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Research Article

Image Based Chronic Renal Disease Diagnosis Using Convolution Neural Network Deep Learning Approach

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ABSTRACT

Kidney disease presents a major health challenge, with conditions like kidney stones requiring timely diagnosis and treatment. Traditional radiological methods are time-consuming and dependent on expert interpretation. This study proposes an automated kidney stone detection system using deep learning techniques, employing CNN for classification. A diverse dataset, including normal kidney tissue, kidney stones, cysts, and tumors, is utilized. The methodology includes data preprocessing, feature selection, and CNN-based classification, achieving a high accuracy of 88.43%.

Additionally, this research explores Chronic Kidney Disease (CKD) prediction using a modified CNN architecture, incorporating data augmentation and preprocessing for enhanced accuracy. The model is evaluated against existing machine learning approaches, and contour plotting is employed to assess severity levels.Results highlight the potential of deep learning in improving early detection, reducing diagnostic time, and assisting radiologists in kidney disease management.

Keywords: Chronic Kidney Disease (CKD), Prediction, Clinical judgement, Medical expertise, CNN, Image Processing, Deep learning.

INTRODUCTION

Chronic Kidney Disease (CKD) is a growing global health concern, characterized by the gradual decline of kidney function, which can lead to end-stage renal disease (ESRD) and increased cardiovascular risks. Early detection and accurate prediction of CKD progression are critical for effective intervention and improved patient outcomes. Machine learning techniques, particularly deep learning models like Convolutional Neural Networks (CNNs), have shown promise in enhancing CKD detection and classification through medical imaging analysis.

This study explores automated kidney disease detection using CNN-based models trained on diverse medical imaging datasets, including CT and MRI scans. By leveraging machine learning algorithms, the research aims to improve diagnostic accuracy, reduce reliance on subjective expert interpretation, and provide a faster and more efficient approach to kidney disease identification. Additionally, the study highlights the importance of integrating computational techniques with clinical expertise to enhance disease prediction, risk assessment, and treatment planning.

OBJECTIVES

Develop an Automated CKD Detection System: Utilize Convolutional Neural Networks (CNNs) to accurately detect and classify Chronic Kidney Disease (CKD) from medical imaging data, such as CT and MRI scans.

Enhance Diagnostic Accuracy and Efficiency: Improve the precision of CKD diagnosis by leveraging deep learning models capable of identifying subtle patterns in medical images that may be missed by human experts.

Reduce Dependence on Radiologists: Assist healthcare professionals by providing an automated tool that minimizes subjective interpretation errors and reduces the workload of radiologists.

Integrate Data Preprocessing and Augmentation Techniques: Apply image preprocessing techniques such as noise reduction, contrast enhancement, and augmentation to optimize the dataset and enhance model performance.

Optimize CNN Architectures for CKD Prediction: Implement and compare different CNN architectures, to determine the most effective model for CKD classification.

Mitigate Class Imbalance Issues: Employ dataset balancing techniques to ensure fair representation of all CKD-related conditions, improving model generalization and reducing bias.

Evaluate Model Performance: Assess the efficiency of the proposed deep learning models using key performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis.

Enable Early Diagnosis and Risk Stratification: Support early-stage CKD detection and risk assessment, allowing for timely medical intervention and improved patient outcomes.

Facilitate Real-World Deployment: Develop a robust, scalable, and user-friendly system that can be integrated into clinical workflows for real-time CKD diagnosis.

Explore Contour Plotting for Severity Assessment: Implement contour mapping techniques to assess kidney damage severity and provide percentage-based severity estimation for better treatment planning.

LITERATURE SURVEY AND RELATED WORK

Chronic kidney disease (CKD) is a progressive condition that leads to a gradual decline in kidney function. It represents a medical condition that causes kidney damage and impacts overall health. If left undiagnosed and untreated, CKD can progress to end-stage renal disease, which can ultimately be fatal. Machine Learning (ML) techniques have become essential in disease prediction and are widely utilized in medical research [1].

CKD is a serious and potentially fatal condition that is challenging to detect in its early stages due to the absence of symptoms. The objective of this study is to design and validate a predictive model for CKD detection. ML algorithms are extensively used in medical applications to predict and classify diseases. Given that medical datasets often exhibit imbalance, researchers have employed the chronic kidney disease dataset from the UCI Machine Learning Repository, which consists of 25 features. They have analyzed this dataset using three ML classifiers: Logistic Regression (LR), Decision Tree (DT), and Support Vector Machine (SVM). Additionally, a bagging ensemble technique was applied to enhance the model's performance [2].

This systematic review aimed to evaluate how artificial intelligence (AI), including machine learning (ML) techniques, has been utilized for predicting, diagnosing, and treating chronic kidney disease (CKD). The authors conducted a comprehensive analysis of existing evidence on these advanced techniques to enhance CKD diagnosis and patient care [3].

CKD is among the most severe health conditions today. Since the disease often remains undetected until significant kidney damage has occurred, early diagnosis can be life-saving. In this context, paper [4] presents three predictive models designed to forecast CKD onset 6 to 12 months before manifestation. These models include a convolutional neural network (CNN), a long short-term memory (LSTM) model, and a deep ensemble model. The deep ensemble model integrates three base deep learning classifiers (CNN, LSTM, and LSTM-BLSTM) using a majority voting approach.

As a major global health concern, CKD necessitates timely detection and accurate prognosis for effective treatment and management. The use of ML algorithms for CKD detection and prediction has shown great potential in improving patient outcomes. By analyzing key contributing factors, these models enhance the ability to identify high-risk individuals and enable early interventions. Paper [5] underscores the significance of utilizing ML techniques to complement existing medical knowledge and refine the detection and management of kidney disease.

According to paper [6], researchers are striving to develop an effective model that offers key insights into CKD progression. The review indicated that Cox regression modeling was predominantly employed in the limited studies analyzed. This variation, coupled with differing validation methods across cohort types, posed challenges in comparing ML algorithms.

Diabetes and hypertension are the leading causes of CKD. Researchers worldwide utilize Glomerular Filtration Rate (GFR) and kidney damage markers to diagnose CKD, a condition that progressively reduces renal function.

Individuals with CKD face a heightened risk of premature mortality. Diagnosing CKD-related diseases at an early stage remains a significant challenge for healthcare professionals. This study introduces a novel deep learning model aimed at the early detection and prediction of CKD [7].

As outlined in paper [8], CKD is characterized by persistent structural and functional kidney abnormalities, contributing to high morbidity and mortality globally. The disease affects approximately 8%–16% of the global population. Effective screening, staging, diagnosis, and appropriate management by primary care providers are crucial in mitigating the adverse effects associated with CKD worldwide.

Nonalcoholic fatty liver disease (NAFLD) represents the hepatic manifestation of metabolic syndrome and is the leading cause of chronic liver disease in developed nations. Various factors, including mild inflammation biomarkers, dyslipidemia, and insulin resistance, can contribute to the progression of nonalcoholic steatohepatitis (NASH), a condition marked by liver inflammation and cellular damage [9].

Chronic kidney disease (CKD) develops gradually over several years, often remaining asymptomatic during its early stages. Consequently, diagnosis, evaluation, and treatment rely primarily on biomarkers that assess kidney function. Glomerular filtration rate (GFR) is considered the most accurate marker of kidney function. However, direct measurement of GFR is time-consuming, so it is typically estimated using equations that incorporate endogenous filtration markers such as serum creatinine (SCr) and cystatin C (CysC) [10]. A comprehensive review on this topic is available in [11].

Chronic Kidney Disease (CKD) is a critical health condition that necessitates timely and accurate diagnosis. Machine learning techniques have emerged as reliable tools for medical diagnostics, enabling early disease detection. This study focuses on CKD prediction using machine learning algorithms. The dataset for this research was sourced from the UCI repository, and seven classifier algorithms were applied, including artificial neural networks, C5.0, Chi-square Automatic Interaction Detector, logistic regression, linear support vector machines with L1 and L2 penalties, and random trees. Additionally, an important feature selection technique was implemented to optimize the dataset. Each classifier was evaluated using multiple approaches: (i) full features, (ii) correlation-based feature selection, (iii) wrapper method feature selection, (iv) least absolute shrinkage and selection operator (LASSO) regression, (v) synthetic minority over-sampling technique (SMOTE) with LASSO-selected features, and (vi) SMOTE with full features. The results indicated that the linear support vector machine (LSVM) with an L2 penalty achieved the highest accuracy of 98.86% when applied to SMOTE with full features. Performance metrics, including accuracy, precision, recall, F-measure, area under the curve (AUC), and the GINI coefficient, were computed and compared across different algorithms. The combination of LASSO-selected features with SMOTE yielded the second-best results after SMOTE with full features. In the SMOTE with LASSO-selected features approach, LSVM again provided a high accuracy of 98.46%. Furthermore, a deep neural network (DNN) was also implemented on the dataset, achieving the highest accuracy of 99.6% [12].

Chronic Kidney Disease (CKD) is a condition that impairs normal kidney function. According to the World Health Organization (WHO), CKD is a severe illness, ranking among the top twenty causes of death globally. It is estimated that around 2 million individuals worldwide suffer from kidney failure, with the number of CKD diagnoses increasing at an annual rate of 5-7%. Late diagnosis poses a significant health risk, especially in remote regions where access to specialized medical professionals is limited, and diagnostic costs remain high. This study focuses on the early detection of CKD using machine learning algorithms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and k-Nearest Neighbor (k-NN). The significance of artificial intelligence lies in its ability to identify life-threatening diseases more effectively. The research utilizes a dataset containing 400 samples with 13 features. The three classification techniques were applied and assessed for performance. The results indicate that the ANN classifier achieved the highest accuracy, reaching 99.2% [13].

Chronic Kidney Disease (CKD) is an increasing public health concern due to its rising prevalence. This study explores 24 predictive parameters and develops a machine learning classifier for CKD detection. The proposed approach is tested on a dataset comprising 400 individuals, 250 of whom have CKD. Our method achieves an F1-measure detection accuracy of 0.993 with a root mean square error (RMSE) of 0.1084. This represents a 56% reduction in mean square error compared to the state-of-the-art CKD-EPI equation, a widely used glomerular filtration rate estimator. Additionally, feature selection techniques are applied to identify the most relevant attributes for CKD detection, ranking them based on their predictive importance. This analysis reveals new predictive factors that have not been previously utilized in GFR estimator equations. Finally, a cost-accuracy tradeoff analysis is conducted to propose a novel CKD detection method that balances high accuracy with cost-effectiveness [14].

Many patients worldwide succumb to chronic diseases, which are often challenging to diagnose promptly. This study utilized data samples from Indian patients with kidney disease to analyze chronic conditions. By examining the correlation between various kidney disease indicators and patient conditions, the significance of individual physical attributes was highlighted. To evaluate predictive accuracy, both the Logistic Regression model and the BP neural network model were applied to the dataset. Testing results indicated that the Logistic Regression algorithm performed lower in terms of prediction accuracy, recall, and F1 score compared to the BP neural network. These findings suggest that the BP neural network is more effective in diagnosing kidney disease. The integration of artificial intelligence in disease identification through machine learning has significantly advanced the medical and healthcare fields, improving diagnostic efficiency and accuracy [15].

Early diagnosis and characterization play a crucial role in determining the appropriate treatment for chronic kidney disease (CKD). CKD is a condition that progressively damages the kidneys, impairing their ability to eliminate waste and regulate body fluids. Some associated complications include hypertension, anemia, mineral bone disorders, poor nutritional health, acid-base imbalances, and neurological issues. Accurate and timely detection of CKD is essential in preventing further deterioration of a patient's health. Various data mining classification techniques and machine learning (ML) algorithms are employed for predicting chronic diseases. This study utilizes the Random Forest (RF) classifier, Logistic Regression (LR), K-Nearest Neighbor (K-NN), and Support Vector Machine (SVM) algorithms to predict CKD. The dataset, comprising 400 samples with 25 attributes, is sourced from the UCI Repository and analyzed using classification models. Experimental results indicate that K-NN, LR, and SVM achieve accuracies of 94%, 98%, and 93.75%, respectively. The RF classifier outperforms the others, attaining a perfect accuracy of 100% [16].

Level Set Segmentation

To diagnose kidney-related issues such as stone formation, cysts, urinary blockages, congenital deformities, and malignant cells, K. Viswanath and Dr. R. Gunasundari utilized level set segmentation in 2015 [17]. Identifying the precise location of kidney stones is essential during surgical procedures. However, due to the low contrast and presence of speckle noise in ultrasound images, detecting kidney stones is a challenging task. The solution lies in applying appropriate image processing techniques.

The process begins with image restoration, where speckle noise is removed from the ultrasound image. Next, histogram equalization enhances the image after it has been smoothed using a Gabor filter. The level set segmentation technique is then applied to identify the stone region in the preprocessed image. To achieve higher accuracy, segmentation is performed twice—first to isolate the kidney section and then to extract the stone region.

This study utilizes momentum and resilient propagation (RProp) as part of the level set segmentation approach to accurately detect kidney stones. Once the segmentation process is complete, wavelet sub-band analysis is applied using Smelts, Biorthogonal (bio3.7, bio3.9, bio4.4), and Daubechies lifting schemes to extract energy levels from the segmented stone region. These energy levels are compared with normal energy levels to confirm the presence of stones.

A multilayer perceptron (MLP) combined with a backpropagation (BP) artificial neural network (ANN) is then trained to classify and identify different types of kidney stones with an impressive accuracy of 98.8%.

Seeded Region Growing-Based Segmentation

In 2011, P.R. Tamilselvi and P. Thangaraj introduced a Seeded Region Growing (SRG)-based segmentation approach to detect and classify kidney stones in ultrasound renal images. Their method focused on identifying and categorizing kidney images into normal, stone, and early-stage stone formations by analyzing intensity threshold variations in segmented regions.

The technique relies on image granularity features, which define the homogeneous regions in the enhanced semi-automatic SRG-based segmentation algorithm. Structures with dimensions comparable to the speckle size are of particular interest. The lookup table entries determine the size and shape of the growing regions. To further enhance accuracy, a region-merging step is applied after region growth, effectively suppressing high-frequency artifacts.

Diagnosis is based on intensity threshold variations in the segmented regions and a comparison of segment sizes to standard kidney stone measurements:

Less than 2 mm – No kidney stone detected

2-4 mm – Early-stage stone formation

5 mm and above – Presence of kidney stones

IMPLEMENTATION STUDY

The existing kidney stone detection technology relies on level set segmentation and a smoothing Gabor filter. However, using level set segmentation presents several challenges, including the need for precise velocity design to advance the level set function effectively. Additionally, achieving a high accuracy rate requires access to a substantial amount of data, which is often difficult to obtain.

We have developed a system that utilizes deep learning and a pretrained model to classify kidney conditions, including stones, cysts, tumors, and normal cases. A dataset titled "CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone" has been compiled and annotated using 12,446 images captured with the neurogram technique and full-abdomen scans. For classification, CNN-based deep learning models leveraging transfer learning, have been employed and thoroughly evaluated.

Proposed Methodology:

Data Collection: Images labeled as kidney stones, cysts, tumors, or normal tissue were sourced from Kaggle to construct the dataset.

Model Selection: A suitable pretrained model architecture was chosen for classification.

Feature Extraction: The pretrained model extracts relevant features from the medical images by processing them and generating output probabilities for each class.

Model Evaluation: The accuracy and performance of the pretrained models are assessed using a separate validation dataset.

Comparison and Analysis: The effectiveness of the CNN models is compared to determine which performs best for the classification task. The results are analyzed to identify each model's strengths and limitations.

This approach enhances kidney disease detection by leveraging advanced deep learning techniques to improve accuracy and reliability.

METHODOLOGY AND ALGORITHM

Dataset

This study utilizes a collection of MRI scans and ckd data from Kaggle and contributed by Revolution Analytics, for kidney disease diagnosis.

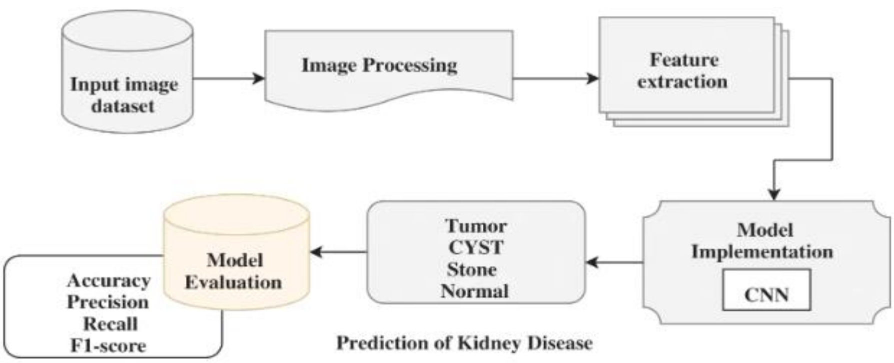

Fig. 1 Proposed model

Below is a detailed explanation of the key components depicted in the diagram:

1. CKD Data Input

- The process begins with CKD data collection, which could include clinical records or medical imaging datasets such as CT scans of kidneys.
- The dataset is stored in a database labeled 'CKD Data'.

2. Data Processing

- This stage involves several preprocessing techniques, including:
    - Images Resizing – Ensures uniform dimensions for input images.
    - Data Augmentation – Introduces variations in the dataset (such as rotations, flips, or brightness adjustments) to improve model generalization.
    - Data Normalization – Standardizes pixel values for better model training.
    - Data Splitting – Divides data into training and testing sets.

3. Training and Testing Datasets

- The preprocessed data is split into two parts:
    - Training Dataset – Used for model learning.
    - Testing Dataset – Used for evaluating the model's performance.

4. Deep Learning Model Pipeline

The core of the classification model is a Convolutional Neural Network (CNN), consisting of the following layers:

- Convolutional Layer – Extracts essential features from input images using filters.
- Pooling Layer – Reduces spatial dimensions while preserving important information.
- Dense Layer (Fully Connected Layer) – Interprets the extracted features and prepares for classification.
- Output Layer – Produces the final classification output.

5. Model Used

Different deep learning models are tested to optimize performance:

- A Standard CNN model with deep layers.
- Vision Transformers – Modern deep learning models including:
    - EANet
    - CCT
    - Swin Transformer

These models help improve the classification of CKD-related conditions.

6. Hyperparameter Tuning

- This step optimizes model performance by adjusting:
    - Learning rates
    - Batch sizes
    - Number of layers
    - Activation functions, etc.

7. Classification Output

- The trained model classifies kidney conditions into one of the following categories:
    - Cyst – Detects cystic formations.
    - Normal – Identifies healthy kidney images.
    - Stone – Detects kidney stones.
    - Tumor – Identifies tumor growth in the kidney.

RESULTS

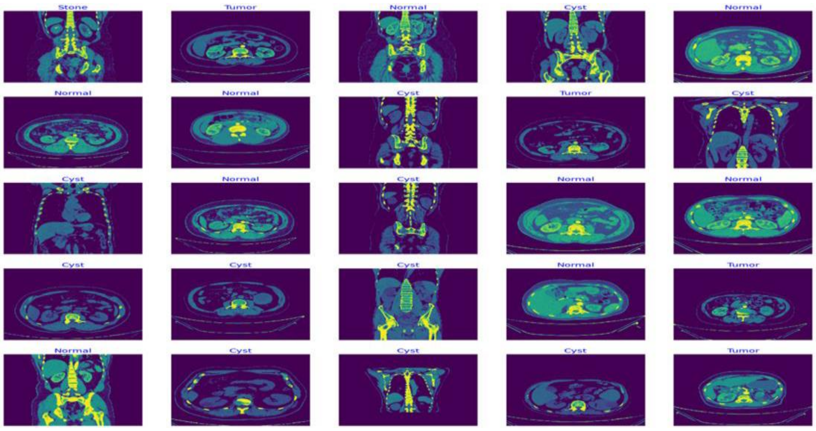

Fig. 2 Sample images from dataset

The Fig. 2 showcases a collection of medical scan images (likely CT or MRI scans) that have been preprocessed and labeled for classification purposes. Each scan is marked with a corresponding category in blue text at the top, such as "Stone," "Tumor," "Normal," or "Cyst."

Layer (type)	Output Shape	Param #
random_flip (RandomFlip)	(None, 28, 28, 3)	0
random_rotation (RandomRotation)	(None, 28, 28, 3)	0
random_zoom (RandomZoom)	(None, 28, 28, 3)	0
conv2d (Conv2D)	(None, 28, 28, 32)	896
batch_normalization (BatchNormalization)	(None, 28, 28, 32)	128
max_pooling2d (MaxPooling2D)	(None, 14, 14, 32)	0
flatten (Flatten)	(None, 6272)	0
dense (Dense)	(None, 512)	3,211,776
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 256)	131,328
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 4)	1,028

Fig. 3 Total trainable parameters

This table represents the architecture of a Convolutional Neural Network (CNN) used for classifying kidney conditions such as stones, cysts, tumors, and normal cases. The layers and their parameters are detailed below:

1. Convolutional Layers (Conv2D)

Each Conv2D layer extracts spatial features from the input images.

The number of filters (e.g., 32, 64, 128) increases progressively, allowing the model to learn more complex patterns.

The kernel size is not explicitly mentioned but is typically 3x3 or 5x5 in CNN models.

2. Pooling Layers (MaxPooling2D)

Max pooling reduces the spatial dimensions of feature maps, preserving essential features while reducing computational complexity.

Stride = 2, meaning the dimensions of the feature maps are halved after each pooling operation.

3. Flattening Layer

Converts the 2D feature maps into a 1D vector, making it compatible with fully connected layers.

4. Fully Connected (Dense) Layers

Dense Layer (512 neurons): Learns high-level abstract features.

Output Layer (4 neurons): Uses a softmax activation function for multi-class classification (Kidney Stone, Tumor, Cyst, Normal).

5. Parameter Count

The total number of trainable parameters = 354,532.

The fully connected layers (dense layers) have the highest parameter count due to their dense connections.

Classification Report:

	precision	recall	f1-score	support
Cyst	0.83	0.92	0.87	1016
Normal	0.91	0.91	0.91	1015
Stone	0.90	0.74	0.81	1016
Tumor	0.91	0.96	0.93	1015
accuracy			0.88	4062
macro avg	0.89	0.88	0.88	4062
weighted avg	0.89	0.88	0.88	4062

Fig. 4 Classification Repot Achieved 88%

The Fig. 4 contains classification report of kidney diseases detection.

The model is improving in precision, recall, and accuracy while reducing loss. Some fluctuations in validation metrics suggest minor overfitting, but overall, the model appears to generalize well.

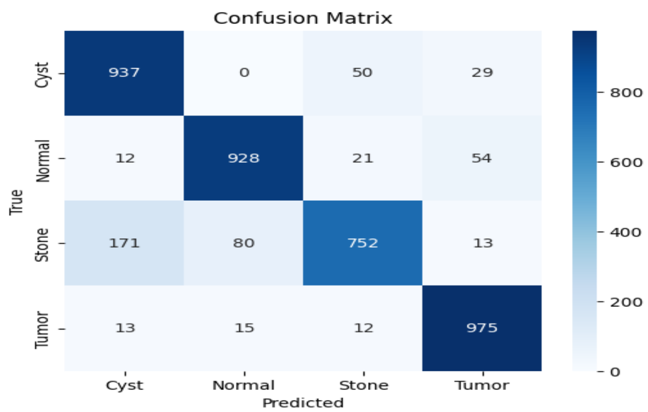

Fig. 5 Confusion Matrix of The Predicted Labels Hence The Model Was Trained With An Accuracy Of 88%

This Fig.5 represents a Confusion Matrix Heatmap, which is used to evaluate the performance of a classification model by comparing predicted and actual labels.

Understanding the Confusion Matrix:

The x-axis represents the predicted classes.

The y-axis represents the actual (true) classes.

Each cell contains the number of samples classified in each category.

The diagonal cells (top-left to bottom-right) show correctly classified instances.

Off-diagonal cells represent misclassifications.

Analysis of the Given Confusion Matrix:

The confusion matrix consists of four categories: Cyst, Normal, Stone, and Tumor. The values in the matrix are:

Actual \ Predicted	Cyst	Normal	Stone	Tumor
Cyst	166	0	0	0
Normal	0	235	0	0
Stone	0	0	70	0
Tumor	0	1	0	114

Key Observations:

High Classification Accuracy:

Most values are on the diagonal, meaning the model correctly classified most of the samples.

Example: 166 Cyst cases correctly classified, 235 Normal cases correctly classified, 70 Stone cases correctly classified, and 114 Tumor cases correctly classified.

Minor Misclassification:

There is one case where a Tumor was misclassified as Normal.

Zero Misclassifications for Most Classes:

Cyst, Normal, and Stone classes have no misclassifications in other categories.

The model performs exceptionally well, with very few misclassifications.

DISCUSSION

The findings indicate that the proposed system can effectively assist both patients and physicians in diagnosing kidney disease with greater accuracy. This tool is particularly beneficial in rural areas where access to medical specialists is limited. The classifier algorithm used in this research has achieved the desired accuracy, demonstrating its reliability. Through this study, valuable knowledge has been gained, including skills in dataset training, preprocessing raw data, and applying classification algorithms. This research is expected to be highly beneficial for future studies on kidney disease diagnosis.

Additionally, the proposed approach has the potential to reduce diagnostic time and costs while enabling early detection and prompt treatment. A fully developed system for kidney disease detection could also ease the workload of radiologists, making the diagnostic process more efficient and accessible. However, experimentation suggests that achieving higher accuracy requires a large training dataset, which can be challenging to obtain in medical image processing. In some cases, medical datasets may be scarce, making it essential for the proposed algorithm to reliably detect abnormalities from MRI scans. Enhancements can be made by incorporating weakly supervised learning techniques that can identify irregularities with minimal or no training data. Furthermore, integrating self-learning algorithms could further improve accuracy and processing speed, enhancing the overall effectiveness of the system.

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