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Research Article

Enhanced Chronic Kidney Disease Detection Using Deep Learning: A Comparative Analysis of CNN and LSTM Models.

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ABSTRACT

Chronic Kidney Disease (CKD) is a degenerative disorder that offers a huge worldwide health threat, frequently resulting in severe complications if not recognized early. Traditional diagnostic methods can be time-consuming, resource-intensive, and subject to human error. With the growth of artificial intelligence in healthcare, deep learning algorithms have emerged as strong tools for accurately and efficiently detecting CKD. This study compares two major deep learning model Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM) for the early detection and categorization of CKD. The models were tested with and without the Synthetic Minority Over-sampling Technique (SMOTE) to resolve data imbalances. Performance criteria such as accuracy, precision, recall, and F1-score were employed for evaluation. CNN with SMOTE had the best performance, with an accuracy of 99%, precision of 99%. In contrast, LSTM with SMOTE had 91% accuracy,89% precision. Also table highlights overall model performance, and shows class wise accuracy for detecting Normal, Cyst, Stone, and Tumor instances, with CNN with SMOTE outperforming LSTM with SMOTE in all classes. Our data demonstrate the efficacy of CNN, particularly when paired with SMOTE, in reaching high diagnostic accuracy.

Keywords: Deep Learning, CKD, CNN, LSTM, Kidney Detection, SMOTE.

INTRODUCTION

A chronic illness known as chronic kidney disease (CKD) is characterized by a progressive loss of kidney function over time. Millions of people are impacted globally, and if addressed, it can result in major health consequences such as kidney failure and cardiovascular illnesses. Early-stage CKD frequently advances silently, thus prompt detection and treatment are essential to preventing irreparable damage. Conventional diagnostic techniques, such as imaging, blood testing, and urine analysis, can be intrusive, labor-intensive, and prone to human error, especially during large-scale screens.

Deep learning, a branch of artificial intelligence (AI), has demonstrated tremendous promise in the field of healthcare in recent years, especially in the areas of disease identification and medical picture analysis. Deep learning models have been effectively used for a variety of medical applications, including tumor identification, diabetic retinopathy categorization, and heart disease prediction. These models are able to autonomously learn characteristics from raw data. Deep learning offers an opportunity to enhance and automate the detection process due to the amount of data generated by medical tests and the challenge of identifying chronic kidney disease (CKD).

Practical work of this particular research work focuses on employing deep learning techniques for the detection of CKD. There is a possibility of coming up with a definitive non-invasive and reliable method for early CKD diagnosis through imaging data and medical examination of blood and urine analysis. We are investigating cutting edge deep learning frameworks including convolutional neural networks (CNNs) for image processing and artificial neural networks (ANNs) for data processing. Our aim is to enhance clinical decision making and therefore improve the quality of patient care through better diagnosis and lower number of misdiagnoses.

The paper is organized as follows: Section 2 reviews related work and presents the problem statement, Section 3 outlines the proposed methodology, Section 4 discusses the results, and Section 5 concludes the paper and suggests future research directions. Section 6 contains the references.

RELATED WORK

"Three-Dimensional Convolutional Neural Network-Based Classification of Chronic Kidney Disease Severity Using MRI" (2024) by Nagawa et al. [3] Using MRI images, the study creates a 3D convolutional neural network (CNN) model to categorize the severity of CKD. With an accuracy of 86.2% the model worked best with pictures of both kidneys. By using deep learning to categorize CKD stages, this method can improve disease management.

"A New Deep Learning Model for Chronic Kidney Disease Prediction" (2023) by ¨Ozdemir et al. [4] This study proposes a unique one-dimensional Convolutional Neural Network (CNN) model for predicting chronic kidney disease (CKD). The model is compared to several machine learning approaches, including Random Forest, KNN, Decision Tree, and SVM. The deep learning model beat traditional machine learning models with amazing accuracy, precision, recall, and F1 scores of around 98.93%.

"Prediction of Chronic Kidney Disease Progression Using Recurrent Neural Network and Electronic Health Records" (2023) by Zhu et al. [5] This research develops an electronic health record (EHR) and applies recurrent neural networks (RNN) to predict the progression of chronic kidney disease (CKD) from stages II/III to IV/V. After training using time-series data on eGFR and other clinical factors, the RNN model outperformed earlier prediction algorithms, with an AUROC score of 0.957.

"Early Detection of Chronic Kidney Disease Using Eurygasters Optimization Algorithm with Ensemble Deep Learning" (2024) by Yousif et al. [6] This paper provides an ensemble deep learning strategy for identifying CKD based on the Eurygasters Optimization Algorithm (EOA). The ensemble approach includes LSTM, BiGRU, and BiLSTM models that were optimized using the shuffling frog hop algorithm. When tested on a CKD dataset, it showed excellent detection performance, with feature selection and hyperparameter optimization contributing to high accuracy.

"Imaging-Based Deep Learning in Kidney Diseases: Recent Progress and Future Prospects" (2024) by Zhang et al. [7] The primary focus of this review is the application of deep learning to medical imaging-based kidney disease identification and treatment. The paper discusses the application of deep learning models for tasks such as organ segmentation, lesion detection, and prognosis prediction. It highlights the challenges faced by deep learning methods in medical imaging, such as issues with data imbalance and interpretability.

METHODS

System Architecture :-

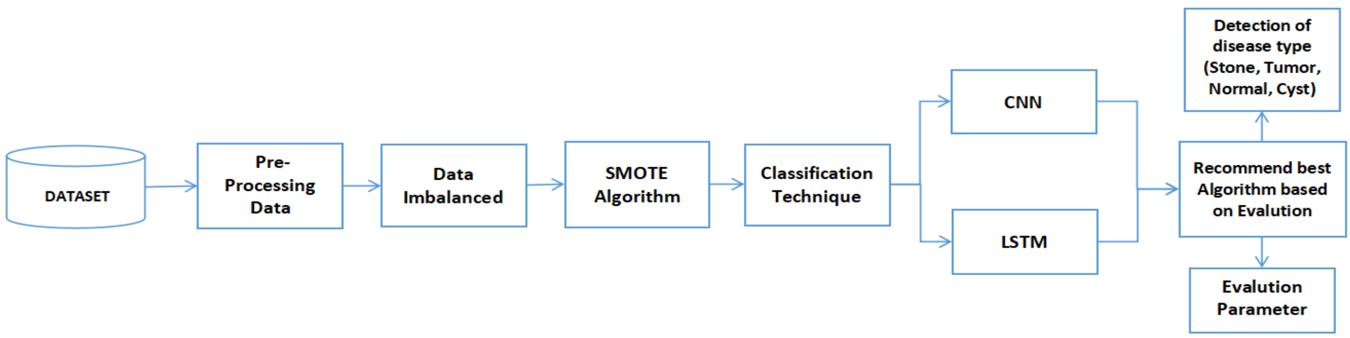


Figure 1 System Architecture of Chronic Kidney Disease

In Fig. 1, the system architecture diagram illustrates the overall workflow. First, Kidney CT Images undergo Prepossessing, where images are re-scaled and noise reduction it helps to removing artifacts or noise from CT Scan images. After prepossessing, the data moves to the Model Selection phase, which includes feature extraction using CNN and sequence modeling with LSTM. Finally, in the Output Module, the trained model predicts kidney disease and is evaluated using performance metrics such as accuracy, precision, recall, and F1-score.

Input Data Module: The system start to take image data that contain various collection of kidney CT images. It's Used to detect the kidney disease using raw input data or images will undergo various processes.

Preprocessing Module: Image Rescaling: In this step, images of different sizes found during web scraping or from sources like the ImageNet, dataset are re-scaled into images of a consistent shape and size, making it easy for models to train with.

Model Selection Module:

CNN : Before any identification of the kidney illness in these photos, a (CNN) is used to extract some features from photos that can give you key stuff available into these images such as edges, textures and patterns etc.

LSTM : The feature set may contains some kind of temporal dependencies, to capture them we pass this feature set to LSTM model (which is a RNN network) and here the output will be n sequence where n units. If the disease course is indicated by the ordered features or image sequence, this could be especially useful.

Output Module:Detecting of Kidney Disease: The algorithm detect which kidney diseases like normal, stone, tumor or cyst.

Performance Metrics: Accuracy, precision, recall, and F1-score are among the metrics that are computed to assess the model's efficacy and provide a thorough grasp of its performance.

Algorithm:-

Overview of CNN-LSTM :-

Convolutional Neural Networks: Images can have their spatial information extracted with the use of Convolutional Neural Networks (CNN). CNN layers are utilized in this study to find important patterns and textures in kidney CT scans that may point to various illness types.

Long Short-Term Memory : One kind of recurrent neural network (RNN) that is particularly good at processing data sequences is the Long Short-Term Memory (LSTM) network. Although LSTMs in this configuration usually work on feature sequences rather than time series, they are utilized here to capture any temporal correlations or sequential dependencies in the processed features.

CNN-LSTM Architecture for CKD Detection

CNN Architecture

CNN Layers: Used to extract spatial features from photos of the kidneys. Convolutional layers known as "Conv2D Layers" are capable of identifying patterns, textures, and edges. To record both low-level and high-level characteristics, you employed several Conv2D layers with progressively higher filters (e.g., 32, 64, 128). MaxPooling Layers: Minimize feature maps' spatial dimensions without sacrificing crucial data. Flattening: To get the 3D output ready for input into the LSTM, it is flattened into a 1D vector following the Convolutional layers.

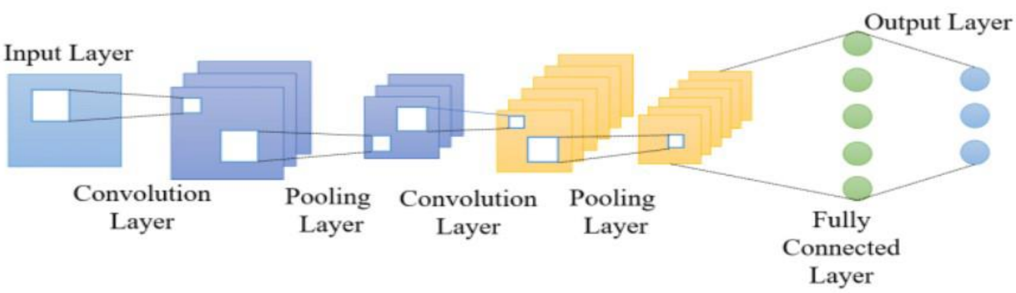


Figure 2 System Architecture of Convolutional Neural Networks.

Figure 2 illustrates the system architecture of a Convolutional Neural Network (CNN), illustrating the process for every layer. In order to extract features, the input image must first travel through a convolutional layer. The data then moves to a pooling layer, which preserves important information while lowering dimensionality. To improve feature extraction, this proces convolutional layer followed by pooling layer may be carried out more than once. A flatten layer receives the output after which it transforms the data into a one-dimensional array. It then advances to a dense (completely linked) layer, where nonlinearity is introduced by using the ReLU activation function. The output classification is then produced by passing the data through a second dense layer that uses the SoftMax activation function. This is an example of a CNN architecture that is straightforward but efficient.

LSTM Architecture

LSTM Layer: After receiving the CNN-extracted features, the LSTM Layer looks for patterns that can indicate dependencies between them. Dense Layers: The characteristics are consolidated by a dense layer that is activated by ReLU. The probability distribution across the classifications (such as "normal," "cyst," "stone," and "tumor") is output by the last dense layer with softmax activation.

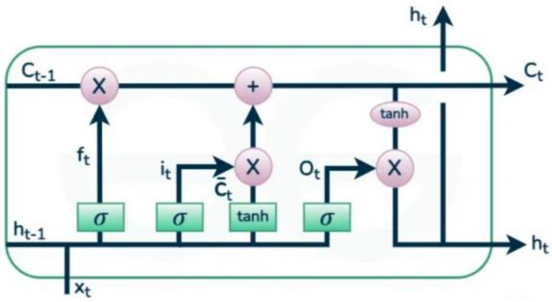


Figure 3 System Architecture of Long-Short Term Memory

Figure 3 illustrates the system architecture of a Long Short-Term Memory (LSTM) network, showing how data transfers between its layers. After passing through the LSTM layer, the input sequence starts the procedure. This layer controls information flow by using specific input, forget, and output gates, allowing the network to detect long-term data dependencies. The LSTM layer iteratively processes the sequence, updating a memory cell at each time step. More LSTM layers can be stacked to increase the model's ability to recognize complex patterns. After passing through a dense (completely connected) layer, the output of the LSTM layer is subjected to nonlinearity generated by the ReLU activation function. The final prediction is then made by running the data through a softmax activation function in the output layer.This enables the LSTM model to efficiently handle sequential input and capture temporal dependencies.

Process Design:-

Data Preprocessing

Image Rescaling: By dividing by 255, all pixel values are resized to fall between [0, 1]. The network trains more quickly and precisely because to this normalization.

Data Augmentation: To improve generalization and decrease overfitting, methods like rotation, shear, zooming, and width/height shifting are used to diversify the training dataset.

Handling Data Imbalance using SMOTE :

SMOTE : SMOTE is a data augmentation technique used to handle imbalanced datasets by generating synthetic samples for the minority class instead of just duplicating existing ones. This helps machine learning models learn better and avoid bias towards the majority class. SMOTE helps balance the dataset so that diseases like Tumor, Stone, Cyst, and Normal are equally represented, leading to better model performance.

Model Training

input data pipeline : It's uses 80\%\ of the dataset for training and 20% for validation. The dataset is separated into training and validation sets.

Training with ImageDataGenerator: To guarantee that every epoch trains on a variety of data, data augmentation is applied in real-time to the images in each batch.

Epochs and Batch Size: To balance training speed and memory utilization, the model is trained for a predetermined number of epochs (e.g., 20) and a batch size (e.g., 32).

Model Evaluation

Validation: To track the model's performance and prevent overfitting, it is assessed on the validation set at the conclusion of each epoch.

Performance Metrics: To show the model's learning progress, accuracy and loss are shown over epochs.

RESULTS

Dataset Details :-

We have used Dataset from kaggle (CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone).

Feature Extraction :-

CNN Layers: The CNN model uses convolutional layers to discern complicated patterns, edges, and textures in images. These factors indicate kidney disorders such tumors, stones, or cysts. Multiple-level feature maps are created using convolutional layers. Higher layers record more specialized patterns related to kidney pathology, whereas lower layers record more general properties such as edges.

Temporal Analysis with CNN-LSTM: In the CNN-LSTM model, an LSTM (Long Short-Term Memory) network gets spatial features retrieved by CNN layers. When a CT image has a series (such as successive slices in a scan), this model can detect spatial-temporal patterns that aid in more accurate classification.

Evaluation Parameters :-

1. Accuracy: Accuracy indicates how closely the results align with the true or expected values. Let consider TP = True Positive, FP = False Positive, TN = True Negative and FN = False Negative. The formula is as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

2. Precision (P): Precision evaluates how consistently close the results are to each other, specifically focusing on the accuracy of positive predictions. The formula is as follows:

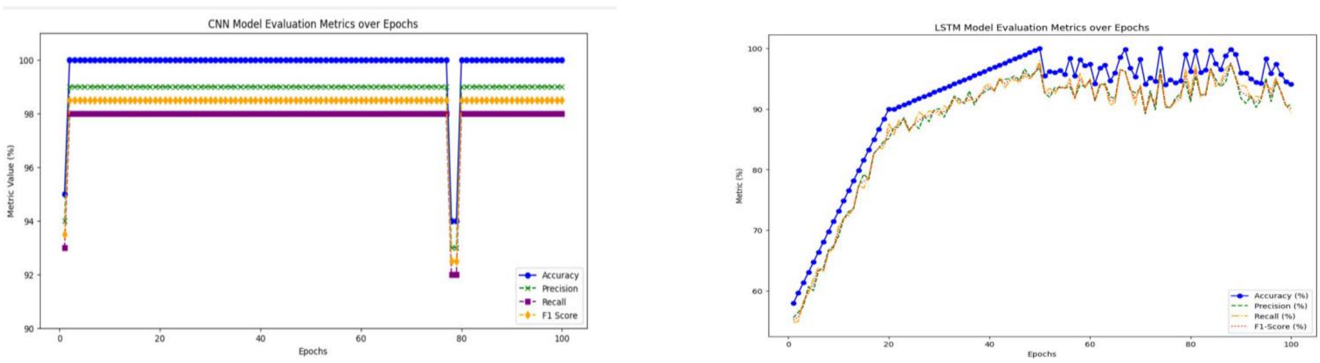
$$Precision = \frac{TP}{TP + FP}$$

3. Recall (Sensitivity)(R): Recall is the model's capacity to recognize every significant event inside a specified category. It represents the ratio of correctly predicted positive instances to all positive instances. This measure assesses how well the model detects all noteworthy cases. This is the formula:

$$Recall = \frac{TP}{TP + FN}$$

4. F1 Score: The F1 score is a composite metric that integrates both recall and precision, it also used both false positives and false negatives. The formula is as follows:

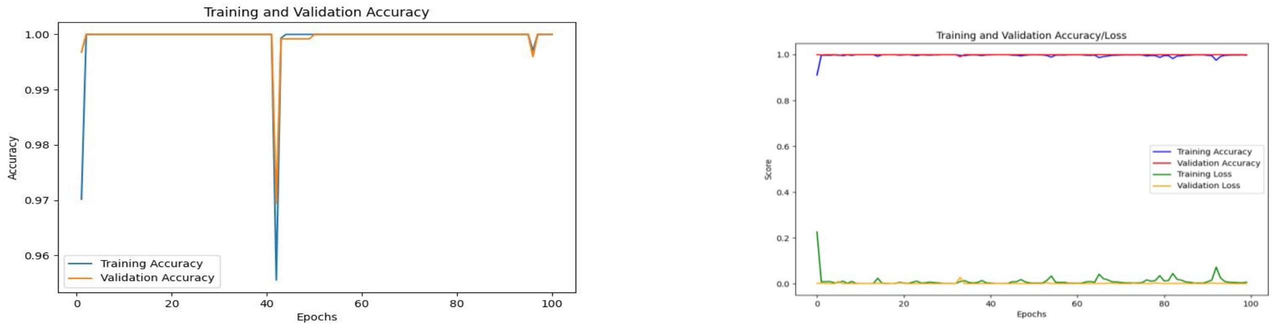
$$F1\,Score = \frac{2 * (P * R)}{(P + R)}$$



(a) (b)

Figure 4 Evaluation Parameter of CNN and LSTM Model without SMOTE.

In fig 4, Examine the evaluation parameter in CNN and LSTM models. While the LSTM model performs well in simpler cases but has a somewhat lower accuracy in complex ones, the CNN model consistently delivers superior accuracy, particularly when recognizing complex conditions like cysts and tumors.



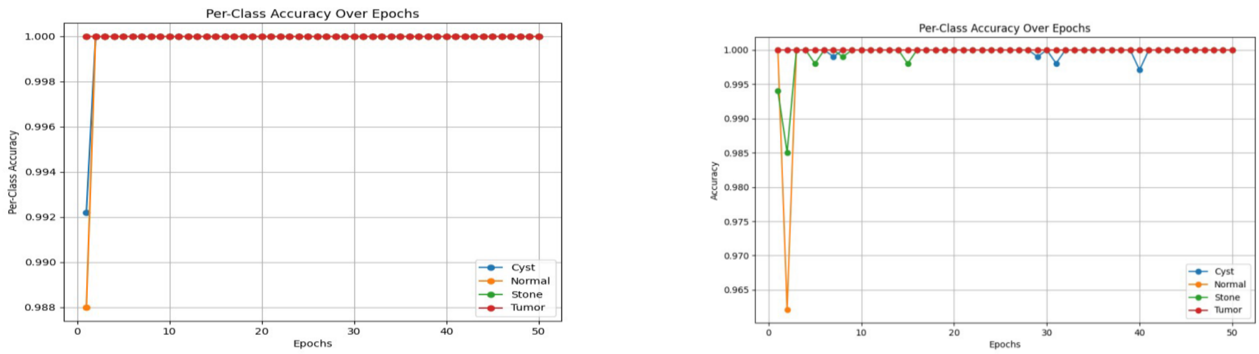
(A) (B)

Figure 5 Evaluation Parameter of CNN and LSTM Model with SMOTE

In fig 5, examine the evaluation parameter in CNN and LSTM models and also using SMOTE to balanced the imbalanced data. While the LSTM model performs well in simpler cases but has a slightly lower accuracy in complex ones, the CNN model consistently delivers superior accuracy, particularly when recognizing complex conditions like cysts and tumors.

Model	METRICS			
	Accuracy	Precision	Recall	F1-Score
CNN Without SMOTE	0.99	0.98	0.97	0.99
CNN With SMOTE	0.99	0.99	0.98	0.99
LSTM Without SMOTE	0.91	0.88	0.86	0.88
LSTM With SMOTE	0.91	0.89	0.87	0.88

In above table, compares and contrasts two deep learning algorithms: CNN and LSTM. Evaluation parameters are used to assess the models. These parameters consist of F1-score, Accuracy, Precision, and Recall.



(p) (q)

Figure 6 Accuracy of all Classes of CKD Using CNN and LSTM With SMOTE.

In fig 6, examine the evaluation parameter in CNN and LSTM models and also using SMOTE to balance the imbalanced data and it has separate type of all disease and compare with them. While the LSTM model performs well in simpler cases but has a slightly lower accuracy in complex ones, the CNN model consistently delivers superior accuracy, particularly when recognizing complex conditions like cysts and tumors.

MODEL	CLASSES			
	NORMAL	CYST	STONE	TUMOR
CNN With SMOTE	0.99	0.99	0.98	0.99
LSTM With SMOTE	0.91	0.89	0.87	0.88

In above table, compares and contrasts two deep learning algorithms: CNN and LSTM with 4 type of classes of CKD are Normal, Cyst, Stone and Tumor. Accuracy are used to assess the models.

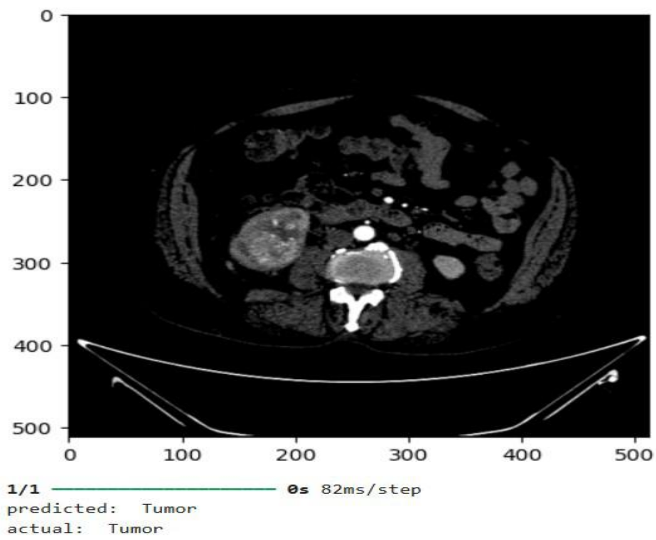


Figure 7 Detection of Kidney Disease Using CNN Model.

In fig 7, shows how to use a CNN model to detect different kidney diseases. The picture shows various kidney abnormalities, including tumors, stones, cysts, and normal kidneys. In this instance, the model correctly recognized a tumor as the kidney ailment in the image that was shown, which is consistent with the diagnosis. In order to enable early and efficient diagnosis for possible medical intervention, the CNN model has demonstrated good performance in identifying such circumstances and precisely and confidently detecting the existence of a tumor.

CONCLUSION AND FUTURE WORKS

In This research we have compared CNN and LSTM models in detecting chronic kidney disease (CKD), We consider conditions such as normal, stone, cyst, and tumor. The results show that the CNN model, especially when combined with the Synthetic Minority Oversampling Technique (SMOTE), consistently achieves higher accuracy across all classes, particularly in complex cases such as cysts and tumors, demonstrating its effectiveness in handling detailed medical imaging and imbalanced datasets. While the LSTM model with SMOTE performed well in simpler situations, it was marginally less accurate for more complex diagnoses. These findings imply that CNNs improved with SMOTE are more suited for CKD detection tasks that demand high precision and robustness, hence facilitating early diagnosis and potentially improving patient outcomes. This study demonstrates that CNNs with SMOTE are a promising technique in practical applications for accurate and quick renal disease detection.

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