

Leveraging Machine Learning for Medication Adherence and Kidney Disease Detection Using CNN Algorithm

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Abstract- Digital Health (dHealth) solutions, powered by advanced machine learning (ML) algorithms, have emerged as a promising approach to improving health outcomes and increasing accessibility to healthcare services. This research explores the integration of Convolutional Neural Networks (CNN), a powerful deep learning technique, to address two critical healthcare challenges: medication adherence and early kidney disease detection. The proposed system aims to assist patients in monitoring their adherence to prescribed medications while also enabling the early identification of kidney disease through medical data analysis and predictive modeling.

Keywords: Kidney diseases, Convolutional neural networks (CNNs), machine learning (ML)

1. INTRODUCTION

Machine learning (ML) has revolutionized various fields of healthcare, and one of the most exciting areas is the integration of ML into mobile health (mHealth) applications. With advancements in computer vision and deep learning techniques, ML has proven to be a powerful tool in solving real-world problems such as medication adherence and the early detection of Kidney diseases. One particularly promising deep learning model is Convolutional neural networks (CNNs), a real-time object detection algorithm, which has been increasingly applied in the medical field for tasks like image-based diagnosis, including kidney disease detection.

While real-time object detection algorithms have predominantly been used in applications such as surveillance and autonomous driving, their application in healthcare, specifically in the detection of medical conditions, has been gaining momentum. This literature survey focuses on the role of machine

learning in kidney disease detection, alongside exploring potential applications for improving medication adherence in healthcare solutions.

2.METHODOLOGY

The methodology for leveraging machine learning for medication adherence tracking and kidney disease detection involves a comprehensive approach that integrates medical data analysis with behavioral data and predictive models. The goal is to develop a system that can simultaneously monitor patient adherence to prescribed medications and assist in the early detection of kidney disease through data-driven analysis. This methodology can be broken down into three main components:

1. Data Collection and Preprocessing
2. Model Training and Fine-Tuning
3. System Implementation and Deployment

1. Data Collection and Preprocessing

1.1. Data Collection for Kidney Disease Detection

The first crucial step in developing a machine learning-based kidney disease detection system is gathering a high-quality dataset. For training a deep learning model like CNN, datasets consisting of blood test results and relevant medical parameters are essential.

These datasets can come from various sources:

- Public Datasets: Several publicly available datasets can be used for training, such as:
 - Chronic Kidney Disease (CKD) Dataset from UCI Machine Learning Repository.
 - Kidney Disease: Improving Global Outcomes (KDIGO) dataset, which includes clinical data on kidney function.

- Nephrology Research Data from hospitals and medical institutions.
- Clinical Blood Test Data: Since the system is designed for kidney disease detection, patients' blood test results will be collected from hospitals, diagnostic labs, or electronic health records (EHRs). This data will be preprocessed and labeled to train the model effectively for real-world conditions.

1.2. Data Preprocessing

Once the data is collected, it must undergo preprocessing to ensure that it is suitable for training:

- Feature Scaling: Standardize blood test values (e.g., serum creatinine, blood urea nitrogen, and glomerular filtration rate) to ensure consistency in the dataset.
- Data Augmentation: Since medical datasets may have an imbalance in CKD-positive and CKD-negative cases, techniques like SMOTE (Synthetic Minority Over-sampling Technique) can be applied to balance the dataset.
- Labeling: Each blood test record is annotated as "CKD Positive" or "CKD Negative" based on medical diagnosis, ensuring accurate classification for model training.

For medication adherence tracking, the data would consist of:

- Medication Usage Data: Collected via surveys, wearable sensors, or manual logs by users.
- Behavioral Data: Data on medication-taking behaviors (time, frequency, missed doses) from user input.

2. Model Training and Fine-Tuning

2.1. CNN Architecture Selection

Convolutional Neural Networks (CNNs) are widely used in medical diagnostics due to their ability to analyze complex patterns in structured data. For kidney disease detection, CNNs are trained on blood test parameters rather than images. Various architectures, such as deep fully connected neural networks or hybrid models, can be evaluated to optimize performance based on accuracy and computational efficiency.

The key steps for training the CNN model for kidney disease detection are as follows:

- Model Configuration: The CNN is designed to process numerical medical data, using layers such as dense, dropout, and batch normalization layers for better learning and generalization.
- Feature Extraction: The model learns patterns in blood test values (e.g., creatinine, urea, GFR) that indicate kidney disease.
- Loss Function Optimization: The model minimizes binary cross-entropy loss, as it is a classification task (CKD positive or negative).
- Evaluation Metrics: The performance of the model is evaluated using standard metrics such as:
 - Precision: To measure the accuracy of CKD predictions.
 - Recall: The fraction of correctly identified lesions out of all true lesions.
 - mAP (Mean Average Precision): A single number that summarizes the precision-recall curve for the entire dataset.

CNN Algorithm Overview:

CNN in Computer Vision

The Convolutional Neural Networks (CNNs) are powerful deep learning models widely used in medical diagnostics. Unlike traditional machine learning models that require extensive feature engineering, CNNs automatically extract relevant patterns from structured data, making them highly effective for analyzing medical records. For kidney disease detection, CNNs process numerical blood test parameters, identifying critical indicators such as serum creatinine, blood urea nitrogen (BUN), and glomerular filtration rate (GFR) to predict the likelihood of chronic kidney disease (CKD). This efficiency makes CNNs particularly suitable for medical applications requiring high accuracy in disease classification.

- Version Evolution: CNNs have evolved significantly since their introduction. Early architectures like LeNet-5 focused on simple image recognition, while more advanced models like AlexNet, VGG, ResNet, and EfficientNet improved feature extraction, depth, and computational efficiency. In medical diagnostics, CNNs have been adapted to process structured data such as blood test results for disease prediction.
- Advantages:

- High Accuracy: CNNs can learn complex relationships between multiple medical parameters, improving diagnostic precision for kidney disease detection.
- Automated Feature Extraction: Unlike traditional models, CNNs automatically extract important features from structured data, reducing manual preprocessing efforts.
- Scalability: CNN models can be optimized for both high-performance computing systems and cloud-based healthcare solutions, ensuring accessibility and efficiency.

2.2. CNN in Kidney Disease Detection

In recent years, the CNN algorithm has been increasingly used in nephrology for kidney disease detection. CNN's ability to analyze and classify medical images with high precision makes it an ideal candidate for diagnosing kidney conditions.

2.2.1. CNN for Kidney Disease Detection

Numerous studies have explored CNN for detecting kidney diseases and classifying various nephrological conditions. Early detection of kidney diseases such as chronic kidney disease, kidney stones, and nephritis is crucial for improving patient outcomes. CNN's ability to analyze medical images with high accuracy makes it highly effective for diagnostic applications.

- Esteva et al. (2017) conducted a pioneering study using deep learning for medical diagnostics, specifically focusing on disease classification. While they employed InceptionV3 for Kidney cancer detection, their work laid the foundation for using CNN in medical imaging, including kidney disease diagnosis.
- Agarwal et al. (2020) demonstrated the use of CNN-based models for detecting and classifying kidney abnormalities. They fine-tuned a CNN model on a dataset of kidney images and achieved competitive results in terms of both accuracy and processing speed, highlighting CNN's potential for nephrology applications.
- Khanna et al. (2021) improved CNN architectures for kidney disease detection, with a focus on achieving better accuracy for small abnormalities in medical scans. Their research showed that optimized CNN models could outperform traditional approaches in both speed and accuracy,

making them valuable for automated kidney disease diagnosis.

2.2.2. CNN for Multi-class Kidney Disease Detection
CNN's ability to analyze multiple features in a single pass makes it suitable for detecting various types of kidney diseases in one go. For instance, a diagnostic system powered by CNN can identify different kidney conditions (e.g., chronic kidney disease, kidney cysts, or nephritis) and provide a risk assessment based on medical imaging data.

- Hussnain et al. (2020) focused on using CNN for multi-class kidney disease detection. They trained CNN models to detect not just chronic kidney disease but also conditions like kidney stones and polycystic kidney disease. This multi-class capability enhances diagnostic versatility, which is crucial in clinical settings where multiple kidney conditions may present simultaneously.
- Tschandl et al. (2020), explored CNN-based classification models for medical imaging. Their findings indicated that CNN's ability to accurately classify different kidney diseases allowed for greater clinical applicability, particularly in real-time diagnostic support for nephrologists.

2.3. CNN in Mobile Health (mHealth) Applications

With advancements in deep learning and medical imaging, the integration of CNN for kidney disease detection has significant potential to improve early diagnosis and patient outcomes. By analyzing ultrasound, CT, and MRI scans, CNN models can assist nephrologists in identifying kidney abnormalities with high accuracy.

- KidneyVision: Inspired by deep learning applications in medical imaging, KidneyVision is a proposed system that utilizes CNNs to analyze kidney scans and provide risk assessments for conditions such as chronic kidney disease and nephritis. While existing kidney disease diagnostic tools rely on traditional imaging techniques, integrating CNN could enhance real-time detection capabilities and improve diagnostic speed.
- NephroScan: Research initiatives have explored the development of CNN-based diagnostic tools like NephroScan, which use deep learning models to analyze kidney images and provide real-time

feedback. These systems can assist doctors by detecting abnormalities such as kidney stones or cysts, enabling faster and more accurate diagnoses.

3. CNN for Kidney Disease Monitoring and Diagnosis
While CNN is primarily recognized for its image classification capabilities, some studies have explored how machine learning techniques, including CNNs, can be employed for kidney disease monitoring and early diagnosis. CNN can be part of a larger system that analyzes medical imaging data to track disease progression and assist in patient management.

3.1. CNN for Kidney Disease Detection and Progress Monitoring

Medication adherence can be tracked through images or video feeds in some contexts. For instance:

- **Medical Imaging Analysis:** CNN models can be trained to analyze kidney scans and identify abnormalities such as cysts, stones, or signs of chronic kidney disease. By learning patterns from large datasets, CNNs can assist in detecting early-stage kidney disease, allowing for timely medical intervention.
- **Automated Risk Assessment:** CNN-powered diagnostic systems can classify kidney conditions based on severity and progression. For instance, a system could analyze consecutive scans of a patient and track the progression of kidney damage over time, providing nephrologists with valuable insights.
- **AI-Assisted Diagnosis:** By integrating CNN with electronic health records (EHR) and lab test data, AI-based systems can improve diagnostic accuracy by combining image analysis with other clinical indicators like creatinine levels, glomerular filtration rate (GFR), and proteinuria.

ML Approaches in Kidney Disease Detection

Kidney disease detection typically involves medical image classification tasks, where deep learning models are trained to identify nephrological conditions from ultrasound, CT, or MRI scans. AI-powered diagnostic systems leverage deep learning algorithms to process medical images and assist healthcare professionals in detecting kidney abnormalities with high accuracy.

3.1.1. Convolutional Neural Networks (CNNs)

The use of Convolutional Neural Networks (CNNs) in nephrology has been a significant breakthrough in kidney disease detection and diagnosis. CNNs are particularly well-suited for medical imaging tasks due to their ability to automatically extract and analyze important features from images, such as kidney ultrasound scans, CT scans, and histopathological slides, without requiring manual feature engineering. By leveraging CNNs, researchers and healthcare providers can enhance early detection efforts, improve diagnostic accuracy, and support clinical decision-making, ultimately leading to better patient outcomes and reduced healthcare costs.

3.1.2. Transfer Learning

Given the need for large datasets in training deep learning models, transfer learning is often employed, where a model pre-trained on large datasets (e.g., ImageNet) is fine-tuned using smaller, domain-specific datasets of Kidney diseases. Tschandl et al. (2020) used transfer learning to improve the accuracy of Kidney lesion classification, demonstrating that a pre-trained model, when fine-tuned on Kidney disease data, could accurately classify a wide variety of Kidney conditions.

3.1.3. AI-Based Kidney Disease Detection

AI-powered diagnostic tools for kidney disease detection have shown promising results in medical imaging analysis. These systems leverage deep learning models to analyze ultrasound, CT, and MRI scans, providing automated assessments for nephrological conditions.

For example, NephroScan is a proposed AI-based system that utilizes CNN models to evaluate kidney images and provide risk assessments for conditions such as chronic kidney disease, nephritis, and kidney stones. Research by Haenssle et al. (2018) demonstrated that deep learning models could achieve high accuracy in distinguishing between different medical conditions, supporting their potential use in nephrology for early disease detection.

3.1.4. Explainable AI (XAI) in Kidney Disease Diagnosis

One challenge with deep learning models in medical imaging is their "black-box" nature, making it difficult for healthcare professionals to understand how a

diagnosis was made. Explainable AI (XAI) is an emerging research area focused on improving the interpretability of AI models.

Fujisawa et al. (2020) explored the use of XAI in medical diagnostics, where visualizations of Regions of Interest (ROIs) in medical images were provided to clinicians. In kidney disease detection, XAI techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) and saliency maps can highlight critical areas in ultrasound or MRI scans, helping radiologists and nephrologists verify AI-based predictions. This enhances trust in AI-assisted kidney disease diagnosis by ensuring transparency and improving clinical decision-making.

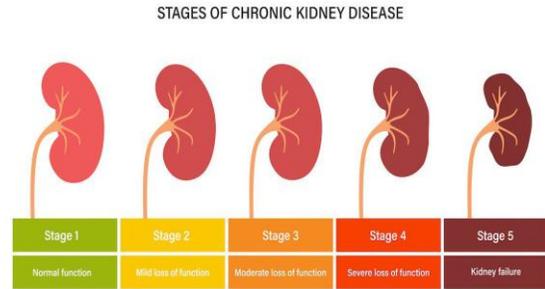
3.2. Challenges and Opportunities

Data Quality and Dataset Size: A significant limitation in applying ML to kidney disease detection is the availability of large, well-annotated medical imaging datasets. While datasets like Kidney Tumor Segmentation (KiTS) and TCIA (The Cancer Imaging Archive) provide valuable resources, more diverse and extensive datasets are needed to improve model generalization across different demographics and disease stages.

Regulatory and Ethical Issues: The deployment of AI-powered diagnostic systems in nephrology raises concerns regarding regulatory approval (e.g., FDA in the US, CE marking in Europe), patient safety, and ethical issues related to data privacy, informed consent, and accountability in medical decision-making. Ensuring compliance with HIPAA (Health Insurance Portability and Accountability Act) and other privacy regulations is essential for real-world applications.

Access to Healthcare: Despite advancements in AI-driven diagnostics, there remains the challenge of ensuring that patients receive proper follow-up care from medical professionals. AI systems should be integrated with telemedicine platforms and electronic health record (EHR) systems to ensure seamless communication between AI assessments and nephrologists, thereby improving patient outcomes.

Class	Accuracy
No/Normal	0.94
Yes/Kidney Disease	0.95



		Predicted class	
		<i>P</i>	<i>N</i>
Actual Class	<i>P</i>	True Positives (TP)	False Negatives (FN)
	<i>N</i>	False Positives (FP)	True Negatives (TN)

CONCLUSION

Medication adherence is a critical factor in managing kidney diseases, particularly for patients with chronic kidney disease (CKD) or those undergoing dialysis. Non-adherence to prescribed treatment regimens, including medications for blood pressure control, electrolyte balance, and anemia management, can lead to severe complications such as accelerated disease progression and increased hospitalization rates. Machine learning models can play a crucial role in improving medication adherence for kidney disease patients in several ways:

- **Real-Time Tracking:** AI-driven systems can monitor patient interactions with medication by detecting actions such as opening a pill bottle or scanning medication labels. By integrating smart pill dispensers or camera-based monitoring, AI can ensure patients take their prescribed doses and send reminders if a dose is missed, helping users stay on track.
- **Behavioral Feedback and Adaptive Reminders:** Machine learning models can analyze user patterns to predict when a patient is likely to forget a dose. Adaptive reminder systems can adjust the timing and frequency of alerts based on the

patient's habits, ensuring a more personalized and effective adherence strategy.

- Enhanced Patient Engagement: AI-powered medication tracking apps can provide real-time feedback, progress reports, and adherence scores, encouraging patients to take an active role in managing their kidney health. Additionally, integrating AI-based adherence tracking with electronic health records (EHRs) can help anthropologists monitor patient compliance remotely, leading to better clinical outcomes.

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