AI-Driven CKD Diagnosis: A Deep Learning Framework for Accurate and Efficient Kidney Disease Detection

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Abstract. This paper presents a deep learning-based approach for the detection of Chronic Kidney Disease (CKD) using Convolutional Neural Networks (CNNs). The proposed method involves a comprehensive pipeline that includes image pre-processing using median filtering, segmentation through Fuzzy C-Means (FCM) clustering, and feature extraction based on statistical and texture-based measures. The CNN classifier is trained on a dataset of kidney images and evaluated based on key performance metrics such as accuracy, sensitivity, and time consumption. Experimental results demonstrate that the proposed CNN model achieves an accuracy of 97% and a sensitivity of 88%, significantly outperforming traditional machine learning algorithms like Naïve Bayes, Decision Tree, and Support Vector Machine (SVM), which achieved accuracies of 91%, 93.2%, and 94.1%, respectively. Additionally, the CNN model shows the lowest time consumption at 21%, highlighting its efficiency in real- time applications. These results confirm the effectiveness of the CNN-based approach for early-stage CKD detection, offering a promising solution for improving diagnostic accuracy in clinical settings.

Keywords: Chronic Kidney Disease (CKD), Image-Based Detection, Convolutional Neural Network (CNN), MATLAB, Kaggle Dataset, Median Filter, Fuzzy C-Means (FCM) Clustering etc.

1 Introduction

CKD (chronic kidney disease) -AKI is a progressive condition that destroys your kidneys for years and leaves it in the final stages where the subject will have kidney failure. As a global health threat, millions of people around the world suffer from obesity. Studies show that CKD is a major cause of morbidity and mortality worldwide, with high incidence observed in low- and middle-income countries (Jha et al., 2013). Detection of CKD at earlier stages is crucial for the management, because early intervention can effectively improve patient outcomes and stop the progression to end-stage renal disease (ESRD) (Nasri et al. 2014). CKD has been traditionally identified by clinical evaluations; and seral creatinine levels and Glomerular Filtration Rate (GFR) are commonly employed as markers of renal function. But, these tests are able to detect the presence of a disease only when it reaches its late-stage pathology where interventions become less productive (Lv & Zhang, 2019). Due to raising awareness, the

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interest in computational methods for diagnosis has increased due to the need of early screening.

Despite significant advancements in medical imaging and machine learning, the current methods for CKD diagnosis present several challenges. Traditional diagnostic methods based on clinical tests may fail to detect early-stage CKD, leading to delayed treatment (Jha et al., 2013). On the other hand, machine learning-based techniques, such as decision trees, support vector machines (SVM), and Naïve Bayes, have been widely used for CKD prediction. While these models have shown some success, they often rely on manual feature extraction, which can be time-consuming and prone to errors (Ifraz et al., 2021). Additionally, many of these approaches fail to capture the complex, non-linear relationships in the data, limiting their ability to provide accurate early-stage detection (Murshid et al., 2019). The accuracy of these models can be further affected by issues such as imbalanced datasets, where there are fewer cases of advanced CKD compared to early-stage disease, leading to poor model performance for certain classes (Almasoud & Ward, 2019).

The motivation behind this work stems from the limitations of traditional and machine learning-based CKD detection methods. Given the critical need for early and accurate diagnosis, there is a compelling need to explore new approaches that can address these challenges. Advances in deep learning, particularly Convolutional Neural Networks (CNNs), have shown great promise in automating feature extraction and learning hierarchical patterns directly from raw data (Ahmed & Alshebly, 2019). Leveraging CNNs for CKD detection can eliminate the need for manual feature engineering, improve the accuracy of early. detection, and enhance the overall performance of diagnostic systems.

This paper aims to present a novel approach to CKD detection that utilizes deep learning techniques, specifically CNNs, to improve early detection and classification of CKD. The objectives are:

- To implement an image-based CKD detection system using CNNs to classify CKD as benign or malignant.
- To propose an effective pre-processing method (Median Filter) for noise reduction in kidney images.
- To enhance segmentation using Fuzzy C-Means (FCM) clustering to isolate key regions of interest.
- To evaluate the model's performance using key metrics such as accuracy, sensitivity, and specificity.

The contributions of this paper are as follows:

- Introduction of a deep learning-based model for CKD detection using CNNs that eliminates the need for manual feature extraction.
- Implementation of a robust pre-processing pipeline with noise removal using the Median Filter and segmentation using Fuzzy C-Means clustering.
- Evaluation of the proposed model on a publicly available dataset, providing insights into its effectiveness for early CKD detection.
- Comprehensive performance analysis, including accuracy, sensitivity, and specificity, to

assess the robustness of the model.

The paper is organized as follows, into various sections. This Literature review is outlined in section 2. The Proposed System, Experimental Results is presented in 4 on section 3. Conclusion and future work of the last sections 5 are given by.

2 Related Works

R. M. Ahmed and O. Q. Alshebly, "Prediction theory and factor affecting in chronic kidney disease (CKD) diagnosis based on ANN and Logistic Regression," (2019). The study gives a comparative analysis between the two models based on their predictive power and most influential factor. The authors focus on the role of machine learning for diagnostic accuracy, and ANN outperforms in this area through the capture of complex nonlinear relationships [1].

C. Wang et al. (2013) This paper presents new urinary biomarkers for the diagnosis of diabetic kidney disease, one of the most important causes of CKD. These biomarkers are explored by the authors as possible means to improve early diagnosis and to follow disease progression. Here, the study of the biomarker-associated perceptions may contribute to the fundamental comprehension of diagnostics that is complementary to machine learning techniques for better CKD prediction [2].

V. Jha et al. (2013) This world-wide view of the CKD problem examines prevalence, socio-economic burden and health care priorities. The study also underscores the variation in CKD detection and treatment between geographical regions, thereby emphasising the need for scalable and effective diagnostics, such as machine learning models, to address this emerging crisis in public health [3].

G. Abraham et al. The study highlights the CKD hotspots in South Asia, with a higher prevalence in those areas, and attributed this to socioeconomic and environmentally factors. It emphasizes the need for preventative measures such as databases, data- driven strategies to reduce the burden of the disease in resource-poor settings [4].

G. M. Ifraz et al. (2021) In this comparative study, multiple machine learning methods including Random Forest, SVM, and k-Nearest Neighbours so on are applied into CKD prediction. This research proves the superior results of intelligent methods in high performance, and expounds that SVM is a reliable tool used for the purpose of CKD classification [5].

H. Nasri (2014): CKD in a global aging society: a public health alert in the light of global aging populations, Nasri addresses CKD as a public health warning. It emphasizes the need to incorporate advanced diagnostic techniques, namely machine learning and N deep learning, as a means to mitigate the challenges of the aging population [6].

CDC (2019) This is a descriptive epidemiologic analysis of chronic kidney disease (CKD) and end-stage renal disease (ESRD) in the United States. Late detection of CKD remains a critical issue. The paper emphasizes the emerging need for an improved diagnosis of diseases in terms of diagnosis in which machine learning has a potential in early and accurate detection of CKD [7].

J.C. Lv L.X. Zhang (2019) The paper details the epidemiology and disease burden of CKD and focuses on renal fibrosis as a protagonist in disease progression. It paves to way for the machine learning based approaches to include the histopathological data to achieve full CKD diagnosis [8].

G. Murshid et al. (2019) This article discusses data mining methodologies (i.e., decision trees and neural networks) for predicting CKD. The study demonstrates the significant of feature selection and data preprocessing in enhancing model performance [9].

O.A. Adejumo et al. (2016) In the present study, the authors examine cases of CKD in Nigeria noting that late presentation remains a challenge. They recommend the implementation of predictive models such as machine learning algorithms, in order to achieve early detection and enhance patient recovery [10].

A. Haratian (2022) Haratian studies the influencing factors of the kidney function based on machine learning algorithms, emphasizes the importance of feature engineering and model free parameters adjustment for effective CKD prediction [11].

N. Razavian et al. (2015) This research predicts type 2 diabetes from claims data and examines risk factors and the implications of population health modeling. The techniques used can also be directly extended for CKD prediction to facilitate its early detection and risk categorization [12].

K.Pujitha etal / (IJCSIT) International Journal of Computer Science and Information Te hcnoogy Vol.2, No.4, August 2010. (2022) Though devoted to parking systems, secured online frameworks are implemented in the paper. The strategies of security could be enhanced to maintain the security of CKD diagnostic systems and protection of patients' records [13].

H. Ilyas et al. (2021) Ilyas et al. apply decision tree algorithms in the diagnosis of CKD, showing the potential of interpretable methods in medical decision support. Their work provides an effort to embed decision trees within hybrid diagnosis engines [14].

M. Almasoud and T.E. Ward (2019) The question behind this study is to develop a CKD diagnosis system using machine learning algorithms in order to use a smaller number of predictors, emphasizing the need of selecting features to enhance the performance of a model and the reduction of diagnosis costs [15].

K.R. Anantha Padmanaban, G. Parthiban2016 the authors use multiple machine learning algorithms such as Naïve Bayes and SVM models to forecast the risk of CKD. This result highlights the promising potential of hybrid approaches which integrate different algorithms for improved prediction [16].

E.M. Senan et al. (2021) This research uses RFE for enhancing the classification of CKD. This study aimed to present a methodological approach to prioritize the most salient waveforms which would lead to more efficient and reliable modeling [17].

A Nishanth and T Thiruvaran (2018) The authors description essential features for early CKD detection and provide a feature-ranking scheme. Their research validates the incorporation of early markers in machine learning models for early interposition [18].

J. Snegha et al. (2020) [19] This paper highlights the role of data mining in CKD prediction and elaborates on clustering and classification methodologies. The role of exploratory data analysis in the development of diagnostic models is highlighted.

S.P. Praveen et al. (2022) Neuro-fuzzy based approach for prediction of CKD the authors combine neural networks and fuzzy logic for CKD prediction. Their hybrid methodology brings enhanced precision and interpretability [20].

O. Alabi (2022) Alabi's work presents a comparative study of the difficulties in predicting CKD in the presence of limited data and advocates rigorous training techniques to improve model predicting performance under these limitations [21].

S. Tekale et al. (2018) In this paper, the authors investigate several machines learning techniques, including k-Nearest Neighbors and Random Forest, to predict CKD, indicating their ability to deal with noisy and incomplete data [22].

UCI Machine Learning Repository the CKD dataset is loaded from the UCI repository whichis most commonly used for machine learning algorithms for evaluation. It disseminates a standard dataset to exercise and validate predictive models, and enhances reproducibility of CKD research [23].

3 Existing Method

The detection of chronic kidney disease (CKD) has long been based on indirect clinical findings such as blood and urine tests that quantify markers such as serum creatinine, blood urea nitrogen and albumin to creatinine ratio. However, such approaches usually identify advanced stages of CKD and impede the early intervention. In order to overcome these constraints, several ML and statistical methods have been proposed to improve early diagnosis and accuracy. Traditional ML algorithms including Naïve Bayes, SVM and Decision Tree have been widely applied for CKD prediction. These techniques rely on structured datasets of clinical and demographic information to construct predictive models. Naïve Bayes is a model good for discriminating with probabilistic while SVM is efficient in high-dimensional numerical data. It offers the interpretability that is beneficial in clinical settings. Fig 1 shows the Existing Method Block Diagram.

Although useful in nature, such traditional ML models often rely on extensive manual feature engineering and may not be able to capture complex, non-linear properties of the data. To enhance robustness and accuracy, advanced methods have been introduced with the use of ensemble learning models such as Random Forest and Gradient Boosting. Moreover, logistic regression and other statistic tools have been also used to detect significant risk factors of CKD, contributing to the understanding of the trajectory of disease. Recently, deep learning models, and in particularly CNNs,1 have gained attention for image-based CKD diagnosis. Compared with conventional techniques, CNN can automatically learn multi-level features of the medical image, so that the diagnosis becomes more accurate 19-21. Such breakthroughs in the field of ML and DL have markedly enhanced detection rate of CKD; however, issues like model-based performance, unbalanced datasets, and generalization among different populations remain.

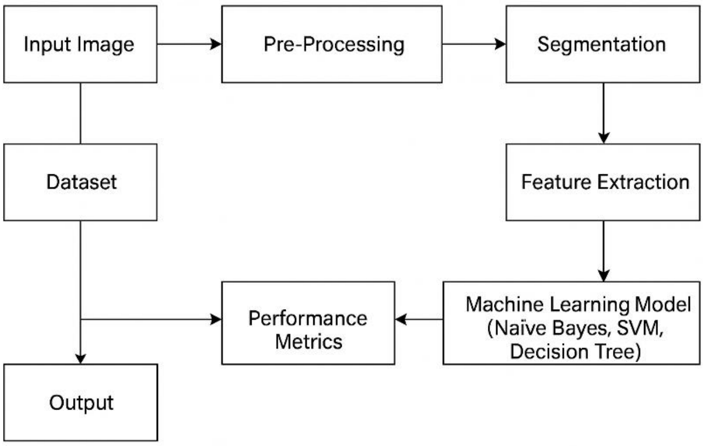

Fig. 1. Existing Method Block Diagram.

4 Proposed Method

The proposed method focuses CKD diagnosis by image with the help of CNN model, developed in MATLAB that can learn automatically and extract intricate details from the medical images. The data input Kaggle dataset and prepossessed with a Median Filter to remove noise, the MQIE. Kidney Segmentation Fuzzy C-means (FCM) clustering for segmentation of Kidney images and get Region of Interest. The features are finally computed from Gray Level Co-occurrence Matrix (GLCM) which helps to gather information related to texture values i.e. essential for classification. These extracted features then are used to train a CNN that whether the disease is benign or malignant. This work removes the 1-handcrafted features and 2-linear limitation of classical machine learning algorithms like Naïve Bayes, SVM, and Decision Tree. which rely heavily on manually-engineered features and cannot model non-linear feature mapping relationships effectively.

Based on the hierarchical features of the CNNs, the introduced approach enhances the classification accuracy and robustness. Evaluation of the performance of the system is presented by means of accuracy, sensitivity and specificity, which are used to give a complete performance measure of the system. This technique improves diagnostic accuracy and enables early detection which is essential for prompt management and better prognosis. Fig. 2. Shows the Proposed Method Block Diagram.

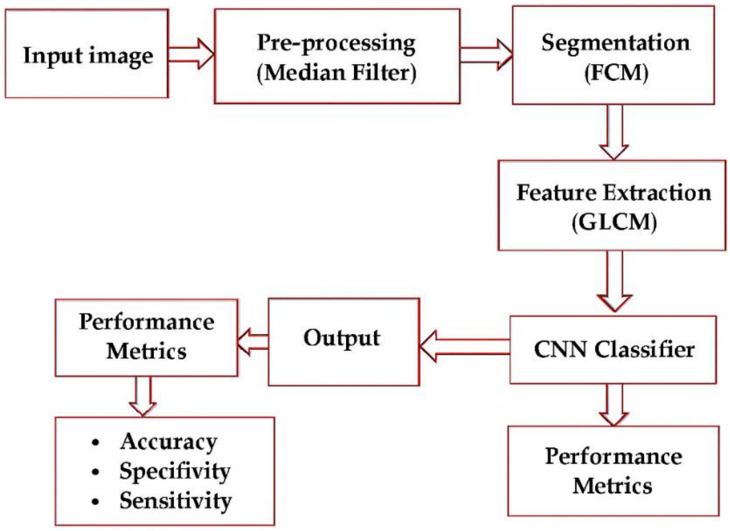

Fig. 2. Proposed Method Block Diagram.

Input Dataset: The dataset is downloaded from Kaggle, which contains medical images and/or clinical information about CKD. It offers input data applications for training and testing the model. This data set is comprised of labeled images for classification of benign and malignant cases, which is the basis of the overall detection process.

Pre-processing (Median Filter): The noise as described above can originate either from the imaging equipment or due to environmental conditions. The Median Filter is used, i.e., the program blurs the picture, taking care of the edges and maintaining the features necessary for correct classifying.

Segmentation (Fuzzy C-Means Clustering - FCM): Firstly, segmentation is performed to isolate the region to be examined, or the region-of-interest (ROI) in the case of kidney images, which is the lesions or the anomalies. Fuzzy C-means (FCM) is deployed to cluster the pixels with similar intensities. This soft clustering technique provides membership probabilities to pixels that enable a more accurate segmentation, especially in medical images with slight differences in intensities.

Feature Extraction (GLCM): Features are computed from the segmented ROI after segmentation to measure texture, shape, and other information of the image. By computing statistical measures including contrast, correlation, energy, and homogeneity, GLCM provides texture features, which are essential to differentiate benign and malignant diseases.

Classifier (Convolutional Neural Network - CNN): The CNN acts as the foundation of the detector. It is composed of convolutional layers, pooling layers and fully connect layers, which can learn hierarchical features automatically from the input data. A CNN processes the produced features to determine whether the images are benign or malignant. It would make system more robust and accuracy by alleviating manually feature selection. Fig 3 shows the Process of CNN.

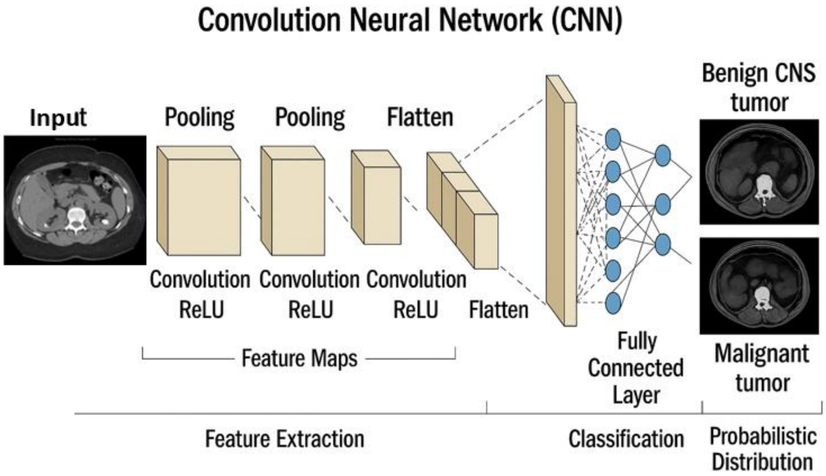

Fig. 3. Process of CNN.

Output (Disease Classification): The output block is the final classification result(statistic) of this disease for benign or malignant. This result provides support to the clinician for deciding for additional tests or treatment.

4.1 Performance Metrics

Accuracy: Measures the overall proportion of correctly classified images. It signifies the percentage of images your model correctly identifies as either containing disasters or not.

$$Accuracy = (True\ Positives + True\ Negatives) / Total\ Images \tag{1}$$

Specificity: Measures the proportion of true negative images correctly classified as not containing disasters. It indicates how well the model avoids false alarms when dealing with non-disaster images.

$$Specificity = True\ Negatives / (True\ Negatives + False\ Positives) \tag{2}$$

Sensitivity (Recall): Measures the proportion of true positive images correctly classified as containing disasters. It indicates how well the model identifies actual disaster instances.

$$Sensitivity = True\ Positives / (True\ Positives + False\ Negatives) \tag{3}$$

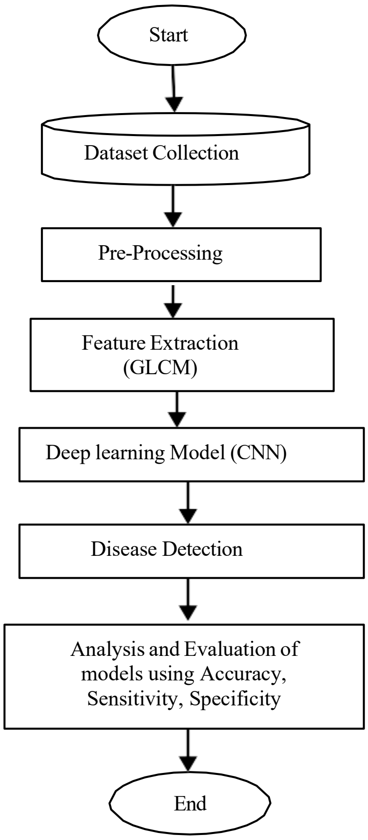

Fig. 4. Implementations of the flow chart.

4.2 Implementation

Fig 4 shows the Implementations of the flow chart.

Load Input Dataset: Load the dataset containing labeled CKD images using imread() or similar functions.

Pre-process Image: Apply a Median Filter to remove noise and improve image quality using medfilt2().

Segment Image: Perform Fuzzy C-Means Clustering (FCM) to segment the kidney region using fcm().

Extract Features: Use GLCM to extract texture features like contrast and correlation from the segmented image.

Train CNN Model: Define a Convolutional Neural Network (CNN) architecture and train it on the extracted features using trainNetwork().

Classify Disease: Use the trained CNN model to classify the CKD images into benign or malignant categories using classify ().

Evaluate Performance: Measure the model's performance using accuracy, sensitivity, and specificity as metrics.

5 Results and Discussions

This Fig 5 shows the raw input image representing a kidney scan. It serves as the starting point for the CKD detection process. The input image may contain noise, poor contrast, or irrelevant details that can affect the accuracy of subsequent image processing and classification tasks.

Fig. 5. Input Image.

This image demonstrates in Fig 6 the results after applying pre-processing techniques such as noise reduction and smoothing. In this step, methods like median filtering are used to remove noise while preserving important features in the image, ensuring that the subsequent analysis focuses on relevant information.

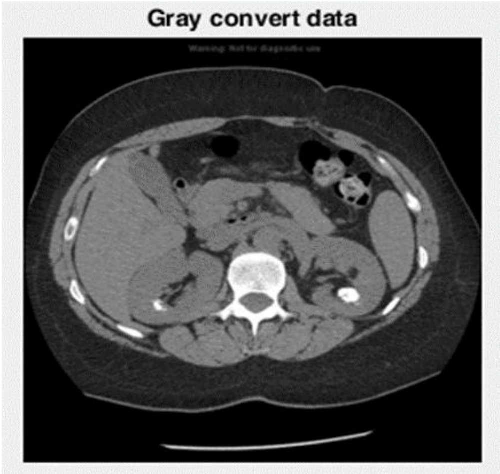

Fig. 6. Pre-processing image.

The enhanced image Fig 7 represents the outcome after applying further image enhancement techniques. The enhancement process sharpens important features, such as edges and textures, to make them more distinguishable. This step ensures that the segmented regions in later stages of processing are clearer and more defined.

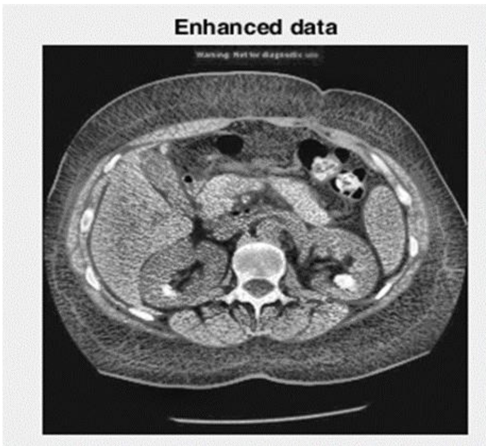

Fig. 7. Enhanced Image.

This image shows in Fig 8 the results of filtering, where unnecessary noise or irrelevant details are removed from the enhanced image. The filtered output is essential for accurate segmentation, as it isolates regions of interest while minimizing the impact of irrelevant information in the image.

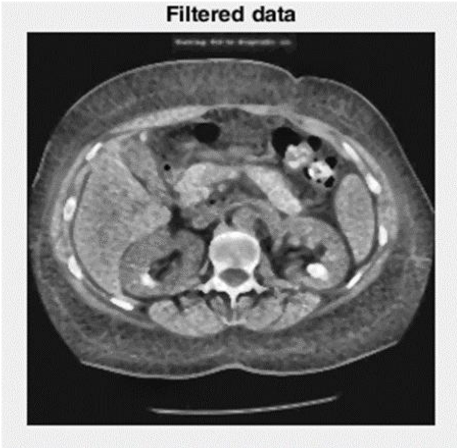

Fig. 8. Filtered Output image.

After filtering, the image is converted into a binary format, shows in Fig 9 where pixels are classified into two categories: one representing the presence of the kidney region or anomalies, and the other representing the background. This binary image simplifies the analysis for segmentation, allowing the model to focus on the relevant areas.

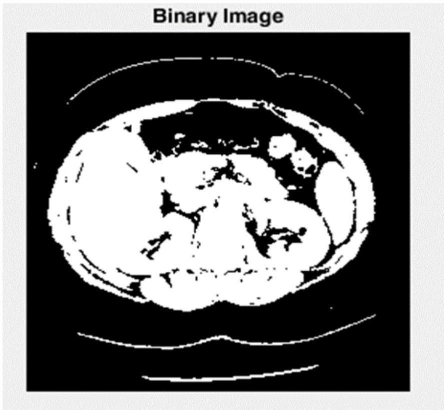

Fig. 9. Binary Image.

Fig. 10. Historical analysis of previous results and trends in CKD detection, including performance metrics, diagnostic evolution, and challenges over time.

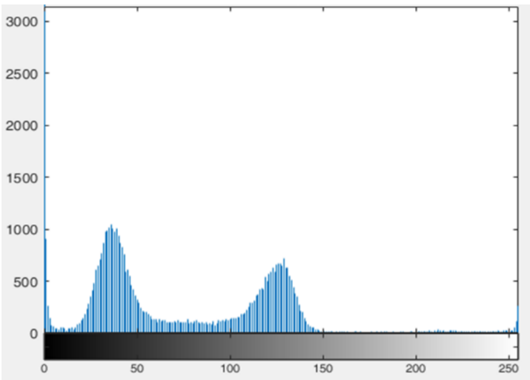

Fig. 10. Historical Analysis.

Table 1. Feature Extraction Values.

Feature	Value
Contrast	0.268857
Correlation	0.947897
Energy	0.203788
Homogeneity	0.894261
Mean	54.564860
Standard Deviation	55.941503
Entropy	5.665558
RMS	12.958511
Variance	2692.109697
Smoothness	1.000000
Kurtosis	3.474948
Skewness	0.970861

Table 1 presents the feature extraction values for a single input image, which are derived using Gray-Level Co- occurrence Matrix (GLCM) and statistical measures. The Contrast value of 0.268857 indicates the level of intensity difference between neighboring pixels, with higher values representing more significant texture changes. Correlation is 0.947897, showing a high linear dependence between pixel pairs. The Energy of 0.203788 reflects the uniformity of the image, with lower values indicating less uniform texture. Homogeneity at 0.894261 suggests a relatively smooth texture, as it measures the closeness of pixel pairs in the image. Mean value of 54.564860 represents the average pixel intensity, while Standard Deviation of 55.941503 indicates the spread of pixel intensity values from the mean. Entropy, with a value of 5.665558, quantifies the randomness of pixel intensities, indicating a relatively high degree of disorder in the image. RMS (Root Mean Square) of 12.958511 is a measure of the image's intensity variation. Variance of 2692.109697 reflects the degree of intensity fluctuation in the image. Smoothness has a value of 1, implying minimal texture roughness. Kurtosis (3.474948) indicates the peakedness of the intensity distribution, with higher values suggesting sharp intensity variations. Lastly, Skewness of 0.970861 indicates the asymmetry in the intensity distribution, with a positive skew showing a tendency towards higher intensity values. These extracted features collectively capture important texture and statistical characteristics of the image, useful for subsequent classification in CKD detection. This graph Fig 11, that compares the accuracy performance of various algorithms used for CKD detection. The x-axis represents the different algorithms, such as Naïve Bayes, Decision Tree, SVM, and CNN, while the y-axis shows the accuracy percentage. The graph visually demonstrates how the accuracy varies across different algorithms, highlighting that the CNN model outperforms the others with the highest accuracy.

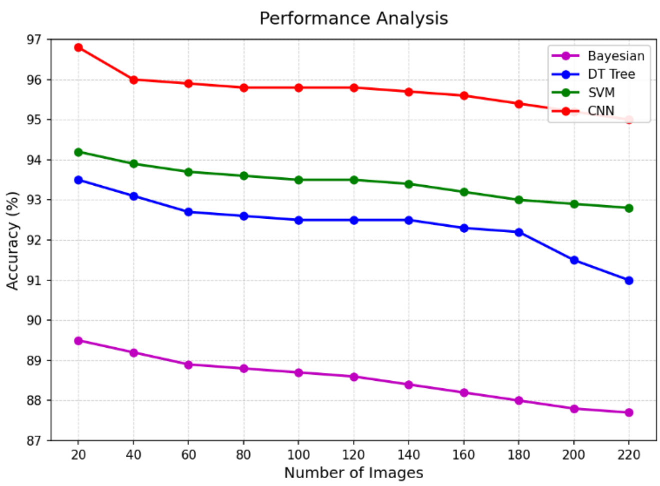

Fig. 11. Accuracy Performance Analyze Graph for different Algorithms.

This graph analyzes the sensitivity of each algorithm, which measures the ability to correctly identify malignant cases. Similar to Fig 12, the x-axis represents the algorithms, and the y-axis shows the sensitivity percentage. The results indicate that the CNN model also achieves the highest sensitivity, making it more effective at detecting CKD in its early stages.

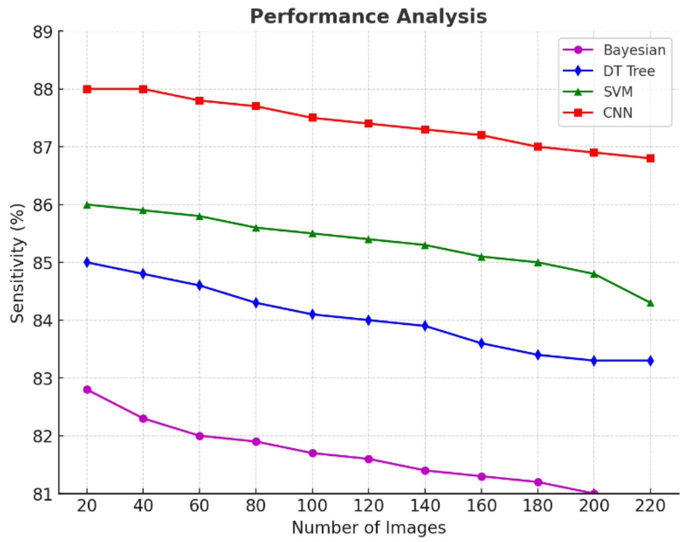

Fig. 12. Sensitivity Performance Analyze Graph for different Algorithms.

This graph illustrates shown in Fig 13 the time consumption for each algorithm. The x-axis represents the different algorithms, while the y-axis shows the time taken to process each input. The CNN model is the most efficient in terms of time consumption, while traditional machine learning models like Naïve Bayes take longer. This graph highlights the balance between performance and efficiency in the proposed method.

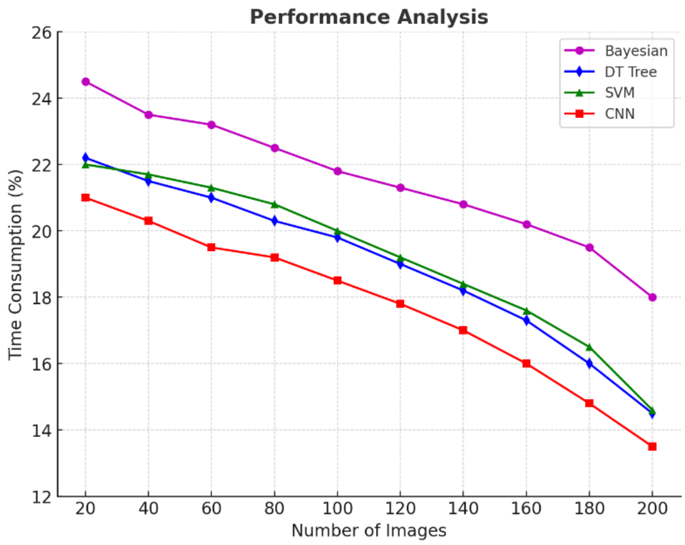

Fig. 13. Time Consumption Analyze Graph for different Algorithms.

5.1 Performance Comparison Table

Table 2. Performance Comparison of Different Algorithms.

S.No	Algorithm	Accuracy (%)	Sensitivity (%)	Time Consumption (%)
1	Naive baives	91	82.5	25
2	Decision Tree	93.2	84.9	23.5
3	SVM	94.1	85.5	23.4
4	CNN (Proposed)	97	88	21

A comparison table ii is tabulated to evaluate the performance of the different algorithms used on CKD detection namely Naïve Bayes, Decision Tree, SVM and proposed CNN model. Naive Bayes algorithm performed the highest accuracy 91% but with the low sensitivity of 82.5%, and it took highest time i.e., as long as 25%. The Decision Tree is a bit improved with an accuracy of 93.2% and sensitivity of 84.9%, but it also takes too long (23.5%). Table 2 shows that SVM delivered the highest accuracy and sensitivity while consuming the least time, with an accuracy of 94.1%, a sensitivity of 85.5% and elapsed time was less (23.4%). Even so, the CNN model is nearly perfect with a 97% accuracy and an 88% sensitivity in comparison to all other methods. Using this model is the fastest in terms of time, with only 21% but has such a good performance already since it has better accuracy and sensitivity comparing to other traditional machine learning models. All results thus far indicate that the CNN model offers the best trade-off between performance and cost for CKD diagnosis as shown by this demo.

5.2 Performance Analysis

6 Conclusion and Future scope

we presented a deep learning solution for diagnosing CKD using CNNs and advanced image processing algorithms. By employing pre-processing techniques (median filtering and segmentation based on FCM), we were able to improve the quality of kidney images and facilitate more accurate classification. Comparison of our CNN model to machine learning based classifiers (Naïve Bayes, Decision Tree and Support Vector Machines) The CNN model showed a superior performance in terms of accuracy, sensitivity and efficiency in CKD detection as compared to the conventional machine learning classifiers. It was validated that CNN-based models could offer a useful alternative to the early diagnosis of CKD, which can effectively reduce time consumption, meanwhile preserve good reliability. The method is promising for potential applications in medical imaging systems to help doctor diagnose CKD more effectively.

6.1 Future scope

Although the proposed approach yields encouraging results, there are potential directions toward improving the model. The system can firstly be extended on a larger more heterogenous dataset to increase the generalization to different patient populations and imaging setting. Integrating multimodal information, for example the combination of image-based features with clinical data (e.g., patient's demographics, lab results) may offer more generalised insights on the tumor types and have the potential to improve the model reproducibility. Further studies on deeper DL frameworks viz. transfer learning or ensemble methods may further enhance the model's accuracy and sensitivity. Further studies could include the construction of real-time CKD detection devices for clinical application, thus providing relevant clinical information to doctors for quick and accurate diagnosis. Finally, a study analyzing the interpretability of CNN model might be beneficial for clinicians to comprehend the reasons for the model's outcome and to boost the trust in AI-assisted diagnosis, via attention mechanisms or saliency mapping, for instance.

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