficient performance. Besides, another automated stone detection is implemented by Yildirim et al [42] using 1799 images of coronal CT. The stone prediction is attained accurately even for a small size with an evaluation of 96.82% accuracy, 98% precision, 96% recall and 97% F1 score respectively.

In some cases, the DL method of VGGNet-19 and Binary SVM is presented by Somasundaram et al [43] for effective feature extraction and classification of kidney stones. This system is performed and validated with a97.32% Recall, 98.07% precision, 99.19 % accuracy, 98.28% specificity and93.2% F1 score respectively. Alongside, the ML/DL method predicted Renal Cell Carcinoma (RCC), urolithiasis, bladder cancer (BCa), and prostate cancer (PCa)based on the PubMed MEDLINE database by Suarez-Ibarrola et al [44]. It provided urological applications with a performance of 94.26% accuracy, 94.51% sensitivity and 96.29% specificity. Also, Artificial intelligence (AI) has been explored for time management to predict the tiny stones. This system can be diagnosed with a minimum CT image computation with a superior 98.52% accuracy, 96.75% sensitivity and 98.12% specificity by Sabuncu et al [45].

Flores-Araiza et al [46] developed the part-prototypes (PPs) methodology with three categories namely the AlexNet model, batch normalization as the backbone (PPN-VGG19bn) and batch normalization of VGG19 (VGG19bn) respectively. The kidney stone classification is processed as a patch image and provided a mathematical analysis with an effective method. The performance of AlexNet attained a 96% accuracy, VGG19bn acquired 99% accuracy and also 98% accuracy for PPN-VGG19bn. Moreover, Li, D et al [47] investigated various DL methodssuch as 3D U-Net, SegNet, Res U-Net, DeepLabV3+, and UNETR for testing and training. These 3D U-Net, SegNet, Res U-Net, DeepLabV3+, and UNETR model has evaluated the accuracy of 98.32%, 97.45%, 89.93%, 95.54% and 98.11% respectively.

In some methods, the kidney stone predictions using an Inception v3 method by Ochoa-Ruiz et al [48] are tested with urinary calculi types in-vivo images. The performance metrics are evaluated with a 97% of weighted precision, 98% of recall and 97% of F1-score correspondingly. Moreover, the Renal Stone Complexity of the Seoul National University (S-ReSC) model is implemented by Jeong et al [49] for stone-free rate prediction of a kidney. The result of the Area Under Curve (AUC) is achieved 0.860 for an effective prediction.

Kim et al [50] aimed urolithiasis prediction based on seven DL models with detailed chemical composition. This method has acquired 1,332 stone images and executed four classes for every DL model. Overall, the Xception DL model performed superior toall others evaluated for all four classes of precision and recall as class 1: 94.24%, 91.73%, class 2: 85.42%, 96.14%, class 3: 86.86%, 99.59% and class 4: 94.96%, 98.82%.Also in another work, the kidney stone prediction survey of DL models such as SVM, NB, and NN are investigated by Sri et al [51]. This survey executed the comparison of performance accuracy with every model's effectiveness.

The DL method like multi-view AlexNet max and multi-View VGGnet max is used to extract the fuse of the various viewpoints for discriminant object features. This system presented by Villalvazo-Avila et al [52] presents a deep-learning method for extracting and fusing image information acquired from different viewpoints for discriminant object features. The result is validated for precision and Recall for multi-view AlexNet max are 95% and 94% and also for multi-View VGG16 max are 94% and 94% respectively. Besides, Kazemi et al [53] developed an ensemble learning for a robust kidney stone prediction with a 97.1% accuracy. This system metrics are acquired with an effective classification result such as precision of 97.1%, recall of 97.1%, F1 score of 97.1% and 99.6% AUC.

Shah et al [54] reviewed AI and its application for the classification of cystoscopic, renal masses diagnosis using an MRI. This work established the reaction of treatment, prognosis, survival and recurrence of genomic and biomarker studies. Alongside, a few DL methods like ensemble model, Logistic Regression (LR) and RF models are used to predict kidney stones using CT images. This system is investigated by Kolli et al [55]. This can be addressed by the metrics in terms of 97.12% precision, 96.83% accuracy and 98.1% Recall respectively. In a few literatures, the abdominal CT dataset is used to segment and classify for both testing and training of kidney stones prediction. The AI- driven diagnostic approaches are explored by Li, D et al [56] with a performance accuracy of 95%, a sensitivity of 88% and a specificity of 91% respectively.

The CNN model-based automatic kidney stone prediction using CT images is implemented by GP et al [57]. This system achieved an effective performance with an accuracy of 96.82%, Recall of 93.22%which is competent enough as distinguished it from previous algorithms. Moreover, Surya et al [58] developed a Backpropagation network and Fuzzy Clustering Mean Algorithm for various steps for medical assistance in kidney stone prediction. These methods are provided with animage pixel with a higher stone prediction accuracy of 97.92%, specificity of 95.79% and sensitivity of 97.23% correspondingly.

The Renal stone diagnosis is presented in radiography based on renal stone disease developed by McCarthy et al [59]. This system used a STONE PLUS prediction tool with innovative management and diagnosis. It provides the best care for patients with a precision of 92%, Recall of 93.41% and sensitivity of 94.21%. Also, Buvaneswari et al [60] discussed a hybrid ButterflyNet and InceptionNet model for kidney stone identification. The performance metrics acquired a 90% F1 Score, 84% accuracy, 88% Recall and 94% precision which provided a superior result than the conventional.

Author	**Methods**	**Metrics evaluation**	**Strength**	**Weakness**
Black et al [41]	CNN and ResNet-101 model for a multi-class kidney stone classification	Recall-94.12% Specificity-97.83%, Precision-94.12%	Multi class based Performance	flexibility and speedy diagnosis

Yildirim et al [42]	CT based automated stone detection	Accuracy-96.82%, precision-98%, Recall-96%, F1 score-97%	Accurate detection even for small size stone	Connectivity
Somasundaram et al [43]	VGGNet-19 for feature extraction and Binary SVM for classification	Recall-97.32%, precision-98.07%, accuracy-99.19 %,specificity-98.28% F1 score-93.2%	QoS	Energy consumption
Suarez-Ibarrola et al [44]	PubMed MEDLINE database-based RCC, BCa, PCa prediction	Accuracy-94.26%, sensitivity-94.51%, specificity-96.29%	Multi-subject detection	Complexity
Sabuncu et al [45]	AI-based CT images	Accuracy-98.52%, sensitivity-96.75%, specificity-98.12%	Computational accuracy	Less Availability
Flores-Araiza et al [46]	PPN-VGG19bn, AlexNet, VGG19bn	All three methods attained Accuracy of 96%, 99% and 98%	Effective mathematical analysis	Display quality
Li, D et al [47]	3D U-Net, SegNet, Res U-Net, DeepLab V3+, and UNETR	Accuracy-98.32%, 97.45%,89.93%, 95.54% and 98.11%	Classification accuracy	Energy consumption
Ochoa-Ruiz et al [48]	Inception v3 method	Precision-97%, Recall-98%, F1-score-97%	Low cost and simple	Low Flexibility and speed
Jeong et al [49]	DL based S-ReSC prediction	AUC-0.860	Performance	Avoid false diagnosis
Kim et al [50]	7model used for kidney stone predict	Precision-94.96%, Recall-98.82%	QoS	Limited functionalities
Sri et al [51]	Survey of DLmethod based kidney stone prediction	-	comparison of performance accuracy	Future ideas
Villalvazo-Avila et al [52]	Multi-view AlexNet max and multi-View VGGnet max	AlexNet max Recall-95%, VGGnet max Recall-94%	Complexity	Energy consumption
Kazemi et al [53]	ensemble learning model	Recall-97.1%, F1 score-97.1%, AUC-99.6%	Lifetime	Reliability, Efficiency
Shah et al [54]	AI model survey	-	Comparison of diagnosis ,methods and materials	Numerical comparison
Kolli et al [55]	Ensemble model, LR and RF models for prediction	Precision-97.12%, Accuracy-96.83%, Recall-98.1%	Memory	Utility, Accuracy
Li, D et al [56]	AI- driven diagnostic approaches	Accuracy-95%, Sensitivity-88%, Specificity 91%	Performance	Training
GP et al [57]	CNN model	Accuracy-96.82%, Recall-93.22%	Cost overhead	Microscopic examination

Surya et al [58]	Back propagation on network and Fuzzy Clustering Mean	Accuracy-97.92%, Specificity-95.79%, Sensitivity-97.23%	Compression and low data loss	Quite complex system
McCarthy et al [59]	Renal stone diagnosis	Precision-92%, Recall-93.41%, Sensitivity-94.21%	Effectiveness	Security
Buvaneswari et al [60]	hybrid Butterfly Net and Inception Net model	F1 Score-90%, Accuracy-84%, Recall-88%, Precision-94%	Portability, real-time Monitoring	Categorise the data Layer

V. PERFORMANCE METRICS

In the medical field, the performance metrics based on classifications are validated in terms of Sensitivity, Accuracy, Specificity, AUC and F1 score respectively. All these metrics are discussed and expressed below.

Sensitivity: It is defined as actual positive cases proportional measurement which is truly detected as positive that is expressed in equation (1).

$$sensitivity = \frac{True_{positive}}{True_{Positive} + False_{Negative}} \quad (1)$$

Specificity: It is the measure of actual negative proportions that is truly predicted as negative which is expressed in equation (2).

$$specificity = \frac{True_{Negative}}{True_{Negative} + False_{Positive}} \quad (2)$$

Accuracy: It is defined as the number of truly predicted divided by the overall predictions that are expressed in equation (3).

$$Accuracy = \frac{True_{Positive} + True_{Negative}}{True_{Negatuve} + True_{Positive} + False_{Positive} + False_{Negative}} \quad (3)$$

F1 Score: It measured the accuracy of testing which evaluated the precision and recall values that havethe best value as 1 and the worst value as 0which is expressed as equation (4).

$$F1\ score = \frac{2\ Recall \times Precision}{Recall + Precision} \quad (4)$$

Recall: It is only concentrated only on Falsely Negative and won't be considered Truly Negatives which is expressed as equation (5).

$$Recall = \frac{True_{Positive}}{True_{Positive} + False_{Negative}} \quad (5)$$

Precision: It is measured only the Falsely Positives and Truly Positives that are expressed as equation (6).

$$precision = \frac{True_{Positive}}{True_{Positive} + False_{Positive}} \quad (6)$$

Where $True_{Positive}$ indicates actually predicted as 1, $True_{Negative}$ denotes actually predicted as 0, $False_{Positive}$ represents the original value as 0 and detected as 1 and $False_{Positive}$ indicates the original value as 1 and detected as 0 respectively.

VI. CONCLUSION

In this article, medical image processing is reviewed for kidney stone prediction. A few kidney stone prediction works are listed and tabulated based on their method, achievement, merits and demerits. From this work, there are detailed explanations are given for every paper with its functions. It is clear to update the recent innovations towards kidney stone prediction. Though there are several challenges that are also still presented in prediction one has to build the QoS of a system by an effective prediction by implementing some optimization algorithm with DL methods for fine-tuned results. Also, the security is not yet improved in these works, so the security has to be concentrated in future enhancements.

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