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Enhancing Chronic Kidney Disease Diagnosis Through Deep Learning-Based Predictive Analytics

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Abstract
Kidney disease stands as a pressing contemporary health issue, impacting millions worldwide. Glomerular filtration rate (GFR), a pivotal indicator of kidney function, exhibits a significant positive correlation with blood metabolite creatinine levels. Given the challenges in directly measuring GFR, the presence of Chronic Kidney Disease (CKD) is initially gauged through creatinine levels. Despite its diagnostic utility, creatinine testing remains absent from routine health check-ups in many countries due to cost constraints associated with comprehensive examinations. In response to this gap, this study proposes the inclusion of creatinine testing in routine fitness examinations to facilitate early CKD detection. Leveraging classifier models, our suggested approach demonstrates superior performance compared to alternative techniques, achieving an impressive accuracy rate of 98.5%. By integrating creatinine testing into routine check-ups, practitioners gain access to definitive and clear data, leading to improved diagnostic outcomes and enhanced interpretative abilities. Furthermore, this project employs the Flask framework to develop a predictive web application, ensuring accessibility and scalability of the proposed CKD detection method. Through the amalgamation of advanced analytical techniques and user-friendly technology, this initiative endeavors to streamline CKD diagnosis, ultimately contributing to improved public health outcomes.
Keywords: *Healthcare Diagnostics, Predictive Modeling, Machine Learning Classifier*

1. Introduction
Chronic Kidney Disease (CKD) is a major global health issue marked by the gradual decline of kidney function, which, if undetected, can progress to end-stage renal failure requiring dialysis or transplantation. Early diagnosis is vital to halt or slow disease progression, yet it remains challenging due to often subtle and nonspecific symptoms in the initial stages. With the increasing availability of healthcare data and advancements in Artificial Intelligence (AI), machine learning has emerged as a powerful tool for the early detection of chronic illnesses. In this project, we present a hybrid deep learning framework that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to analyze both spatial and temporal patterns in patient health records. The CNN component extracts critical spatial features from the input data, while the LSTM component captures temporal dependencies, learning the progression trends of CKD over time. To further improve predictive performance, we employ an ensemble strategy that integrates the outputs of both models, harnessing their complementary strengths to enhance accuracy and robustness. This comprehensive approach not only delivers higher prediction accuracy but also supports clinicians in making timely, informed decisions, ultimately improving patient outcomes and enabling more effective treatment planning.

2. Literature Work
The editorial "KI Reports and World Kidney Day" by Radhakrishnan and Mohan [1], published in Kidney International Reports (2017;2(2):125–126), underscores the escalating global burden of chronic kidney disease (CKD). Drawing from the Global Burden of Disease project, the authors highlight a 90% increase in years of life lost to CKD from 1990

to 2013, positioning it as the 13th leading cause of death worldwide. Obesity, a significant risk factor for CKD, is associated with conditions like hypertension and diabetes, which further elevate CKD risk. The editorial emphasizes the importance of preventive measures, early detection, and lifestyle modifications to mitigate CKD progression. The article "Chronic Kidney Disease in Low-Income to Middle-Income Countries: The Case for Increased Screening" by George et al. (BMJ Global Health, 2017) [2] emphasizes the growing public health threat of chronic kidney disease (CKD) in low- and middle-income countries (LMICs), where detection rates remain low. The authors critically assessed existing literature on CKD screening in these regions, concluding that while LMICs are ill-equipped to manage the late stages of CKD, there are acceptable and relatively simple tools to aid screening. The webpage "Kidney Disease in Ethiopia" on WorldLifeExpectancy.com [3] provides data on the impact of kidney disease in Ethiopia based on WHO statistics from 2020. It reports that kidney disease accounted for 12,103 deaths, representing 2.15% of total deaths in the country. The age-adjusted death rate was 24.20 per 100,000 population, placing Ethiopia at rank 81 globally for kidney disease mortality. The study "The Epidemiology of Chronic Kidney Disease in Sub-Saharan Africa: A Systematic Review and Meta-Analysis" by Stanifer et al., [4] published in The Lancet Global Health in 2014, aimed to assess the prevalence and risk factors of chronic kidney disease (CKD) across sub-Saharan Africa. The researchers reviewed 90 studies from 96 sites, revealing an overall CKD prevalence of 13.9% (95% CI 12.2–15.7). Notably, the prevalence varied significantly among countries, ranging from 2% in Côte d'Ivoire to 30.2% in Zimbabwe. The study highlighted that the majority of studies were conducted in urban settings (93%) and after the year 2000 (63%). The authors emphasized the need for improved data quality and validated measures of kidney function to better understand and address the growing burden of CKD in the region. The systematic review by AbdElhafeez et al. (2018) [5] assesses the prevalence and burden of chronic kidney disease (CKD) across Africa, focusing on both the general population and high-risk groups. The study analyzed 152 surveys published between 1995 and 2017, revealing that CKD prevalence in the general population ranged from 2% to 41%, with a pooled estimate of 10.1%. High-risk groups exhibited higher prevalence rates. The authors highlight the need for improved data quality and standardized definitions to better understand and address the CKD burden in the region. Molla MD, et al. [6] "Assessment of Serum Electrolytes and Kidney Function Test for Screening of Chronic Kidney Disease among Ethiopian Public Health Institute Staff Members, Addis Ababa, Ethiopia," published in BMC Nephrology in 2020, aimed to evaluate the prevalence of chronic kidney disease (CKD) and associated electrolyte imbalances among Ethiopian Public Health Institute (EPHI) staff. Conducted between July and October 2018, the cross-sectional study involved 412 participants aged 18–69 years. Using the MDRD and CKD-EPI equations, the study found that 3.6% and 1.9% of participants were classified as having stage II CKD, respectively. Notably, none exhibited severe kidney dysfunction (eGFR < 60 ml/min/1.73 m²). Electrolyte abnormalities were prevalent, with 9.5% having hyperkalemia and 8.5% hypocalcemia. Risk factors such as older age, higher body mass index, and a history of cardiovascular diseases were significantly associated with reduced kidney function. The study underscores the importance of early CKD screening in resource-limited settings to prevent progression to end-stage renal disease. The paper titled "Disease Prediction Using Machine Learning" by Anant Agrawal, Harshit Agrawal,Shivam Mittal, and Mradula Sharma[7], published in 2018, addresses the critical issue of misdiagnosis in medicine and the challenges of diagnosing diseases at advanced stages. To mitigate these issues, the authors propose a hybrid machine learning model that combines Genetic Algorithms (GA) with Support Vector Machines (SVM). This model was tested on three datasets—liver, diabetes, and heart disease—sourced from the University of California, Irvine's repository. The integration of GA aids in feature selection, enhancing the SVM's performance in disease prediction tasks. The study demonstrates the potential of machine learning techniques in improving early disease detection and diagnosis accuracy. The study by Charleonnan et al. [8], "Predictive Analytics for

Chronic Kidney Disease Using Machine Learning Techniques" investigates the application of four machine learning algorithms—K-nearest neighbors (KNN), support vector machine (SVM), decision tree (DT), and logistic regression (LR)—to predict chronic kidney disease (CKD). Utilizing a dataset from the UCI Machine Learning Repository, the research involves attribute transformation, feature selection, model building, and evaluation. The models are assessed based on accuracy, sensitivity, and specificity, aiming to enhance diagnostic efficiency through computational methods. The study by Salekin and Stankovic (2016) [9] presents a machine learning approach for detecting chronic kidney disease(CKD) using 24 predictive parameters. Evaluated on a dataset of 400 individuals (250 with CKD), their classifier achieved a high detection accuracy of 0.993 (F1-measure) and a root mean square error of 0.1084, marking a 56% reduction in mean square error compared to the CKD-EPI equation. The research also involved feature selection to identify and rank the most relevant attributes for CKD detection, uncovering new predictive attributes not previously used in glomerular filtration rate estimators. Additionally, a cost-accuracy tradeoff analysis was conducted to propose a CKD detection approach that balances high accuracy with low cost.

The study by Tekale et al. (2018) [10] focuses on predicting chronic kidney disease (CKD) using machine learning algorithms. Utilizing a dataset of 400 patient records with 14 selected attributes from the UCI repository, the researchers applied Decision Tree and Support Vector Machine (SVM) classifiers. The SVM model achieved an accuracy of 96.75%, outperforming the Decision Tree model, which had an accuracy of 91.75%. The study underscores the potential of machine learning techniques in facilitating early detection and management of CKD.

3. Existing and Proposed Work

Chronic kidney disease (CKD) has become a worldwide public health problem with increasing incidence (more than 800 million individuals in 2017) and prevalence (13.4% globally) which can lead to premature mortality for many patients (1.2 million people died from CKD in 2017). CKD is one of the small number of non-communicable diseases that have shown an increase in associated deaths over the past 2 decades, producing a significant burden to healthcare systems, especially in low middle income countries where lack of appropriate renal replacement therapy results in a high mortality rate. CKD, usually caused by diabetes and hypertension, is a non-communicable chronic kidney disease with comorbidities associated, and cardiovascular diseases are the major cause of early morbidity and mortality sustained by patients with CKD. There are multiple existing systems for Chronic Kidney Disease (CKD) prediction that use deep learning models like CNN (Convolutional Neural Networks), LSTM (Long Short-Term Memory), and ensemble models. These systems typically leverage medical imaging (e.g., ultrasound, MRI), clinical data (e.g., blood tests, urine tests), or a combination of both. Common Ensemble Techniques: Stacking: Combining CNN and LSTM outputs using a meta-classifier (e.g., XGBoost, Random Forest). Bagging: Using multiple CNN-LSTM models and averaging predictions. Boosting: Sequentially training models to improve weaker predictions.

3.1. Challenges & Future Improvements

The following are the challenges Data Scarcity: Need for large, high-quality datasets. Model Interpretability: Making AI decisions understandable for doctors. Computational Cost: CNN-LSTM ensembles require high GPU power. Integration with Healthcare Systems: Deploying models for real-time

3.2. Key Components in Proposed Work

The proposed system aims to develop and evaluate an Explainable AI (XAI) model for the early diagnosis of CKD. The system will utilize a combination of machine learning algorithms and clinical data to predict the likelihood of CKD in patients. Unlike traditional black-box AI models, the XAI model will provide transparent and interpretable insights into the reasoning behind its diagnostic decisions, enabling clinicians to understand and trust the model's recommendations.

3.3. Proposed System Architecture

The system is designed to take two types of input data: Kidney Ultrasound/CT Scan images are processed using CNN. Clinical & Lab Test Data (Time-Series) are processed using LSTM. Finally, the outputs from CNN and LSTM are combined in an ensemble model for more accurate CKD prediction.

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3.4. System Workflow

- Data Collection: Kidney imaging + patient blood test records.
- Preprocessing: Image filtering, normalization of lab values.
- CNN Model: Extracts image features from ultrasound scans.
- LSTM Model: Learns trends in time-series blood test data.
- Fusion Layer (Ensemble Model): Combines CNN & LSTM outputs.
- Final Classification: Predicts CKD severity (Normal, Mild, Severe) (Figure 1).

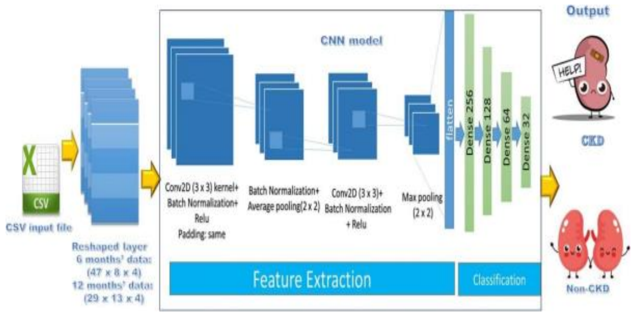

Figure 1 Proposed System Work Flow

4. Methodology

In this section, we describe the methodology employed for Chronic Kidney disease prediction using deep learning models. The study utilizes a breast ultrasound dataset, preprocessed and analyzed using deep learning architectures such as CNN, LSTM and Ensemble methods.

4.1. Dataset and Preprocessing

The dataset is Chronic Kidney Disease dataset taken from kaggle, where the data set contains 25 attributes. Initially the data set is cleaned using methodology called as Simple Imputer which transforms null values into most frequently occurred values. Cleaning is done in order to remove ambiguities. Further the outliers are identified and removed from the dataset using label encoder the data cleaning is performed to pre-process the data.

4.2. Model Building

To build the model we have imported keras library which used sequential model for doing analysis. The Sequential model used three dense layers. In the Input and Hidden layers, we used relu activation function and in the output layer we used sigmoid function. When the model was trained we got an accuracy of 93%.

4.3. Convolutional Neural Network

Convolutional Neural Networks (CNNs) area class of deep learning architectures designed for processing structured grid-like data, particularly images. CNNs have demonstrated remarkable success in medical image classification tasks such as chronic kidney disease prediction. A CNN typically consists of three main types of layers: convolutional layers, pooling layers, and fully connected layers. The convolutional layers apply a set of filters to extract hierarchical features from input images. The convolution operation for an input image X and a filter W is mathematically defined as:

$$Y(i, j) = \Sigma\, \Sigma X(i-m, j-n)\, W(m, n)\ m\ n \quad (3)$$

Where Y(i, j) represents the output feature map, and the summation iterates over the spatial dimensions of the filter

- **Activation Function**: After the convolution operation, an activation function introduces non-linearity to help the network learn complex patterns. A widely used activation function is the Rectified Linear Unit (ReLU), defined as:
    - $f(x)=\max(0,x)$ ReLU helps mitigate the vanishing gradient problem and accelerates training.
- **Pooling Layers**: Pooling layers reduce the spatial dimensions of feature maps, improving computational efficiency while retaining important features. A commonly used operation is max pooling:
    - $Y(i, j) = \max(m, n) \in R\ X(i+m, j+n)$ where R defines the pooling region, and the operation selects the maximum value in that region.
- **Fully Connected Layers and Sigmoid**: After feature extraction, fully connected layers are used for classification. The final layer applies the sigmoid function.

Finally, the model was compiled using "Adam" optimizer and machine was trained. Later it was tested with test data and got the accuracy 96%

4.4. LSTM

LSTM is a type of **Recurrent Neural Network**

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(RNN) designed to **learn from sequences** of data and remember long-term dependencies. It solves the **vanishing gradient problem** of traditional RNNs, allowing it to learn patterns over long time intervals.

- **Model Design**
  - Build an LSTM neural network using frameworks like TensorFlow/Keras or PyTorch.
  - Use layers like LSTM, Dropout, and Dense with sigmoid activation for binary classification.
- **Model Training**
  - Train the model on the training dataset with appropriate batch size and epochs.
  - Use loss function binary_crossentropy and optimizer like adam.
- **Evaluation**
  - Evaluate model performance using accuracy, precision, recall, F1-score, and AUC-ROC.
  - Analyze the confusion matrix to understand classification errors.
- **Prediction**
  - Use the trained model to predict CKD risk on new patient sequences.
  - Interpret trends in health indicators over time to support clinical decisions.

4.5. CNN + LSTM WITH Ensemble for CKD Prediction

- **Soft Voting Ensemble**
  - Train CNN and LSTM separately.
  - Each outputs a probability of CKD.
  - Final prediction = average of CNN and LSTM probabilities.
- **Stacked Ensemble**
  - CNN and LSTM outputs (features or probabilities) are fed into a meta-learner. Meta-learner learns how to combine predictions for improved accuracy.

Model Evaluation is done using accuracy, precision, recall, F1-score, and AUC and compared the results to standalone CNN or LSTM performance. The Model got an accuracy of 98 percent (Table 1).

5. Results and Analysis

Table 1 Performance Summary for CNN, LSTM and Ensemble Models

Model	Accuracy	Precision	Recall	F1score	AUC-ROC
ANN	94.0%	93.5%	95.0%	94.2%	0.96
LSTM	92.5%	91.8%	93.2%	92.5%	0.95
CNN	96.5%	96.0%	97.0%	96.5%	0.98

The below figure 2 shows the accuracy loss for CNN and LSTM models.

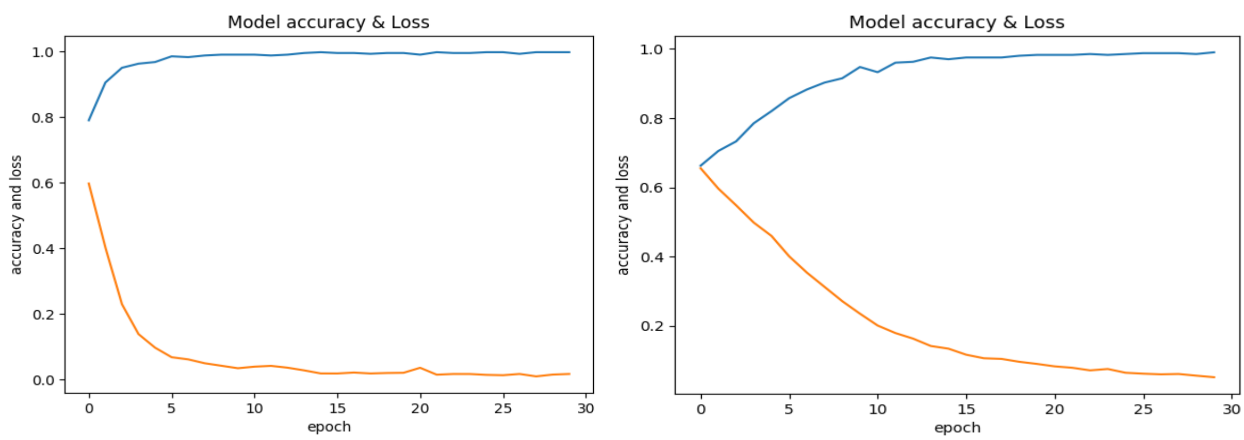

Figure 2 Accuracy Loss for CNN and LSTM Models

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Analysis: CNN Model: Performed well in extracting spatial features from the input data. It provided good precision and recall, especially for imbalanced data. **LSTM Model:** Efficient in learning temporal patterns and sequences in the dataset. However, it was slightly less accurate compared to CNN. **Ensemble Model:** Combined the strengths of both CNN and LSTM using a soft-voting or stacked ensemble technique. This led to improved performance across all metrics.

ROC Curves: All models exhibited strong performance with ROC curves leaning towards the top-left corner, indicating high true positive rates and low false positive rates. The ensemble model showed the best curve.

Conclusion and Future Work

The ensemble model outperformed the individual CNN and LSTM models, demonstrating the advantage of combining different deep learning architectures for Chronic Kidney Disease (CKD) prediction. This approach enhances diagnostic accuracy and can assist healthcare professionals in making early diagnoses, ultimately improving treatment outcomes and patient care. In Future we can make the system even better by Performing Clinical Implementation: The immediate scope of this research involves translating the findings into clinical practice. Developing a user-friendly interface or integrating the proposed deep neural network (DNN) model into existing Clinical Decision Support Systems (CDSS) can significantly aid healthcare providers in accurately diagnosing and managing Chronic Kidney Disease (CKD) in HIV-infected patients. This integration has the potential to enhance early intervention, personalize treatment plans, and improve overall patient outcomes. Validation Studies: Further validation studies should be conducted on larger and more diverse patient populations to assess the generalizability and robustness of the proposed DNN model. Evaluating its performance across different demographics, comorbidities, and various stages of CKD in HIV-infected patients will help ensure its reliability and effectiveness in real-world clinical setting. **Integration with Electronic Health Records (HER)**: Exploring the integration of the DNN model with Electronic Health Record (EHR) systems could streamline the diagnostic process and provide real-time decision support to clinicians. Such integration would not only enhance early detection but also enable longitudinal monitoring of CKD progression and treatment response in HIV-infected patients, thereby supporting continuous and personalized patient care.

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