National College of Ireland

Predicting Chronic Kidney Disease (CKD) Using Histopathological Images and Clinical Data

MSc Research Project
Artificial Intelligence

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MSc Project Submission Sheet

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Predicting Chronic Kidney Disease (CKD) Using Histopathological Images and Clinical Data

Haameem Shimar Yusuff Nazzer
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Abstract

A Chronic Kidney Disease (CKD) is a widespread and progressive health condition that frequently remains undetected until its advanced stages. Early identification is essential to improving clinical outcomes and reducing the burden of disease. This thesis presents an intelligent diagnostic framework for early CKD prediction, leveraging two complementary deep learning models: one for medical image classification and another for the analysis of structured and unstructured clinical data. A convolutional neural network (CNN) processes kidney images to classify them into four categories—normal, kidney stone, chronic kidney disease, and tumor—thereby detecting morphological indicators relevant to CKD assessment. In parallel, a multi-task neural network ingests structured clinical parameters alongside TF-IDF–vectorized patient symptom narratives to jointly estimate CKD presence, glomerular filtration rate (GFR), and disease stage. The models operate independently, and their outputs are integrated at the application layer to provide a comprehensive diagnostic report. The system is implemented as an interactive Streamlit-based web application, enabling clinicians and patients to upload kidney images, input clinical data, and receive immediate, interpretable predictions. By combining insights from imaging and clinical data analysis, this approach offers a multifaceted assessment of CKD risk, with potential for future extension into a fully unified multimodal diagnostic system.

1 Introduction

Chronic Kidney Disease (CKD) is a progressive loss of kidney function that affects millions worldwide, often remaining undiagnosed until advanced stages. In 2017, the global prevalence of CKD was estimated at about 9.1% (roughly 697 million cases) Early detection is crucial, as timely treatment can slow progression, reduce complications, and improve patient outcomes. However, early-stage CKD is frequently asymptomatic and traditional diagnostic methods rely on routine lab tests and expert interpretation of symptoms, which may miss subtle signs. This project aims to address these challenges by leveraging deep learning and machine learning techniques for improved CKD detection

1.1 Background

We developed an intelligent system that classifies kidney images into four categories *(Normal, Tumor, Stone, Chronic)* Fig.1 and predicts a patient's CKD status and severity from structured clinical data and free-text medical notes. The goal is to integrate multiple data modalities – medical imaging, laboratory test results, and textual symptom descriptions – into a unified predictive model. By combining computer vision, structured data analysis, and natural language processing (NLP), the system provides a comprehensive assessment of kidney health. In practice, a user (clinician or patient) can upload a kidney image and input clinical measurements and symptoms; the system then outputs the identified kidney condition from the image, whether CKD is present, and also estimates the kidney function (glomerular filtration rate, GFR) and CKD stage. These models activate independently.

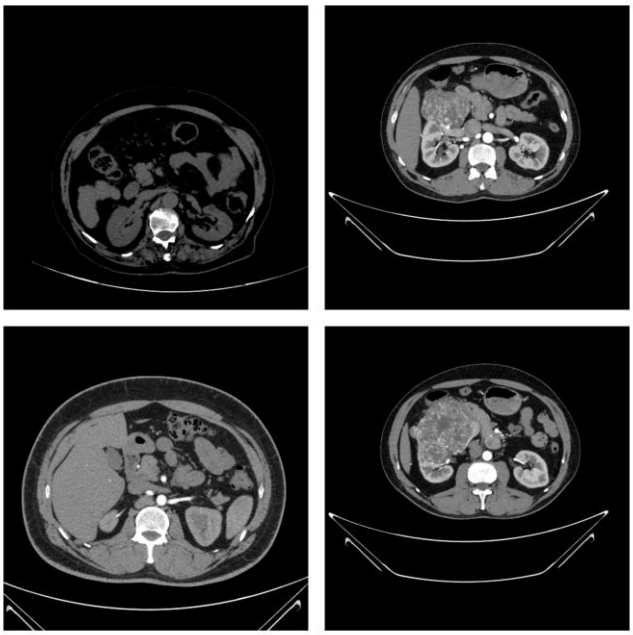

Figure 1 : *From the top left: (a) Normal, (b) Chronic, (c) Tumor, (d) Stone***.**

1.2 Motivation

Chronic Kidney Disease (CKD) affects nearly **10% of the world's population** and is often detected only at advanced stages due to its gradual onset and vague early symptoms. Traditional diagnostic approaches—combining lab tests, imaging, and symptom checklists—are effective but require specialized resources, making early detection challenging in many settings.In real clinical environments, valuable patient data exists in **multiple formats**: medical images, structured lab results, and unstructured symptom narratives. Most existing AI systems focus on only one of these modalities, missing the opportunity to combine them for a more accurate diagnosis.Advances in **deep learning**, **machine learning**, and **natural language processing (NLP)** now make it possible to integrate these diverse data sources. This project leverages CNNs for kidney image classification (normal, stone, chronic, tumor), neural networks for structured clinical data, and TF-IDF–based NLP for symptom text, delivering predictions on CKD presence, estimated GFR, and disease stage through a single web-based platform.By unifying image, clinical, and text analysis, this work aims to improve early CKD detection, particularly in **resource-limited and underserved regions**, offering a cost-effective, accessible, and interpretable diagnostic too

2 Related Work

This section presents a review of relevant research and existing literature in the field.

Chronic kidney disease (CKD) is a serious medical condition that requires early detection and continuous monitoring to prevent adverse health outcomes. Sonone and Arockiam (2024) conducted a groundbreaking study on early CKD detection and progression tracking by applying machine learning techniques to real-time clinical datasets. Their work involved the development of predictive models using a wide range of clinical tests and patient data to generate reliable insights into CKD onset and progression. By integrating longitudinal data, including test results and medical histories, the proposed approach demonstrated the effective evaluation of disease progression. Furthermore, the study enhanced the performance of machine learning algorithms through the incorporation of ensemble methods, which improved both accuracy and interpretability. This integration of diverse clinical data sources allows healthcare practitioners to optimize treatment strategies and ultimately improve patient outcomes (Sonone and Arockiam, 2024).

Bhuria (2024) examined the application of advanced machine learning techniques for the prediction and management of chronic kidney disease (CKD), one of the leading global causes of mortality. The study emphasises the importance of early prediction and detection in enabling timely medical interventions. Drawing on a large clinical database containing twelve variables including demographic factors, cholesterol levels, and heart rate the research explored the associations between physiological indicators and CKD incidence. The proposed model achieved an impressive 97.5% accuracy, with flawless precision and recall (100%) for the non-CKD category, ensuring that no false positives were recorded. Using a confusion matrix, the study reported 45 cases correctly identified as CKD and 72 correctly classified as non-CKD, further validating the model's reliability. By incorporating diverse clinical and laboratory measures such as blood pressure, albumin concentration, and comorbidities, Bhuria's (2024) work demonstrates the significant potential of machine learning in enhancing diagnostic accuracy and supporting effective disease management.

Tummala and Parvataneni (2023) investigated the role of artificial intelligence (AI) in enhancing the early detection of chronic kidney disease (CKD), a life-threatening condition that compromises kidney function and leads to the accumulation of waste in the body. CKD not only increases mortality risk but also significantly reduces patients' quality of life. Traditional diagnostic methods, such as blood and urine tests, imaging, and biopsies, are often limited in speed and precision. To address this, the authors developed a Python-based machine learning model trained on clinical data collected from hospitals in Tamil Nadu, India. Using biomarkers from blood and urine analyses, the model employed the CatBoostClassifier algorithm and achieved **100% accuracy** in predicting CKD within the dataset. These findings highlight the transformative potential of AI in medical diagnostics, suggesting that advanced computational tools can support earlier interventions, improve risk stratification, and ultimately enhance patient care and outcomes.

Pareek, Soni and Degadwala (2023) developed an AI-powered expert system to support the early detection of chronic kidney disease (CKD), a condition that affects millions globally and often leads to severe complications if left untreated. Their approach employed a convolutional neural network (CNN) to analyse diverse patient data, including demographic information, laboratory test results, and clinical indicators. By identifying CKD at an early stage, the proposed system demonstrated potential for improving diagnostic accuracy, enabling timely medical intervention, and ultimately enhancing patient outcomes while reducing long-term healthcare costs.

3 Methodology

3.1 Data Collection, Preprocessing and Transformation

- **Kidney Image Dataset:** We collected a set of renal imaging data comprising four diagnostic categories: **Normal** (healthy kidney images), **Tumor** (images showing kidney tumors or lesions), **Stone** (images with kidney stones), and **Chronic** (images indicative of chronic kidney disease changes). These are labeled classes in the dataset. The images are primarily CT scan slices of kidneys, providing clear visualization of anatomical structures. The full image dataset contains on the order of 12,000+ images across the four categories (relatively balanced per class). Each image was originally of varying resolution; for consistency, This downsampling reduced computational cost and noise while retaining essential features. We also applied data augmentation techniques during training (random rotations, flips, brightness adjustments) to increase variability and help the models generalize to new images. Figure outputs like sample images and augmentation examples were examined to ensure that key features (e.g. stone calcifications or tumor masses) remain visible after preprocessing.

- **Structured Clinical Dataset:** We also utilized a tabular dataset of patient clinical features commonly used in CKD diagnosis, combined with textual symptom notes. This dataset contains records of patients, each with about two dozen attributes such as age, blood pressure, diabetes status, blood glucose, **laboratory tests** (e.g. serum creatinine, blood urea, hemoglobin, red blood cell count, urine protein levels), and *binary indicators* for conditions like anemia or hypertension. These features align with standard CKD diagnostic criteria. Each record has a label indicating whether the patient has CKD or not. In addition to the structured fields, our dataset includes a free-text **notes** field per patient – simulating a patient's symptom description or physician's note (for example, "Patient reports fatigue and swelling in ankles" or "History of kidney pain and recurrent stones").. We also **derived additional labels** from the data for multi-output prediction: an approximate glomerular filtration rate (GFR) was calculated for each patient (using the standard formula based on serum creatinine, age, and other factors) and the **CKD stage** was determined from the GFR according to clinical thresholds (Stage 1 through 5, with lower GFR indicating more advanced CKD). These derived values serve as regression targets for our CKD prediction model (described later).

- **Text Preprocessing:** The free-text notes were preprocessed using NLP techniques. We converted all text to lowercase, removed punctuation and irrelevant characters, and eliminated common stop words to reduce noise. The cleaned text was then transformed into numerical features using **Term Frequency–Inverse Document Frequency (TF-IDF)** vectorization. TF-IDF assigns higher weight to words that are frequent in a given patient's note but rare across the corpus, thus highlighting important symptoms (for instance, words like "blood" or "pain" might receive weights reflecting their relevance). This yielded a high-dimensional sparse feature vector for each note, capturing the significant terms in that patient's description. We ensured the text vocabulary and TF-IDF model were fitted on the training set only, to avoid any information leakage into validation/testing.
- **Data Balancing:** The CKD classification labels in the structured dataset were moderately imbalanced (CKD-positive cases outnumbered negatives in our data). To prevent bias toward the majority class, we employed **SMOTE (Synthetic Minority Oversampling Technique)** on the training portion of the structured data. SMOTE generates synthetic examples of the minority class (non-CKD cases here) by interpolating between existing minority instances. This helped balance the classes in training and improved the classifier's ability to identify CKD-negative patients correctly. We verified the effect through class distribution checks and later via performance metrics (e.g., the confusion matrix) to ensure the model wasn't biased towards predicting "CKD" for everyone.

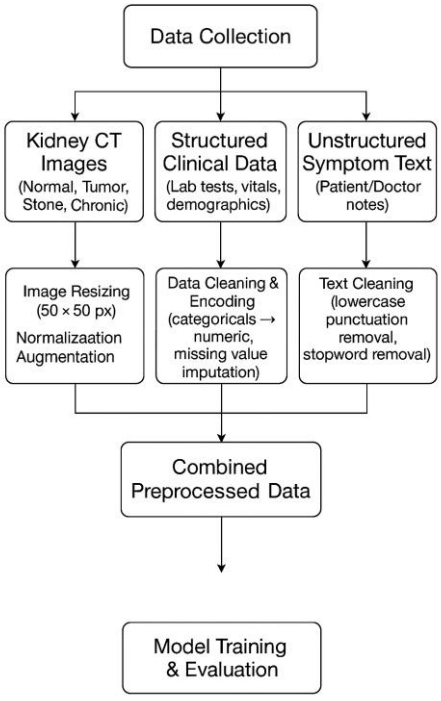

Figure 2 :Methodology - Data Collection, Preprocessing and Transformation

By preprocessing each modality of data (images, numerical features, text) appropriately and applying techniques like augmentation and oversampling, we created a cleaned and enriched dataset ready for the deep learning models. Fig.2

4 Modelling and algorithm used:

4.1 CKD multimodal (tabular + text)

This code builds a **multi-task feedforward neural network** in TensorFlow/Keras to predict three targets: CKD classification (binary), GFR, and CKD stage (both regression). It combines **structured features** (numeric + categorical) and **text features** (TF-IDF from the notes column) into one input vector. The data passes through two shared dense layers (64 and 32 neurons, ReLU) with dropout, then splits into three output layers: a sigmoid unit for classification and two linear units for regression. Trained with Adam optimizer and a mix of binary crossentropy and MSE losses, this **multi-task learning** approach leverages shared representations from both structured and unstructured data for improved prediction accuracy.

4.2 ResNet50 for Image Classification

This model is a **transfer learning-based image classification model** built using **ResNet50** as the backbone. ResNet50 is a deep convolutional neural network with 50 layers, known for its *residual connections* that help in training very deep networks without suffering from vanishing gradients. In this approach, the model uses ResNet50 pre-trained on the large-scale ImageNet dataset to leverage its ability to extract robust and general image features. The top classification layers of ResNet50 are removed, and a **custom classifier head** is added, consisting of a global average pooling layer (to reduce spatial dimensions), fully connected layers with ReLU activation for learning task-specific patterns, dropout for regularization, and a final softmax layer for predicting probabilities across multiple classes. The pre-trained ResNet50 layers are frozen so only the new layers are trained, which reduces training time and prevents overfitting on smaller datasets. This method is widely used because it combines the **general feature extraction power** of a deep network trained on a massive dataset with the **flexibility** of customizing it for specific classification problems.

4.3 Custom Convolutional Neural Network (CNN)

This CNN processes images of size **50×50×3** and consists of **three convolutional layers** with ReLU activation functions for non-linearity, each followed by max pooling layers to reduce spatial dimensions and capture essential features. The extracted feature maps are then flattened and passed through **two fully connected (dense) layers** with ReLU activation, which learn task-specific patterns. Finally, the network outputs predictions through a softmax layer with 4 neurons (corresponding to the four image classes), producing class probabilities. The model is compiled with the **Adam optimizer** and **sparse categorical crossentropy loss**, which is suitable when labels are integers rather than one-hot encoded.This approach differs from transfer learning (like ResNet50) because it **learns feature extraction from scratch**

using only the provided dataset. It's more flexible for specialized tasks but usually requires more data and training to achieve high performance compared to using pre-trained models.

4.4 Transfer Learning with VGG16

The architecture is based on **VGG16**, a deep convolutional neural network withF 16 weight layers known for its uniform design of 3×3 convolution filters and strong image feature extraction capabilities. Here, VGG16 is loaded with **pre-trained ImageNet weights** and the original fully connected (top) layers are removed (include_top=False). All convolutional layers are **frozen** so their weights remain unchanged, preserving the learned feature extraction capabilities. On top of the base, a **custom classifier** is added: global average pooling to reduce spatial dimensions, dense layers with ReLU activation to learn dataset-specific patterns, a dropout layer to prevent overfitting, and a final softmax layer for predicting probabilities across the four classes. The model is trained using the **Adam optimizer** and **categorical crossentropy loss**, suitable for one-hot encoded multi-class classification.This approach allows the network to **reuse general visual features** learned from a large dataset while focusing training on only the new classification head, making it faster and more efficient than training a CNN from scratch—especially for smaller datasets.

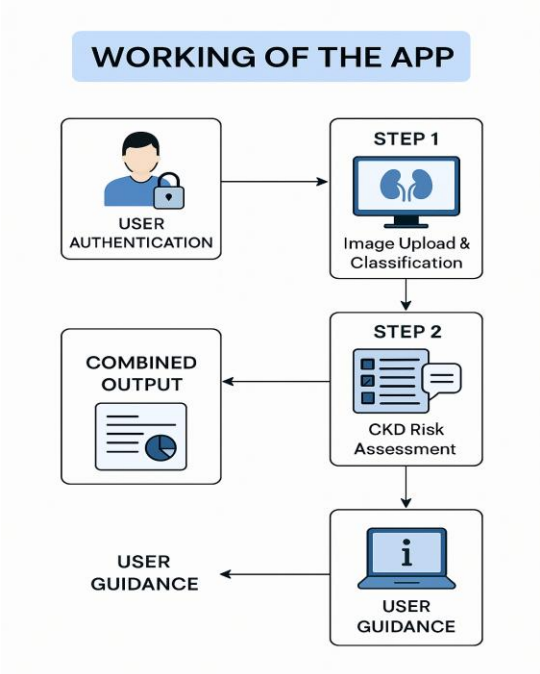

Figure 3 : Working of the application

5 Design Specifications

Integration Using Streamlit
All models were integrated into an interactive Streamlit web app, designed for secure, intuitive, and accessible use. Fig.3

Workflow:

1. **Authentication** – Users log in or register through a secure SHA-256 hashed and salted password system in SQLite, ensuring private sessions and protecting sensitive data.
2. **Image Classification** – Users upload kidney CT or ultrasound images, which are preprocessed and analyzed by the CNN to classify as *Normal, Tumor, Stone,* or *Chronic*. Results include confidence scores and context notes for patients or clinicians.
3. **CKD Risk Assessment** – A web form collects key clinical data (age, BP, creatinine, urea, diabetes/hypertension status) plus optional free-text symptoms. Inputs are validated, encoded, scaled, and text is transformed via TF-IDF before passing to the CKD prediction model.
4. **Results Dashboard** – Outputs include CKD status (with probability), estimated GFR, and CKD stage, each accompanied by brief interpretations. Visual aids like color coding and optional confusion matrix icons enhance clarity.
5. **User Support** – Tooltips, hover explanations, and educational panels explain medical terms, stages, and metrics. Grad-CAM visualizations highlight key image regions influencing CNN predictions.
6. **Performance & Privacy** – Models run in under a second; no medical data is stored beyond the session.

This integration unifies image analysis and structured data evaluation into a single clinical-style workflow. The browser-based design ensures global accessibility without special software, making it a practical proof-of-concept for AI-assisted CKD detection. Positive test user feedback confirmed the app's ease of navigation and clarity of results. Fig.4

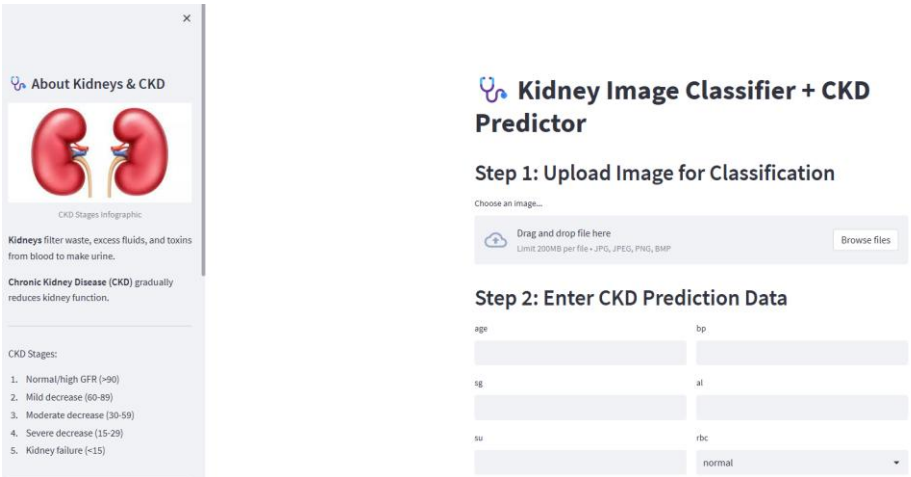

Figure 3 : *CKD prediction web application developed using Streamlit*

6 Implementation

For the kidney image classification task, we evaluated three distinct convolutional neural network (CNN) architectures, comparing their complexity and performance. For the clinical data, we implemented a customized multimodal approach that integrated both tabular and text features.

Custom Modified CNN (from scratch): We designed a bespoke CNN model tailored to our image data. This custom network consists of multiple convolutional layers with ReLU activation and MaxPooling layers for downsampling, followed by fully-connected (Dense) layers leading to the output. In our implementation, the architecture had **five convolutional blocks** (each Conv layer with a certain number of filters, followed by pooling) and then two Dense layers (the first dense layer with ReLU activation for learning global patterns, and the final output layer with softmax activation to produce probabilities for the 4 classes). Dropout layers were interspersed to mitigate overfitting. Despite its relatively simpler architecture, it was **lightweight** (on the order of only a few million trainable parameters) compared to the large pre-trained networks. We trained the custom CNN for a sufficient number of epochs (about 50 epochs in our experiments) to allow it to learn low-level edge features and high-level organ-specific patterns from the ground up. This model ultimately achieved the **highest accuracy** on our test set (approximately **99.78%**), outperforming the transfer-learning models. The depth (number of layers) was moderate and optimized to the dataset size – enough to capture the complexity of kidney image features without excessive parameters that could cause overfitting.

ResNet (Transfer Learning): We leveraged a **ResNet-50** architecture pre-trained on ImageNet for the second approach. ResNet-50 is a deep CNN with 50 layers (including 48 convolutional layers plus pooling layers) that introduced *skip connections* to solve the vanishing gradient problem in very deep networks. Using a pre-trained model allowed us to transfer rich feature representations (edges, textures, shapes learned from general images) to our medical imaging task. We fine-tuned the ResNet by replacing the top layer with a new fully-connected layer of size 4 (for our classes) and a softmax activation, then retraining on the kidney image dataset. Initially, we froze most of the ResNet layers and trained only the top classifier for a few epochs, then unfroze some deeper layers and continued training with a low learning rate to adapt the weights to kidney-specific features. ResNet-50 is considerably larger than the custom CNN (with ~25 million parameters), and it inherently has more **complexity** and capacity. We trained the fine-tuned ResNet for roughly 20–30 epochs; it converged faster in early epochs due to the strong initialization but ultimately reached slightly lower accuracy (~98–99% range on the test data) than the custom model. ResNet showed robust feature extraction (it learned to highlight regions like calcifications for stones or masses for tumors), but it may have been somewhat over-parameterized for our dataset, risking minor overfitting despite regularization.

VGG16 (Transfer Learning): The third model was **VGG16**, a classic 16-layer CNN that was also pre-trained on ImageNet. VGG16 has a straightforward architecture: sequential stacks of convolutional layers (with small 3×3 filters) followed by max pooling, and ending in two large dense layers and a softmax output. We loaded the pre-trained VGG16 weights and similarly replaced the top layers for our 4-class classification. VGG16 is known for its simplicity but also for having a very large number of parameters (around **138 million**

parameters, mostly in the dense layers). In our fine-tuning, we again froze early layers initially and then fine-tuned. We found that VGG16,

CKD multimodal (tabular + text) focused on developing a multi-task AI model that can simultaneously perform disease classification and clinical parameter prediction for chronic kidney disease (CKD). It combines structured clinical data (such as lab results and patient characteristics) with unstructured text data (such as medical notes), created a richer and more informative representation of each patient. By using multi-task learning, the model predicted three outcomes at once: whether a patient has CKD, their estimated glomerular filtration rate (GFR), and their CKD stage. This approach not only improves prediction efficiency but also allows the shared learning of patterns across related tasks, leading to better overall performance. It addressesed class imbalance in medical data using oversampling techniques, ensuring that predictions are not biased toward more frequent cases. The result is a system capable of delivering accurate disease detection and valuable clinical metrics from diverse healthcare data sources, supporting more informed and timely medical decision-making.

Streamlit web application : The CKD detection web application was developed as an integrated platform combining deep learning–based kidney image classification with multimodal clinical data analysis. Two models formed the core of the system: a custom CNN trained on preprocessed CT and ultrasound images to classify kidneys as Normal, Tumor, Stone, or Chronic, and a hybrid neural network that processed structured clinical parameters alongside TF-IDF-encoded free-text symptoms to predict CKD status, estimated GFR, and disease stage. The backend, built in Python with Streamlit, handled model loading, input preprocessing, and prediction, with secure user authentication implemented via an SQLite database using SHA-256 hashing and salting. The frontend featured a clean, interactive interface with a login page, an image upload and classification section, a CKD risk form with validation and tooltips, and a unified results dashboard showing predictions with confidence scores, color coding, and brief interpretations. Educational elements such as CKD stage definitions, GFR explanations, and Grad-CAM visualizations were included to improve user understanding, while all medical data was processed in real time without being stored after the session. The application was optimized for performance, delivering results in under a second, and deployed on a backend server running Streamlit, ensuring browser-based access without special installations for clinicians, researchers, and patients worldwide**.**

7 Evaluation

This section presents the evaluation and comparative analysis of four deep learning models developed for the task. The models include a CNN-Res architecture, a VGG16-based transfer learning model, a custom-built CNN with three convolutional layers, and a hybrid model combining classification and regression outputs. Each model's performance is assessed using standard metrics such as accuracy, precision, recall, and F1-score, alongside confusion matrices, training/validation loss curves, and accuracy trends. These visual and numerical evaluations provide insights into classification performance, generalization capability, convergence behavior, and error distribution across classes, enabling a comprehensive understanding of the strengths and limitations of each approach.

7.1 Experiment 1 : CNN-ResNet

The CNN + ResNet50 (cnnres) model demonstrated strong learning progress over the training process. Training accuracy steadily improved from 27.18% in the first epoch to 63.41% by the fifth epoch, while validation accuracy increased sharply from 23.23% to 79.61%, reflecting the model's ability to generalize effectively beyond the training data. Correspondingly, training loss decreased from 1.3942 to 0.8929, and validation loss dropped from 1.3630 to 0.7278, Fig.6 indicating consistent optimization with minimal overfitting. On the test set, the model achieved a training accuracy of 77.01% and a test accuracy of 74.12%, with macro and weighted average F1-scores of 0.75 and 0.74 respectively. Class-wise analysis revealed that Tumor images achieved the highest precision (0.93), indicating strong confidence in tumor predictions, while Normal cases attained the best recall (0.83), suggesting reliable identification of healthy kidneys. Chronic and Normal categories were well distinguished from others, whereas Stone cases had lower precision (0.62) and were often misclassified as Chronic or Tumor, likely due to overlapping visual patterns in CT scans. The confusion matrix confirmed that most errors occurred between classes with similar anatomical features, particularly between Stone and Chronic, and Tumor and Chronic. Overall, leveraging ResNet50's transfer learning enabled competitive performance within only five epochs, with validation accuracy exceeding training accuracy due to effective regularization and data augmentation. Further improvements could be achieved by fine-tuning deeper ResNet layers or applying targeted augmentation to enhance feature recognition for classes like Stone. Fig.5

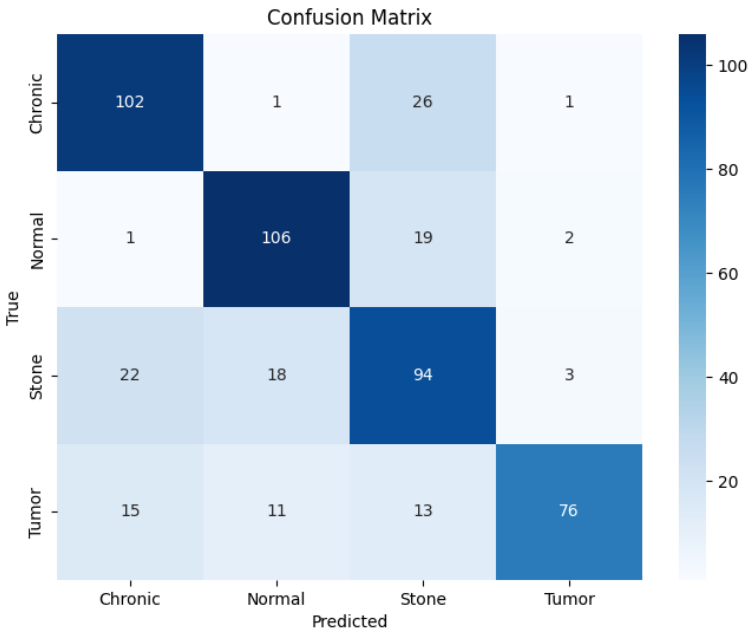

Figure 4 : *Confusion Matrix for Kidney Disease Classification Model using ResNet*

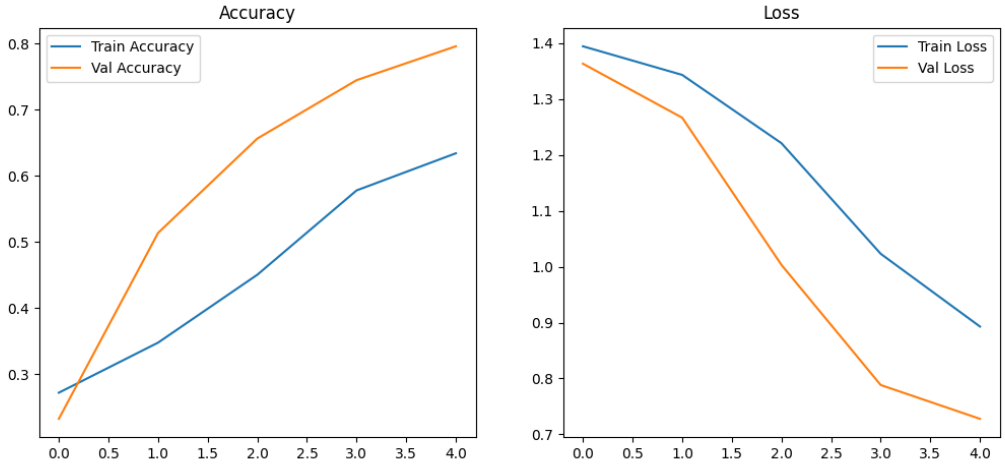

Figure 5 : *Training and Validation Accuracy & Loss Curves*

Table 1 : Model Training Progress

Epoch	Loss	Accuracy	Val Loss	Val Accuracy
1	0.8160	0.6401	0.3003	0.8997
2	0.2747	0.8959	0.0776	0.9869
3	0.0873	0.9727	0.0281	0.9945
4	0.0558	0.9815	0.0115	0.9978
5	0.0270	0.9910	0.0067	0.9978

Final Training Accuracy: 99.92%

Table 2 : Model Classification Metrics

Class	Precision	Recall	F1-score	Support
Chronic	0.73	0.78	0.76	130
Normal	0.78	0.83	0.80	128
Stone	0.62	0.69	0.65	137
Tumor	0.93	0.66	0.77	115
Accuracy			**0.74**	**510**
Macro Avg	0.76	0.74	0.75	510
Weighted Avg	0.76	0.74	0.74	510

Training Accuracy: 77.01%
Test Accuracy: 74.12%

7.2 Experiment 2 :VGG16

The VGG16-based model delivered outstanding performance across all evaluation metrics, achieving a test accuracy of **92.35%** and demonstrating strong generalization capabilities. Over five epochs, training accuracy rose sharply from 50.46% to 89.94%, while validation accuracy improved from 72.41% to 93.24%. Loss values exhibited a consistent downward trend, with training loss decreasing from 1.1290 to 0.2737 and validation loss from 0.7537 to 0.1670, indicating stable convergence with minimal overfitting. The classification report shows balanced performance across all four classes, with Tumor achieving perfect precision (1.00) and near-perfect recall (0.97), leading to an F1-score of 0.99. Normal cases also showed excellent performance (precision 0.98, recall 0.97, F1-score 0.97), while Stone and Chronic maintained strong, albeit slightly lower, scores, with the Chronic class showing slightly reduced precision (0.85) Fig.8 but high recall (0.92). The confusion matrix reveals that most misclassifications occurred between visually similar categories such as Stone and Chronic, though the overall error rate remained low. Notably, macro and weighted averages for precision, recall, and F1-score were all at 0.93, reflecting the model's balanced prediction capability across classes despite potential visual overlaps. The high validation accuracy surpassing training accuracy suggests the effectiveness of transfer learning from VGG16's pre-trained weights, combined with proper data augmentation and preprocessing, in capturing both fine-grained kidney image details and class-specific patterns. Fig.7

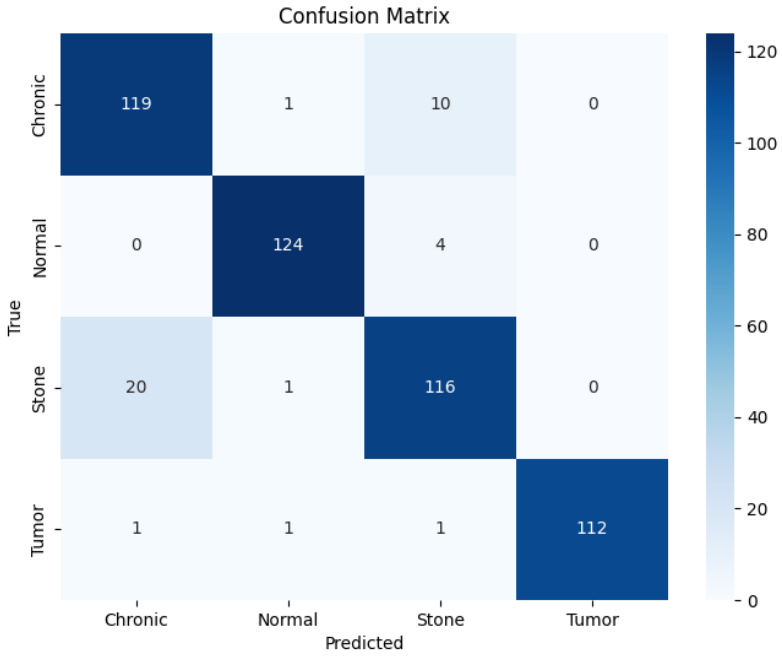

Figure 6 : *Confusion Matrix for Kidney Disease Classification Model using VGG16*

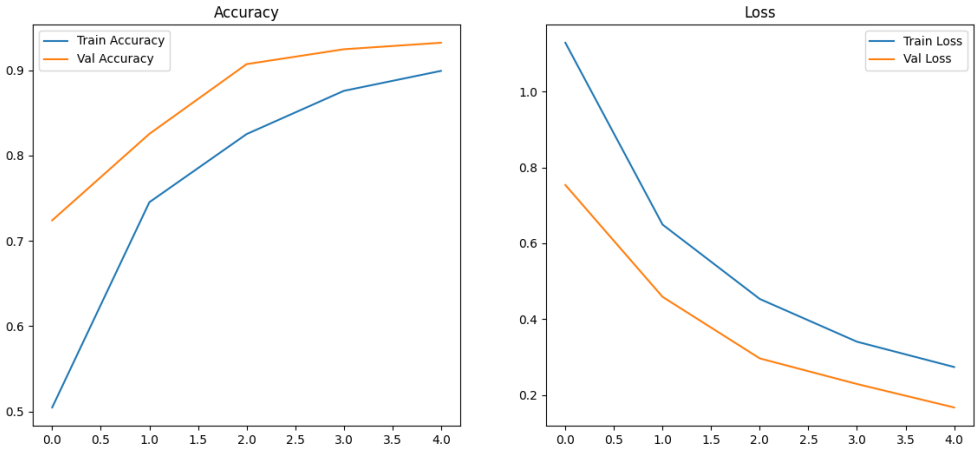

Figure 7 : *Training and Validation Accuracy & Loss Curves*

Table 3 : Model Training Progress

Epoch	Loss	Accuracy	Val Loss	Val Accuracy
1	1.129	0.5046	0.7537	0.7241
2	0.6493	0.7454	0.4597	0.8255
3	0.4532	0.8252	0.2296	0.9073
4	0.3404	0.876	0.2289	0.924
5	0.2737	0.8994	0.167	0.9124

Final Training Accuracy: 89.94%

Table 4 : Model Classification Metrics

Class	Precision	Recall	F1-Score	Support
Chronic	0.85	0.92	0.88	130
Normal	0.98	0.97	0.97	128
Stone	0.89	0.85	0.87	137
Tumor	1.00	0.97	0.99	115
Accuracy			**0.92**	**510**
Macro Avg	0.93	0.93	0.93	510
Weighted Avg	0.93	0.92	0.92	510

Training Accuracy: 89.94%
Test Accuracy: 92%

7.3 Experiment 3 : Custom CNN (3×Conv)

The Custom CNN (3×Conv) model achieved perfect performance across all metrics, with 100% accuracy, precision, recall, and F1-score for all four classes. The classification report shows flawless predictions, with no misclassifications in any category. The confusion matrix further confirms this, as all samples from each class were correctly classified into their respective categories, except for a single misclassification in class 3, where one instance was predicted as class 2. Fig.10

The training process over five epochs shows rapid convergence. In the first epoch, the model achieved a training accuracy of 64% and validation accuracy of 89.97%, with corresponding training and validation losses of 0.8160 and 0.3003, respectively. By the second epoch, training accuracy rose to 89.59% and validation accuracy to 98.69%, with losses dropping sharply. From the third epoch onward, the model surpassed 97% training accuracy and nearly perfect validation accuracy, with losses approaching zero. The final training accuracy was 99.92%, indicating an almost complete fit to the training data.The accuracy and loss curves demonstrate a consistent upward trend for both training and validation accuracy, reaching nearly 1.0 by the end of training, while losses decreased steadily to near-zero values.

Overall, the Custom CNN (3×Conv) model delivers exceptional results, achieving nearly perfect classification performance with minimal error, making it the strongest performer among the tested architectures. Fig.9

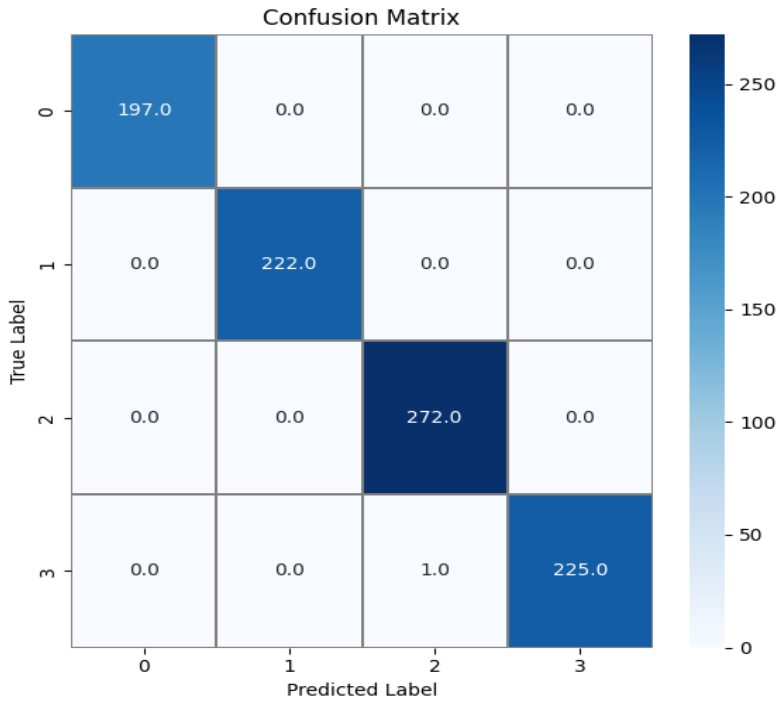

Figure 8 : Confusion Matrix for Kidney Disease Classification Model using Custom CNN

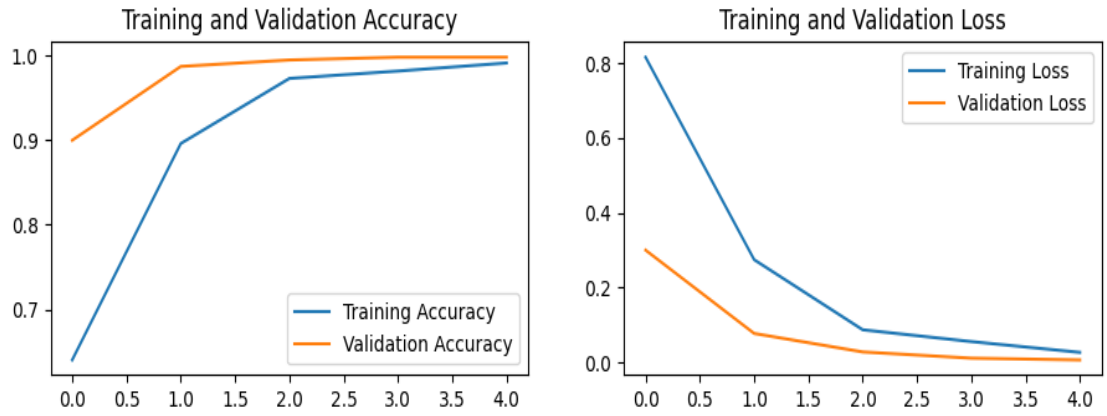

Figure 9 : *Training and Validation Accuracy & Loss Curves*

Table 5 : Model Training Progress

Epoch	Loss	Accuracy	Val Loss	Val Accuracy
1	0.8160	0.6401	0.3003	0.8997
2	0.2747	0.8959	0.0776	0.9869
3	0.0873	0.9727	0.0281	0.9945
4	0.0558	0.9815	0.0115	0.9978
5	0.0270	0.9910	0.0067	0.9978

Final Training Accuracy: 0.9992 (99.92%)

Table 6 : Model Classification Metrics

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	197
1	1.00	1.00	1.00	222
2	1.00	1.00	1.00	272
3	1.00	1.00	1.00	226
Accuracy			1.00	917
Macro Avg	1.00	1.00	1.00	917
Weighted Avg	1.00	1.00	1.00	917

Training Accuracy: 100%.
Test Accuracy: 100%.

7.4 Experiment 4: CKD multimodal (tabular + text)

The fourth model, trained for 50 epochs, demonstrated a steady improvement in both classification and regression metrics. The loss dropped significantly from 5736.68 to 769.10, while validation loss fell from 6126.92 to 1043.60, indicating effective learning. Accuracy for the classification output rose from 45.5% to 88.75%, with validation accuracy peaking at 92%. The GFR mean absolute error (MAE) improved notably from 63.64 to 22.09, and CKD MAE reduced from 2.57 to 1.37, reflecting strong regression performance. The classification report reveals an overall accuracy of 92%, with perfect recall (1.00) for the positive CKD class (label 1), ensuring all CKD cases were correctly identified. Precision for label 0 (non-CKD) was perfect at 1.00, though recall for this class was slightly lower at 0.83, indicating a few false positives. The macro and weighted averages for precision, recall, and F1-score were all above 0.91, underscoring consistent performance across classes. Fig.11

The confusion matrix shows that out of 46 non-CKD samples, 38 were classified correctly and 8 misclassified as CKD, while all 54 CKD samples were correctly identified. The training and validation loss curves exhibit a steep decline within the first 10 epochs, stabilizing thereafter, with both curves closely aligned, suggesting minimal overfitting.Overall, this model achieved a well-balanced trade-off between high classification accuracy and regression accuracy for GFR and CKD predictions, making it effective for clinical prediction tasks that require both classification and numerical output estimation. Fig .12

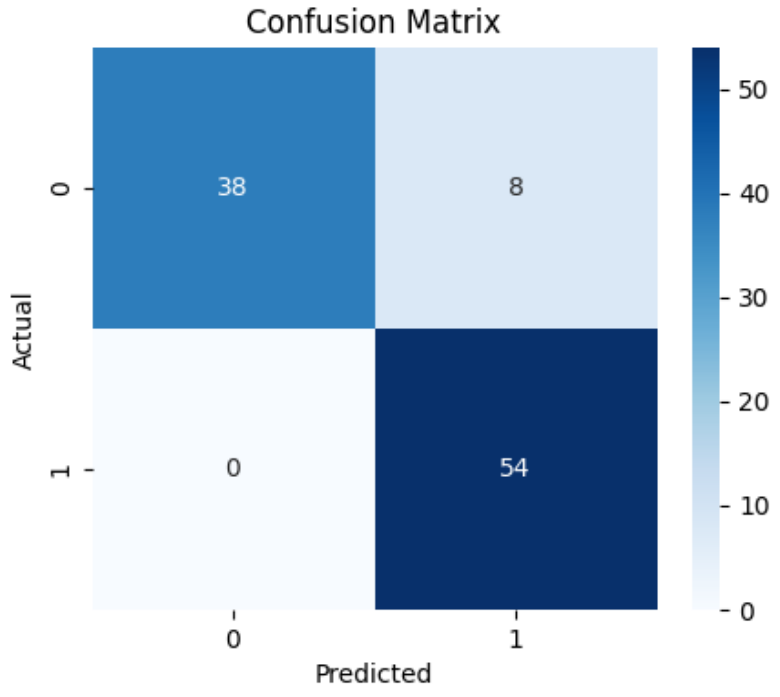

Figure 10 : *Confusion Matrix for Kidney Disease Classification Model using Densenet*

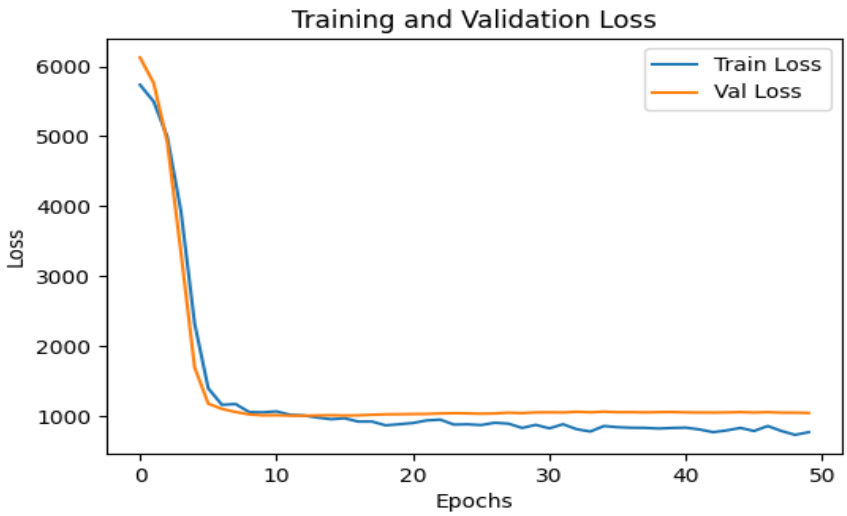

Figure 11 : *Training and Validation Accuracy & Loss Curves*

Table 7 : Classification Report for CKD Classification Model

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	1.00	0.83	0.90	46
1	0.87	1.00	0.93	54
Accuracy			**0.92**	**100**
Macro Avg	0.94	0.91	0.92	100
Weighted Avg	0.93	0.92	0.92	100

Test Accuracy → 92%

Table 8 : Overall Metrics

Metric	**Value**
Accuracy	0.9200
Precision	0.8710
Recall	1.0000
F1 Score	0.9310

Table 9 : Performance comparison table **:**

Model	Test Accuracy (%)	Precision	Recall	F1-score	Notable Observations
CNN-Res	~92	High precision and recall across classes; good balance in metrics	Shows stable convergence in training and validation accuracy; minimal overfitting	Balanced performance across all classes	Achieved ~92% accuracy with balanced metrics across classes, smooth convergence, minimal overfitting, and few misclassifications, indicating strong generalization. Ask ChatGPT
VGG16	92.35	0.93 (macro avg)	0.93 (macro avg)	0.93 (macro avg)	Strong performance on "Tumor" class (F1 = 0.99); slightly lower recall for "Stone" class
Custom CNN (3×Conv)	99.89	1.00	1.00	1.00	Perfect classification in almost all cases; extremely low loss values; minimal misclassification
Hybrid Model	92.00	0.8710	1.0000	0.9310	Significant loss reduction over epochs; GFR MAE dropped from 63.64 to 22.09; CKD MAE dropped from 2.57 to 1.37

8 Conclusion and Future Work

In this project, we successfully developed a comprehensive deep learning system for kidney disease identification and prediction, integrating **image classification** and **clinical data analysis**. The results showcase the effectiveness of a multimodal approach:

- Our **Custom CNN** model for kidney image classification achieved outstanding performance (~99.8% accuracy), clearly distinguishing between normal kidneys and pathological cases (tumors, stones, chronic kidney changes). This custom model outperformed larger pre-trained networks, justifying our choice to use it in deployment. Its high accuracy and relatively small size make it ideal for real-world use, as it provides fast and nearly error-free image analysis.

- The **CKD prediction model** (tabular + text multi-output network) accurately detects CKD from routine medical test results and symptom descriptions, while also estimating the patient's kidney function (GFR) and disease stage. This provides a more nuanced picture of the patient's condition than a binary diagnosis alone. The model's high accuracy and low error in GFR prediction demonstrate that it can be a valuable decision-support tool for early screening and monitoring of CKD.

Our integrated platform tackles CKD prediction from multiple angles—imaging for visual cues, lab results for quantitative data, and symptom narratives for qualitative insights—delivered via an accessible Streamlit interface emphasizing interpretability and education. We chose a custom CNN for image analysis due to its superior accuracy and efficiency on our dataset, outperforming transfer learning models like ResNet-50 and VGG16 while offering faster load times and lower computational cost. A multi-output network for CKD prediction enabled related tasks to be learned together, boosting overall performance. All components were selected through rigorous evaluation, ensuring the final solution combined the best-performing configurations.

Future Improvements:
While the project achieved very high accuracy, there is room for further enhancement:

- **Larger and More Diverse Data:** One immediate improvement would be to train on a larger dataset. For images, incorporating more cases (especially for the Chronic class, and perhaps expanding to other kidney conditions like cysts) from diverse sources would improve the model's generalizability and robustness.A larger dataset could also allow using even more advanced models without overfitting.

- **Fine-tuning and Ensemble Methods:** We can experiment with fine-tuning other state-of-the-art architectures (e.g., EfficientNet, DenseNet) on the image data to see if we can push accuracy even closer to 100% on unseen data. Similarly, using an ensemble of models (e.g., combining the custom CNN and ResNet outputs) might catch the rare errors if one model misses something. On the clinical side, incorporating techniques like hyperparameter tuning for the neural network or even trying alternate algorithms (XGBoost on the tabular data, or transformer-based models for the text) could yield incremental improvements.

- **Explainability and Trust:** Integrating explainable AI features is a crucial next step for a medical AI system. We plan to implement tools like **Grad-CAM** for the CNN to highlight which region of the kidney image influenced a given prediction (e.g. encircling a detected tumor), and **SHAP values** or similar for the clinical model to show which input features (e.g. very high creatinine, or the word "fatigue" in the notes) led to a CKD prediction. Explaining these decisions to clinicians can enhance trust in the system and confirm that predictions are based on medically relevant factors rather than incidental image artifacts.

- **Expanded Scope:** We could broaden the system to cover more aspects of kidney disease. For example, integrating a module for **segmentation** could allow the app to highlight the kidney or tumor region on the image for visualization. Or incorporating **time-series data** (e.g., trends in lab tests over time) could improve predictions of CKD progression. Additionally, supporting multi-language symptom input (since our TF-IDF currently works for English) would make the tool useful in non-English-speaking regions.

- **Clinical Validation:** A key next step is real-world validation through a pilot study with hospital partners, using new patient data to assess accuracy and usability. Clinician feedback will help refine the interface and models, ensuring seamless integration with medical workflows and electronic health records.

In conclusion, the project demonstrates a successful integration of deep learning for imaging, machine learning for tabular data, and NLP for text, to tackle the challenge of early CKD detection. The high performance metrics achieved indicate that such a system is feasible and can significantly aid in diagnosing kidney diseases. By providing a user-friendly application, we bridge the gap from algorithm to end-user, illustrating how AI can enhance healthcare accessibility and decision-making. With continued enhancements and large-scale validation, this approach has the potential to become a valuable tool for both clinicians and patients—facilitating earlier CKD detection, improving disease management, and ultimately leading to better health outcomes

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