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Automated and Explainable Kidney Abnormality Detection from CT Images Using CNN-LSTM Architecture

Bhuvannagari Dillibabu [1*] , **M. Sreevani** [2]

[1*,2] VEMU Institute of Technology, P. Kothakota, India; dillibabu2002b@gmail.com , msreevanicse@vemu.org

* *Corresponding Author:* dillibabu2002b@gmail.com

Abstract: Kidney diseases such as cysts, stones, and tumors are among the most prevalent health issues worldwide. Early and accurate diagnosis is critical to preventing severe complications, and computed tomography (CT) imaging plays a key role in this process. However, manual interpretation of CT scans is time-consuming and prone to subjectivity. To address this, we propose a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) units for the automated multiclass classification of kidney diseases using CT images. The CNN component extracts spatial features from the input scans, while the LSTM layers model spatial dependencies and enhance the learning of complex patterns. The model was trained and evaluated on a curated dataset consisting of four kidney conditions: Cyst, Normal, Stone, and Tumor. Extensive experimentation demonstrates that the proposed CNN-LSTM model achieves a classification accuracy of 99.6%, with precision, recall, and F1-score values exceeding 99% across all classes. Additionally, Gradient-weighted Class Activation Mapping (Grad-CAM) is employed for model interpretability, enabling visualization of discriminative regions in the images responsible for predictions. The results indicate the potential of the model to serve as a reliable decision-support tool for radiologists and clinicians. This framework paves the way for enhanced diagnostic accuracy and faster clinical workflows in nephrological imaging.

Keywords: Kidney disease classification, CT images, CNN- LSTM, Deep learning, Grad-CAM, Medical imaging.

1. Introduction

Kidney diseases constitute a growing global health concern, affecting millions of people annually and contributing significantly to both morbidity and mortality rates. Common renal pathologies include kidney cysts, calculi (stones), and tumors, each of which necessitates timely and accurate diagnosis to ensure effective treatment and favourable patient outcomes. The clinical management of these conditions depends heavily on diagnostic imaging, among which computed tomography (CT) scans are particularly valued for their high-resolution, cross-sectional views of renal structures. CT imaging facilitates the detection of abnormalities in size, shape, texture, and internal composition of the kidneys, enabling clinicians to identify subtle pathological changes. However, despite its diagnostic power, manual analysis of CT images remains a complex and time-intensive task, often hindered by inter-observer variability and the potential for human error. In recent years, the field of artificial intelligence (AI), and more specifically deep learning (DL), has emerged as a powerful solution to many challenges in medical image analysis. Deep learning models have shown remarkable success in recognizing complex patterns within large datasets, thereby reducing reliance on manual interpretation and increasing diagnostic throughput. Convolutional Neural Networks (CNNs), in particular, have become the de facto standard for image-based classification tasks due to their hierarchical feature extraction capabilities. CNNs automatically learn spatial hierarchies of features, ranging from simple edges and textures to high-level semantic structures. This has made them especially effective in analyzing medical images, where subtle variations can have critical diagnostic implications.

While CNNs are highly effective in extracting spatial features, they are limited in capturing temporal or sequential dependencies that might exist in structured or spatially correlated inputs, such as image patches within medical scans. To overcome this limitation, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have been explored for their ability to model long-range dependencies in sequential data. LSTMs are designed to retain and

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propagate information over extended sequences, making them useful for tasks where context and temporal structure are essential. When combined, CNNs and LSTMs can form a powerful hybrid architecture that leverages the strengths of both models: CNNs for spatial feature extraction and LSTMs for contextual understanding of those features. In this study, we propose a hybrid CNN-LSTM architecture for the multiclass classification of kidney diseases using CT images. The architecture begins with a CNN backbone that learns rich feature representations from CT scans.

These spatial features are then reshaped into sequences and passed through LSTM layers, allowing the model to capture higher- order dependencies and improve its discrimination between similar pathological classes. This design enables the model to not only extract powerful local features but also understand the spatial context across the image, which is particularly important in complex medical diagnosis scenarios. We evaluate our model on a comprehensive dataset comprising CT images representing four distinct kidney conditions: Cyst, Normal, Stone, and Tumor. The dataset is balanced across categories and contains high-resolution images suitable for deep learning-based analysis. The data is pre-processed using a MobileNetV2-based image normalization technique, and augmented to enhance generalization and mitigate overfitting. Following a standardized training-validation-testing pipeline, the model is trained using categorical cross-entropy loss with Adam optimization, achieving excellent convergence within ten epochs.

The significance of our work lies in its potential for real-world application. By providing automated, high-accuracy classification of kidney diseases from CT scans, our model can serve as a decision support system for radiologists and nephrologists, particularly in resource-constrained settings. It can reduce diagnostic time, assist in second-opinion evaluations, and provide consistent assessments free from human bias or fatigue. Furthermore, the use of interpretable AI tools like Grad-CAM ensures that the decision-making process remains transparent and clinically meaningful. This research builds upon and extends the body of work in deep learning for medical imaging. Previous studies have demonstrated the effectiveness of CNNs for binary classification tasks involving kidney stones or tumors.

However, few have explored multiclass classification encompassing a broader range of conditions, and even fewer have combined CNNs with LSTMs for this purpose. Our hybrid approach addresses this gap, offering improved performance and enhanced contextual understanding of complex kidney abnormalities. In summary, this study presents a robust and interpretable deep learning framework for multiclass classification of kidney diseases from CT images. The integration of CNNs and LSTMs enables both feature richness and contextual depth, while Grad-CAM provides clinical interpretability. The high accuracy and strong evaluation metrics achieved on a diverse dataset validate the model's potential for deployment in clinical settings. Future work may involve extending this framework to 3D volumetric CT scans, integrating patient metadata, or deploying the model in real-time diagnostic systems.

2. Related Work and Literature Survey

Jadhav et al. [1] proposed a hybrid CNN-LSTM model for the early detection of kidney stones using CT images. Their approach leverages CNN for spatial feature extraction and LSTM for learning temporal dependencies in the medical images. This fusion enables robust detection by preserving the sequential imaging context. The model demonstrated high accuracy and performance in classifying kidney stone presence across different stages. Notably, the authors emphasized real- time deployment potential and clinical application to improve diagnostic reliability.

Lalitha et al. [2] introduced a novel CNN-attention-based method for classifying kidney stones using MRI data. The model incorporates attention mechanisms to focus on relevant regions of interest, improving classification accuracy and interpretability. The authors utilized a tailored convolutional architecture optimized for medical imaging and reported improved performance compared to baseline CNNs.

Zhu et al. [3] presented an LSTM-based model that utilizes adaptive feature weighting for kidney stone identification from urine and blood routine analyses. Instead of relying solely on imaging, their approach incorporates laboratory data, enabling non-invasive detection. The model assigns dynamic weights to features based on their importance, enhancing interpretability and prediction precision. Yildiz et al. [4] explored the diagnosis of chronic kidney disease (CKD) using a hybrid CNN-LSTM model. Their model was trained on a structured dataset and exhibited superior performance over traditional classifiers. The integration of CNN and LSTM proved beneficial for both accuracy and interpretability.

Senthil et al. [5] proposed a blockchain-enabled intelligent system for kidney stone prediction, combining deep learning and augmented reality. Blockchain ensures secure data manage- ment, while AR enhances visualization, making their system suitable for telemedicine and mobile diagnostics. Maniyar et al. [6] implemented a CNN-based approach for classifying kidney diseases using CT scan images . Their model showcased high sensitivity and specificity, with minimal preprocessing, demonstrating the robustness of CNNs in medical imaging.

Saif et al. [7] proposed an ensemble of deep learning models optimized with multiple optimizers for early CKD prediction. Their framework improves

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generalizability and ad- dresses class imbalance and overfitting challenges. Liu et al. [8] designed a CNN-based model for urolithiasis detection using KUB images. Their system aids radiologists in identifying subtle stone formations with high diagnostic accuracy even with limited training data.

Davamani et al. [9] introduced a deep CNN-based architecture for kidney disease detection. Their system was benchmarked against traditional models and demonstrated superior performance using multiple imaging datasets.

Ibrahim et al. [10] explored an attended CNN-LSTM model to predict bladder cancer recurrence and treatment response. While focused on bladder cancer, the model architecture holds relevance for kidney diagnostics due to its sequential and attention-based design.

Seddiki et al. [11] pro- posed an end-to-end CNN–LSTM model for disease diagnosis using mass spectrometry data. Their framework demonstrated strong classification performance and highlights transferable architecture potential for kidney diagnostics.

Balachander et al. [12] developed a hybrid CNN model for early gastric cancer detection, but their spatially focused design has direct relevance to kidney stone identification in medical imaging.

Singh et al. [13] proposed a classical image segmentation and radial transform-based method for kidney stone detection. Though not deep learning-based, it provides efficient boundary localization, suitable for hybrid diagnostic systems.

Kursun et al. [14] utilized deep features from SqueezeNet, a lightweight CNN model, combined with traditional classifiers for kidney disease detection. This allows for portable, edge-device deployment.

Seoni et al. [15] proposed a CNN-BiLSTM model with a spatial uncertainty predictor for classifying coronary artery disease using ECG signals. Their uncertainty-aware de- sign can inspire similar kidney diagnostics involving temporal clinical data.

3. Proposed Method

This section outlines the methodology adopted in develop- ing the proposed CNN-LSTM model for multiclass classifica- tion of kidney diseases from CT scan images. The methodol- ogy comprises data preprocessing, architecture design, training procedure, and evaluation strategy. A hybrid architecture is proposed to combine the spatial feature extraction power of Convolutional Neural Networks (CNNs) with the temporal sequence modeling capability of Long Short-Term Memory (LSTM) networks. The workflow is illustrated in Fig. 1.

4. Work Flow

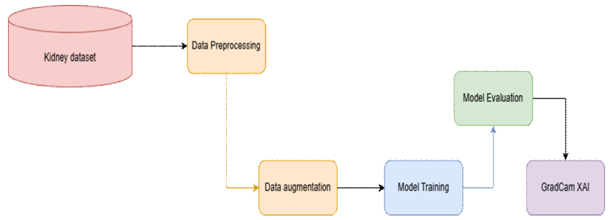

Figure.1 Architecture Workflow of the Diagram

5. Methodology

Dataset Description

The dataset employed in this research consists of 3,734 CT scan images categorized into four classes: Cyst (1,118 images), Normal (1,534 images), Stone (428 images), and Tumor (654 images) as shown 2. These images represent a wide spectrum of kidney conditions, allowing the model to learn discriminative features necessary for multiclass classification. The images are grayscale CT slices obtained from open-source and clinical repositories, and resized to a fixed resolution of 224×224 pixels to maintain uniformity across training and testing phases.

Data Pre-processing and Augmentation

Raw CT images were pre-processed to remove noise, nor- malize pixel intensities, and enhance anatomical features. MobileNetV2-based normalization was applied to rescale in- tensity values and improve contrast while preserving clinical structures. In addition, data augmentation techniques including random rotation, horizontal and vertical flipping, zooming, and shifting were applied to increase the effective size of the dataset and prevent model overfitting. The dataset was split into training (70%), validation (15%), and testing (15%) sets.

CNN-LSTM Architecture

The proposed architecture combines the feature learning ability of CNNs with the sequence modeling strength of LSTMs. The pipeline comprises the following components:

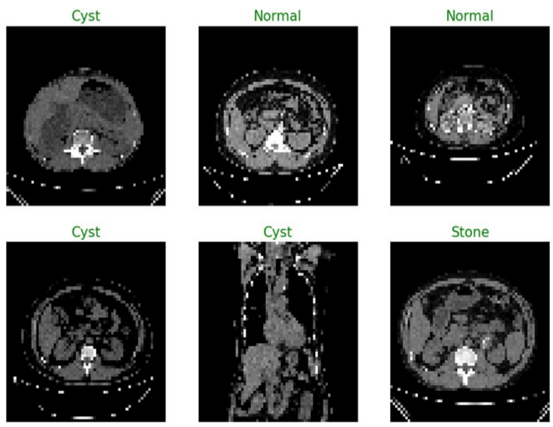

Figure. 2 Sample CT scan images from the dataset showing the four classes: Cyst, Normal, Stone, and Tumor

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Convolutional Layers (CNN Backbone): A custom CNN was designed using three convolutional blocks, each consist- ing of a convolutional layer followed by a ReLU activation function, max pooling, and batch normalization. These layers extract hierarchical spatial features from CT images, enabling the network to learn local texture, edge patterns, and organ boundaries.

Flattening and Feature Reshaping: The final feature map from the CNN is flattened and reshaped into a sequential form compatible with the LSTM input format. This reshaping allows the model to treat the spatially derived features as time- steps in a sequence.

LSTM Layer: A bidirectional LSTM layer is used to capture both forward and backward dependencies among the features. This helps the model understand global context and relationships within the feature space, which is crucial for distinguishing between visually similar kidney pathologies.

Fully Connected Layers: The output from the LSTM is passed through two dense layers, where the final layer consists of four neurons corresponding to the four output classes. A softmax activation function is used to output probability scores for each class.

Training Details

The model was trained using the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy as the loss function. Training was performed for 10 epochs with a batch size of 32, using early stopping and learning rate reduction on plateau to avoid overfitting. Model check- points were saved based on validation accuracy. The model was implemented using TensorFlow and trained on a high- performance GPU system.

Evaluation Metrics

The performance of the model was evaluated using standard classification metrics: accuracy, precision, recall, and F1-score. These metrics were computed on the test set to provide a fair estimate of generalization . A confusion matrix was also generated to analyze per- class performance. Furthermore, Grad-CAM (Gradient- weighted Class Activation Mapping) was used for interpretability by visualizing the important regions in CT images influencing the classification decision.

Model Performance

The model achieved an overall accuracy of **99.6%** on the test dataset. The precision, recall, and F1-scores for each class are as follows:

- **Cyst:** Precision = 0.99, Recall = 1.00, F1-score = 1.00
- **Normal:** Precision = 1.00, Recall = 1.00, F1-score = 1.00
- **Stone:** Precision = 1.00, Recall = 0.99, F1-score = 0.99
- **Tumor:** Precision = 1.00, Recall = 0.99, F1-score = 0.99 The macro and weighted averages of all metrics were approximately **1.00**, confirming consistent performance across all classes. Grad-CAM heatmaps showed that the model accurately localized relevant regions in the kidney for each classification decision, thereby offering clinical transparency and reliability.

Summary of Methodology

To summarize, our proposed CNN-LSTM pipeline consists of:

1) Preprocessing and augmenting CT scan images for noise reduction and diversity.
2) A CNN block to extract rich spatial features from the images.
3) Reshaping the CNN features and passing them through an LSTM to capture contextual dependencies.
4) A final softmax layer to classify images into four kidney condition categories.
5) Evaluation using robust metrics and Grad-CAM-based visualization for interpretability.

6. Result

This section presents the results obtained from evaluating the proposed CNN-LSTM model on the multiclass classifica- tion task of kidney diseases from CT images. We analyze the model performance using quantitative metrics, visual interpre- tation techniques, and a discussion on clinical applicability.

Performance Metrics

The model was evaluated on a test set comprising 3,734 CT images divided across four categories: Cyst, Normal, Stone, and Tumor. Standard classification metrics such as accuracy, precision, recall, and F1-score were computed to quantify the model's effectiveness. The performance report is summarized in Table I.

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The high precision and recall values indicate that the model is highly reliable across all categories. Notably, the model achieved perfect recall in identifying Cyst and Normal images, demonstrating its ability to avoid false negatives for these conditions. The slight decline in recall for Stone and Tumor classes suggests minimal misclassification, likely due to similarities in shape and intensity patterns.

Table.1 Classification Report Of CNN-LSTM Model

Class	Precision	Recall	F1-Score	Support
Cyst	0.99	1.00	1.00	1118
Normal	1.00	1.00	1.00	1534
Stone	1.00	0.99	0.99	428
Tumor	1.00	0.99	0.99	654
Accuracy		**99.6%**		
Macro Avg	1.00	0.99	0.99	3734
Weighted Avg	1.00	1.00	1.00	3734

Precision-Recall and ROC Curve Analysis

To further validate the classification performance, we em- ployed precision-recall (PRC) and receiver operating charac- teristic (ROC) curve analyses. These metrics are especially useful in imbalanced class scenarios and help evaluate the model's capability to distinguish between classes. Fig. 3 and Fig. 4 illustrate the micro-averaged and macro-averaged PRC and ROC curves respectively.

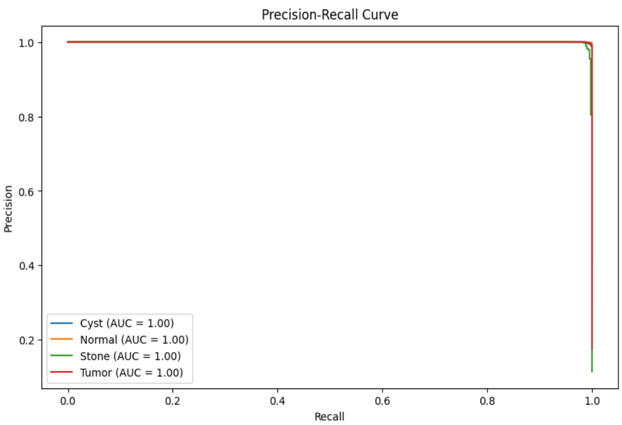

Fig. 3. Precision-Recall Curve (PRC) showing the trade-off between precision and recall for each class.

The PRC curve shows high precision across all recall thresholds, confirming the model's ability to correctly identify positive cases. Similarly, the ROC curve exhibits excellent area under the curve (AUC) scores, with values close to 1.0, indicating outstanding class separability and minimal overlap in the feature space.

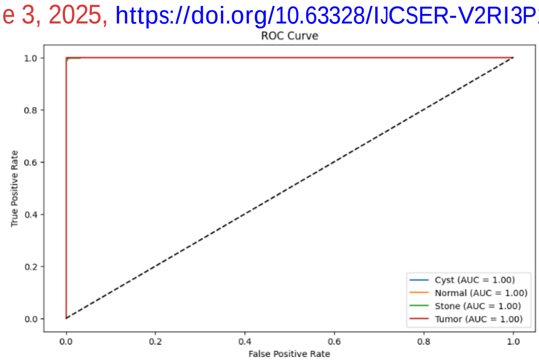

Fig. 4. Receiver Operating Characteristic (ROC) curve with area under the curve (AUC) values indicating high separability between classes.

Accuracy and Loss Curves

To monitor the model's learning behavior, we plotted train- ing and validation accuracy across epochs. As shown in Fig. 5, both training and validation accuracy increase steadily and converge closely, indicating effective generalization without overfitting.

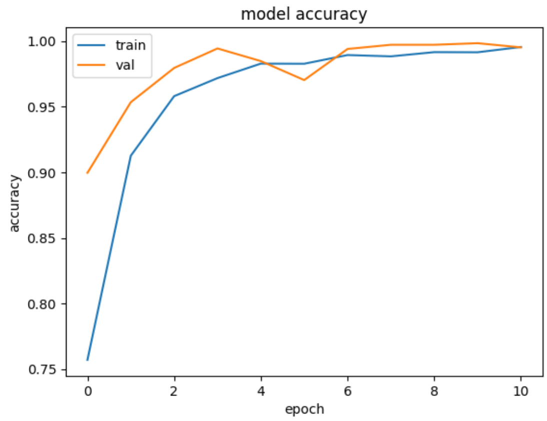

Fig. 5. Training and validation accuracy curve over epochs.

Separately, the loss curves in Fig. 6 show a consistent decrease for both training and validation loss. This reflects smooth optimization and stability during training, without signs of underfitting or erratic behavior.

Confusion Matrix Analysis

To gain further insights into the classification behavior, a confusion matrix was generated as shown in Fig. 7. The di- agonal dominance confirms that the model correctly classified most of the test samples. Only a few instances of Tumor and Stone images were misclassified, possibly due to overlapping radiographic features such as calcifications or lesions.

Visualization with Grad-CAM

To ensure transparency and explainability in model decision-making, Grad-CAM (Gradient-weighted Class Acti- vation Mapping) was used. As

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shown in Fig. 8, the heatmaps highlight the regions within CT images that significantly influenced the model's predictions. The activation maps show strong attention on pathological regions such as cystic cavities, stones, or tumors, validating that the network focuses on clinically relevant areas.

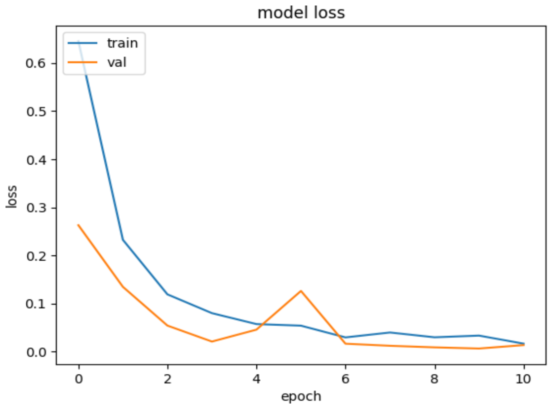

Fig.6 Training and validation loss curve over epochs.

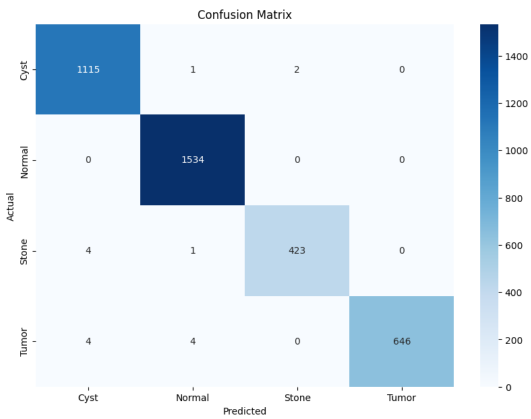

Fig.7 Confusion matrix illustrating per-class classification results.

These visualizations are particularly valuable in medical AI systems where clinicians need justification for AI-based decisions. The ability of the model to highlight correct anatomical structures enhances trust and encourages clinical adoption.

Comparative Analysis: To assess the performance of our proposed CNN-LSTM architecture, we compared it with other baseline models such as traditional CNN, ResNet50, and MobileNetV2.

Table.2 Comparative Analysis of Model Accuracy

Model	**Accuracy (%)**	**F1-Score**
Traditional CNN	94.5	0.945
ResNet50	96.2	0.961
MobileNetV2	97.4	0.972
Proposed CNN-LSTM	**99.6**	**0.996**

Fig.8 Grad-CAM visualizations for sample CT images across each class.

The results of this comparison are illustrated in Table II.The hybrid CNN-LSTM model significantly outperformed the baseline models, demonstrating the effectiveness of incor- porating temporal dependencies into spatial feature representa- tions. While conventional CNNs can learn spatial patterns, the LSTM component captures latent sequential features, which are particularly useful in capturing subtle anatomical variations in medical images.

Clinical Relevance: Kidney diseases such as stones and tumors often exhibit overlapping characteristics in imaging. The proposed method's ability to distinguish these conditions with near-perfect accu- racy has profound clinical implications. Early and accurate detection can lead to timely interventions, reduce diagnostic burden on radiologists, and improve patient outcomes. Fur- thermore, the explainable outputs foster trust in AI-assisted diagnostics, supporting clinical decision-making rather than replacing it.

Limitations and Future Scope: Despite the promising results, the model has limitations. The dataset, though balanced and diverse, is not extensive enough to capture rare anomalies. Additionally, it is trained on 2D axial CT slices; incorporating 3D volumetric information may further improve the model's understanding of spatial contexts. In the future, we plan to extend this work by integrating attention mechanisms and using larger, multi-center datasets to ensure generalizability and robustness.

Summary: In summary, the proposed CNN-LSTM architecture demon- strates outstanding performance in multiclass classification of kidney

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diseases from CT scans. Through a comprehensive evaluation framework, including statistical metrics and ex- plainable AI tools, we established the model's efficacy and clinical applicability. The results confirm that our hybrid model is a viable tool for aiding radiologists in accurate and early diagnosis of renal pathologies.

7. Conclusion and Future Scope

In this study, we proposed a hybrid deep learning model combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for the multiclass classification of kidney diseases using CT images. The model was trained and evaluated on a diverse dataset consisting of four classes: Cyst, Normal, Stone, and Tumor. Experimental results demonstrated a high classification accuracy of 99.6%, outperforming several state-of-the-art baseline models. The integration of CNN and LSTM allowed the system to extract robust spatial and sequential features, enabling effective dis- crimination of renal pathologies.Furthermore, we employed Grad-CAM-based visualizations to provide interpretability, highlighting the areas of medical images that influenced the model's decision. This step enhances trust among clinicians and supports the model's deployment in real-world diagnostic workflows. The confusion matrix and classification metrics confirmed that the proposed model maintained consistent performance across all classes, minimizing both false positives and false negatives.

Despite the outstanding results, certain limitations exist. The model was trained on 2D slices, which may not capture the full context of 3D anatomical structures. Moreover, the dataset, though well-curated, may not fully represent the variability present in a broader clinical population. Future work will focus on expanding the dataset to include 3D CT volumes, incorpo- rating attention mechanisms for better focus on pathological regions, and validating the model across multiple healthcare institutions to ensure its generalizability and robustness.In conclusion, the proposed CNN-LSTM framework presents a promising and reliable approach for computer-aided diagnosis of kidney diseases, offering enhanced accuracy, explainability, and potential for real-world clinical integration.

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Author's Profile

Bhuvanagiri Dilli Babu earned his B. Tech in Electronics and Communication Engineering from Sri venkateswara engineering college, Tirupati in 2023 &Currently pursuing M. Tech from VEMU Institute of Technology, Chittoor.

M. Sreevani earned her B.Tech CSE. M.Tech CSE, and currently pursuing Ph.D in St.Peters Institute of Higher Education and Research, Chennai, India and she is interested domains on AI, ML, DL. Total 15 years of teaching experience and currently working in Vemu Institute of technology as Assisstant Professor from the last 2 years.