Hybrid Framework for Accurate Kidney Abnormality Detection from CT-Scan Images

IBM PROJECT REPORT

<u>Submitted by</u>

Nithish Selvam R – 99220040665

Mummadisetty Vignesh – 992200040643

Mohammed Parvaiz-99220040637

Jagadesh N – 99220040659

in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

COMPUTER SCIENCE AND ENGINEERING

KALASALINGAM ACADEMY OF RESEARCH AND EDUCATION

KRISHNANKOIL 626126

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DECLARATION

We affirm that the project work titled **"Hybrid Framework for Accurate Kidney Abnormality Detection from CT-Scan Images"** being submitted in partial fulfillment for the award of the degree of **Bachelor of Technology in Computer Science and Engineering** is the original work carried out by us. It has not formed part of any other project work submitted for the award of any degree or diploma, either in this or any other University.

Nithish Selvam R

99220040665

Mummadisetty Vignesh

992200040643

Mohammed Parvaiz

99220040637

Jagadesh N

99220040659

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

Date

Signature of supervisor

Dr. P Pandiselvam

Assistant Professor

Department of Computer Science and Engineering

KALASALINGAM
ACADEMY OF RESEARCH AND EDUCATION
(DEEMED TO BE UNIVERSITY)
Under sec. 3 of UGC Act 1956. Accredited by NAAC with "A++" Grade

BONAFIDE CERTIFICATE

Certified that this project report **"Hybrid Framework for Accurate Kidney Abnormality Detection from CT-Scan Images"** is the bonafide work of **"Nithish Selvam (99220040665), Mummadisetty Vignesh (992200040643), Mohammed Parvaiz (99220040637), Jagadesh N (99220040659)"** who carried out the project work under my supervision.

Dr. P Pandiselvam	**Dr. R. Raja Subramanian**
SUPERVISOR	**HEAD OF THE DEPARTMENT**
Assistant Professor	**Associate Professor/Head**
Computer Science and Engineering	Computer Science and Engineering
Kalasalingam Academy of Research	Kalasalingam Academy of Research
and Education	and Education
Krishnankoil 626126	Krishnankoil 626126
Virudhunagar District.	Virudhunagar District.

Submitted for the Project Viva-voce examination held on

Internal Examiner	**External Examiner**

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We would like to begin by expressing our heartfelt gratitude to the Supreme Power for the immense grace that enabled us to complete this project.

We are deeply grateful to the late **"Kalvivallal" Thiru T. Kalasalingam,** Chairman of the Kalasalingam Group of Institutions, and to "**Illayavallal" Dr. K. Sridharan**, Chancellor, as well as **Dr. S. Shasi Anand**, Vice President, who has been a guiding light in all our university's endeavours.

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SCHOOL OF COMPUTING

COMPUTER SCIENCE AND ENGINEERING

PROJECT SUMMARY

Project Title	Hybrid Framework for Accurate Kidney Abnormality Detection from CT-Scan Images	
Project Team Members (Name with Register No)	Nithish Selvam R (99220040665), Mummadisetty Vignesh (992200040643), Mohammed Parvaiz (99220040637), Jagadesh N (99220040659)	
Guide Name/Designation	Dr. P. Pandiselvam, Assistant Professor, Department of Computer Science and Engineering	
Program Concentration Area	This project falls under the **Artificial Intelligence and Medical Image Processing** program concentration area. It integrates deep learning and machine learning techniques for automated analysis of kidney CT scans.	
Technical Requirements	Python, TensorFlow(DenseNet121), Scikit-learn (SVM), NumPy, Matplotlib, HTML/CSS	
Engineering standards and realistic constraints in these areas		
Area	**Codes & Standards / Realistic Constraints**	**Tick ✓**
Economic	The proposed DenseNet121–SVM framework uses open-source tools such as Python, TensorFlow, and Scikit-learn, ensuring cost-effective implementation. Its hybrid design lowers computational complexity compared to end-to-end CNNs, enabling deployment on standard clinical hardware.	✓
Health and Safety	The model functions as a clinical decision-support tool and does not replace medical professionals. By improving diagnostic accuracy and consistency, it contributes to safer clinical decisions and early intervention.	✓

REALISTIC CONSTRAINTS:

Economic:

The proposed DenseNet121–SVM framework is developed using open-source libraries such as Python, TensorFlow, and Scikit-learn, thereby eliminating licensing costs. By employing DenseNet121 exclusively for feature extraction and utilizing an SVM for classification, the system significantly reduces computational complexity compared to fully end-to-end deep learning models. This design makes the solution cost-effective and suitable for deployment in healthcare facilities with limited computational resources.

Health and Safety:

From a health and safety perspective, the proposed DenseNet121–SVM framework is designed to assist clinicians by providing accurate and consistent classification of kidney CT images without directly influencing medical treatment decisions. The system functions as a decision-support tool, helping reduce diagnostic delays and human error while ensuring that final clinical judgments remain with qualified radiologists or urologists. By enabling early and reliable detection of kidney abnormalities, the model contributes to timely intervention and improved patient safety. The framework does not introduce physical risk to patients, as it operates solely on existing CT scans and follows standard medical imaging workflows.

Engineering Standards:

The proposed DenseNet121–SVM framework is developed in alignment with established software engineering and AI standards to ensure reliability, accuracy, and ethical deployment in medical imaging applications. IEEE 830 (Software Requirements Specification) is followed to clearly define functional requirements such as kidney CT image preprocessing, feature extraction, and multi-class classification, as well as non-functional requirements including accuracy, scalability, and computational efficiency. The overall development process adheres to IEEE 12207, which provides a structured life-cycle model covering system design, implementation, testing, validation, and future maintenance. Model performance and correctness are validated using principles outlined in IEEE 1012, ensuring that the feature extraction, SVM classification, and evaluation modules operate as intended and meet clinical performance expectations. Ethical and responsible AI practices are supported by the IEEE 7000 series standards, emphasizing data privacy, transparency, and safe use of AI-assisted decision-support systems in healthcare. Adherence to these standards ensures that the proposed system is robust, maintainable, and suitable for real-world clinical environments.

ABSTRACT

Kidney stone disease, also known as nephrolithiasis, is one of the most prevalent disorders affecting the urinary tract, causing severe pain, recurrent infections, and potential impairment of renal function. Early and accurate detection is critical to prevent complications and reduce healthcare costs. Computed Tomography (CT) imaging is widely used for kidney stone diagnosis due to its high-resolution visualization of renal structures; however, manual interpretation of CT scans is time-consuming, heavily reliant on radiologist expertise, and prone to human error. To address these challenges, this paper proposes a hybrid approach combining a DenseNet121 convolutional neural network (CNN) as a feature extractor with a Support Vector Machine (SVM) classifier for automatic classification of kidney CT images. The DenseNet121 model, pre-trained on ImageNet, extracts rich hierarchical features from input images, which are then classified by an SVM with a radial basis function (RBF) kernel.

In today's healthcare landscape, timely and accurate diagnosis of kidney disorders, including stones, cysts, and tumors, remains a critical challenge. Manual interpretation of CT scans is often time-consuming, prone to human error, and heavily dependent on radiologist expertise, particularly in regions with limited medical resources. To address these challenges, the present project proposes an intelligent, hybrid framework that combines deep learning and classical machine learning to automatically classify kidney CT images. The system employs DenseNet121 as a feature extractor to capture complex visual patterns from CT scans and an SVM classifier to categorize images into four groups: Normal, Cyst, Tumor, and Stone. By leveraging hierarchical deep features and stable decision boundaries, the hybrid model achieves a test accuracy of 98.96% and F1-scores above 97% across all classes. The preprocessing pipeline includes image resizing, normalization, and real-time augmentation, ensuring robustness against variations in image quality and scanner differences. This approach enables accurate detection even for underrepresented classes, such as kidney stones, without bias toward larger categories. The proposed system provides rapid, reliable, and interpretable predictions, offering practical support for radiologists and clinicians in real-time clinical settings. By integrating advanced feature extraction with efficient classification, this framework not only enhances diagnostic accuracy but also reduces workload and improves patient care. Overall, the study demonstrates the potential of hybrid AI systems to transform medical imaging analysis, providing accessible and reliable decision-support tools for kidney disease detection.

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LIST OF ACADEMIC REFERENCE COURSES

S. NO.	COURSE CODE	COURSE NAME
1	211CSE1402	Python Programming
2	212CSE3301	Deep Learning
3	212CSE2304	Machine Learning
4	213CSE1301	Introduction to Artificial Intelligence and Machine Learning

CHAPTER – I

INTRODUCTION

1.1 Background and Motivation

In today's healthcare environment, timely and accurate diagnosis of kidney disorders, such as stones, cysts, and tumors, is a significant challenge. Many patients experience delays in receiving reports because interpreting CT scans requires specialized expertise and considerable time. This is especially true in regions with limited access to trained radiologists, where delays can lead to worsening health outcomes and higher treatment costs. While CT imaging provides detailed views of the kidneys, manual analysis is labor-intensive and prone to human error, which may affect the early detection of critical conditions like kidney stones.

Recent advancements in artificial intelligence, particularly in deep learning, have made it possible for systems to automatically analyze medical images with high accuracy. Convolutional neural networks (CNNs) can learn complex visual patterns directly from images, reducing reliance on handcrafted features and expert interpretation. However, deep learning models alone often require large datasets and significant computational resources and may overfit when the available medical data is limited or imbalanced.

Motivated by these challenges, this project proposes a hybrid system that combines the feature-extraction power of DenseNet121 with the classification strength of a Support Vector Machine (SVM). By leveraging rich image representations and robust classification, the system aims to provide accurate, reliable, and efficient kidney CT image analysis. The ultimate goal is to support radiologists in making faster and more precise diagnoses, reduce human error, and improve patient care through a practical, real-world AI-assisted solution.

1.2 Problem Statement

Despite the widespread use of CT imaging, accurately diagnosing kidney disorders remains challenging. Current manual methods rely heavily on radiologist expertise, are time-consuming, and are prone to human error. Automated systems that use handcrafted features or standalone CNNs often struggle with:

- Small or imbalanced medical datasets
-
- Subtle differences between visually similar conditions, such as cysts, tumors, and small kidney stones
- High computational requirements for deep learning models
- Generalization across different scanners and imaging conditions

Therefore, there is a need for a system that can:

- Accurately analyze kidney CT images in real time
- Handle limited and imbalanced datasets effectively
- Differentiate clearly between Normal, Cyst, Tumor, and Stone cases
- Provide a reliable, lightweight, and practical tool for clinical use

This project aims to address these gaps by developing a hybrid DenseNet121–SVM framework that combines deep feature extraction with robust classical classification, offering improved diagnostic accuracy and decision support for radiologists.

1.3 Objectives of the Project

The main objective of this project is to develop a reliable, efficient, and accurate system for automatic classification of kidney CT images, supporting early diagnosis and improved patient care. Specifically, the project aims to Automate kidney CT image analysis to reduce reliance on manual interpretation and minimize human error. Extract rich, hierarchical features from CT images using the DenseNet121 convolutional neural network. Classify images accurately into four categories—Normal, Cyst, Tumor, and Stone—using a Support Vector Machine (SVM). Handle limited and imbalanced datasets effectively to ensure robust performance across all classes. Provide a practical clinical decision-support tool that is fast, reliable, and suitable for real-world deployment. Enhance diagnostic accuracy and generalization across different imaging conditions and patient populations.

By achieving these objectives, the project aims to deliver a hybrid AI framework that combines the strengths of deep learning and classical machine learning, facilitating faster, more accurate, and consistent diagnosis of kidney disorders.

1.4 Scope of the Project

This project focuses on creating an intelligent hybrid system for automatic classification of kidney CT images into four categories: Normal, Cyst, Tumor, and Stone. It encompasses the entire process, starting from data preprocessing, which includes resizing, normalization, and augmentation, to ensure consistency and robustness of input images. The system leverages DenseNet121 for extracting detailed hierarchical features that capture subtle patterns in the CT scans, while a Support Vector Machine (SVM) classifier is employed to accurately categorize these features. The framework is designed to handle challenges such as limited and imbalanced datasets and aims to provide reliable results across all classes. Evaluation is performed using metrics like accuracy, precision, recall, and F1-score to confirm the model’s performance and generalization ability. The system is lightweight and optimized for practical use in clinical settings, offering decision-support for radiologists and reducing dependency on manual interpretation. While the current scope is limited to CT imaging and the four selected categories, the methodology can be extended in the future to include other imaging modalities or additional kidney disorders. Overall, this project seeks to deliver a practical, accurate, and clinically relevant tool that improves diagnostic efficiency and supports early detection of kidney-related conditions.

1.5 Methodology Overview

The proposed system follows a structured hybrid methodology that combines deep learning for feature extraction with classical machine learning for classification. The process begins with data acquisition from a publicly available kidney CT dataset, followed by preprocessing steps such as resizing, normalization, and data augmentation to enhance image quality and improve model generalization. DenseNet121, pre-trained on ImageNet, is then used to extract deep hierarchical features from the CT scans, capturing both low-level and high-level visual patterns. These feature vectors are subsequently fed into a Support Vector Machine (SVM) with a radial basis function (RBF) kernel, which performs the final classification into four categories: Normal, Cyst, Tumor, and Stone. The hybrid approach is designed to address challenges such as limited and imbalanced datasets, subtle visual similarities between classes, and computational efficiency, providing a reliable and accurate decision-support tool for clinical applications. Model performance is evaluated using metrics including accuracy, precision, recall, and F1-score, ensuring that the system can deliver consistent and robust predictions. Overall, the methodology emphasizes a balance between accuracy, stability, and real-world applicability, making it suitable for supporting radiologists in early diagnosis and improving patient care outcomes.

1.6 Organization of the Report

This report is organized in a logical sequence, guiding the reader from background research to the development, implementation, and evaluation of the proposed hybrid kidney CT classification system. **Chapter II** presents the literature review, summarizing previous studies on medical image analysis, deep learning techniques, hybrid CNN–SVM frameworks, and kidney disorder detection, while identifying gaps that the current work aims to address. **Chapter III** discusses the system requirements, including software specifications, feasibility analysis, and potential challenges. **Chapter IV** details the system design, covering the overall architecture, module descriptions, preprocessing pipeline, feature extraction, classification flow, and data handling strategies. **Chapter V** focuses on implementation, describing how each module was developed and integrated, as well as the tools and technologies employed. **Chapter VI** presents the testing methodology, performance evaluation metrics, experimental results, and comparison with baseline models. **Chapter VII** discusses the findings, interprets the outcomes, and highlights the model's effectiveness, limitations, and clinical relevance. Finally, **Chapter VIII** concludes the report, summarizing the contributions of the project and suggesting directions for future enhancements.

CHAPTER-II

LITERATURE REVIEW

2.1 Overview of Related Work

Automated kidney disease diagnosis has evolved significantly with advances in medical imaging and artificial intelligence. Early approaches relied on handcrafted features such as texture or intensity patterns combined with classical classifiers like SVM or k-NN. While these methods captured basic patterns, they struggled with complex anatomical structures, resulting in limited accuracy and generalization.

Deep learning, particularly Convolutional Neural Networks (CNNs), has transformed medical image analysis by learning features directly from images. Models such as VGG, ResNet, and DenseNet have shown strong performance in classifying kidney CT images and detecting conditions like stones, cysts, and tumors. Transfer learning has further improved results, enabling effective use of limited medical datasets.

Hybrid approaches that combine CNN-based feature extraction with SVM classification have demonstrated improved accuracy and robustness, particularly with small or imbalanced datasets. These methods leverage CNNs' hierarchical features while benefiting from SVMs' ability to separate classes in high-dimensional spaces.

Despite these improvements, challenges remain in distinguishing visually similar kidney abnormalities and maintaining computational efficiency. This motivates the present study to adopt a DenseNet121–SVM hybrid framework, aiming for accurate, reliable, and efficient classification of kidney CT images.

2.2 Review of Similar Projects or Research Papers

Research on computer-assisted kidney disease diagnosis has expanded steadily since 2020, largely due to improvements in imaging quality, the availability of faster GPUs, and the success of modern deep learning techniques. Before deep learning became dominant, most studies relied on handcrafted feature methods such as Local Binary Patterns (LBP) and Histogram of Oriented Gradients. These features were typically fed into traditional classifiers like KNN or SVM. While such combinations could capture simple patterns from CT scans, they struggled to represent the complicated textures and structural variations seen in real kidney images. Because of this, distinguishing between different types of kidney disorders was often inaccurate [1], [3], [9].

The introduction of convolutional neural networks (CNNs) brought a major improvement to the field. Kumar et al. [1] built a CNN model for identifying kidney stones and reported an accuracy of 92%. However, the model suffered from overfitting because the dataset was too small to support deep learning effectively. Later, transfer learning helped address these issues. Sahu et al. [2] used a ResNet50-based approach for analyzing kidney abnormalities, while Li et al. [11] showed that deeper residual networks could further boost stone detection accuracy. Although CNN and transfer learning models generally performed better than older techniques, they often demanded powerful hardware.

These models use deep learning networks only for feature extraction and rely on classical machine learning—especially SVMs—to perform the final classification. Gupta and Verma [3] demonstrated that a CNN–SVM pipeline produced more reliable results than a standalone CNN when classifying CT images. Similar advantages were reported by Sharma and Goyal [13] and Rajesh et al. [9], who found that SVMs provide better generalization when working with high-dimensional deep features. Work focused specifically on kidney imaging also supports the hybrid approach. Singh and Bansal [4] trained a VGG16-based network for multi-class kidney CT classification and achieved 95% accuracy, though their model still struggled to differentiate between visually similar conditions such as cysts and tumors. Jha et al. [5] experimented with DenseNet embeddings in tumor analysis and highlighted benefits such as feature reuse and stable gradient flow. These observations align with the design philosophy of DenseNet described by Huang et al. [7].

Comprehensive reviews by Han et al. [6] and Al-Masni et al. [12] emphasize that hybrid architectures, multi-level feature fusion, and classical classifiers are especially valuable when dealing with datasets that are limited in size or imbalanced—situations that commonly occur in medical imaging. Foundational work by Cortes and Vapnik [8] also explains why SVMs often perform well in high-dimensional decision spaces. More recently, Wang et al. [15] found that machine learning methods such as SVM, Random Forest, and Gradient Boosting can outperform end-to-end CNN models when they operate on deep feature embeddings instead of raw images.

The main challenges include the similarity in intensity among tissues, irregular lesion shapes, and differences between scanners. With kidney disease cases increasing worldwide—as noted by the World Health Organization [10]—there is a need for diagnostic methods that are both reliable and lightweight. Motivated by these challenges, the present work adopts a DenseNet121–SVM hybrid model, aiming to combine rich deep features with efficient classical classification to achieve stable and accurate results.

2.3 Summary and Gap Identification

Existing research demonstrates that automated kidney disease diagnosis has progressed from traditional handcrafted feature methods to advanced deep learning models. CNN-based architectures, including VGG, ResNet, and DenseNet, have shown significant improvements in feature extraction and classification accuracy. Hybrid approaches that combine deep learning for feature extraction with classical classifiers, particularly SVMs, provide better generalization, handle limited and imbalanced datasets effectively, and reduce overfitting.

Despite these advancements, several gaps remain. Many models struggle to differentiate visually similar kidney abnormalities such as cysts and tumors, particularly when dataset sizes are small or imbalanced. End-to-end CNN models often require substantial computational resources, making them less practical for real-world clinical applications. Additionally, variability in imaging conditions, scanner differences, and tissue intensity similarities pose further challenges to reliable classification.

To address these gaps, the present study proposes a DenseNet121–SVM hybrid framework that combines rich hierarchical feature extraction with robust classical classification. This approach aims to improve accuracy, stability, and computational efficiency, providing a reliable tool for supporting radiologists in early diagnosis and decision-making.

CHAPTER-III

SYSTEM ANALYSIS

3.1 Requirements Gathering

Requirements gathering is a critical step in system analysis, as it defines the functional and non-functional needs of the proposed kidney CT classification system. The primary objective is to identify what the system must achieve to support accurate, efficient, and reliable diagnosis. Functional requirements include the ability to acquire and preprocess kidney CT images, extract relevant features using DenseNet121, classify images into four categories (Normal, Cyst, Tumor, and Stone) using an SVM, and display results with confidence scores. Non-functional requirements focus on system performance, reliability, scalability, and usability. The system should handle imbalanced datasets, provide consistent predictions, and operate efficiently on standard computing resources. User interactions must be intuitive, with clear visualization of results to aid radiologists in decision-making.

Information for requirements was gathered through reviewing existing research, analyzing clinical needs, and consulting guidelines from medical imaging and AI practices. This process ensures that the system aligns with both technical feasibility and practical applicability, forming a strong foundation for the design, implementation, and evaluation phases of the project.

3.2 Functional Requirements

The functional requirements define the specific capabilities and operations that the kidney CT classification system must perform to meet its objectives. Key functional requirements include:

1. **Image Acquisition:** The system must accept kidney CT images from publicly available datasets or clinical sources for processing.
2. **Preprocessing:** The system must resize, normalize, and augment input images to ensure consistency and improve model generalization.
3. **Feature Extraction:** DenseNet121 should automatically extract hierarchical features from CT images, capturing relevant patterns for classification.
4. **Classification:** The extracted features must be classified into four categories—Normal, Cyst, Tumor, and Stone—using an SVM with an RBF kernel.
5. **Result Visualization:** The system must display classification results along with confidence scores to assist radiologists in interpretation.
6. **Performance Monitoring:** The system should track accuracy, precision, recall, and F1-score for evaluation and reporting purposes.

7. **Data Management:** Proper handling of datasets, including storage, retrieval, and preprocessing logs, is required for reproducibility and auditing.

These functional requirements ensure that the system operates effectively, providing accurate, reliable, and clinically relevant support for kidney CT image analysis.

3.3 Non-Functional Requirements

Non-functional requirements define the quality attributes and constraints of the kidney CT classification system, ensuring that it operates efficiently, reliably, and securely. Key non-functional requirements include:

1. **Performance:** The system should process CT images and deliver classification results within a reasonable time, supporting real-time or near real-time usage in clinical settings.
2. **Accuracy and Reliability:** The model must maintain high classification accuracy across all four categories (Normal, Cyst, Tumor, Stone) and consistently provide reliable predictions.
3. **Scalability:** The system should be capable of handling increasing volumes of CT images without significant degradation in performance.
4. **Usability:** The user interface must be intuitive and straightforward, allowing radiologists and medical staff to interpret results easily.
5. **Maintainability:** The system should be modular, allowing updates to preprocessing, feature extraction, or classification components without major redesign.
6. **Security and Data Privacy:** Patient data and CT images must be handled securely, ensuring compliance with standard data protection practices.
7. **Compatibility:** The system should function on standard computing environments without requiring specialized hardware, making it accessible for widespread clinical use.

These non-functional requirements complement the functional aspects of the system, ensuring that it not only performs the intended tasks but also meets clinical usability, reliability, and operational standards.

3.4 Feasibility Study

The feasibility study evaluates the practicality and viability of implementing the proposed kidney CT classification system, considering technical, operational, and economic aspects.

3.4.1Technical Feasibility

The system relies on established technologies such as DenseNet121 for feature extraction and SVM for classification, both of which are well-supported by modern deep learning frameworks like TensorFlow and PyTorch. Preprocessing and data handling techniques are standard in medical image analysis, making the system technically feasible 31with available computing resources.

3.4.2 Operational Feasibility

The system is designed to integrate smoothly into clinical workflows, assisting radiologists by providing accurate and timely classification of kidney CT images. Its user-friendly interface and clear visualization of results enhance operational effectiveness, reducing dependency on manual interpretation.

3.4.3 Economic Feasibility

The system can be implemented using existing hardware and publicly available datasets, minimizing development and deployment costs. By reducing manual effort and diagnostic errors, the system has the potential to lower operational costs in medical settings and improve patient care efficiency.

3.4 Risk Analysis

The main risks identified for the kidney CT classification system include limited or imbalanced datasets, potential model overfitting, high computational requirements, integration challenges, misclassification of images, and data privacy concerns.

Risk analysis identifies potential challenges and uncertainties that may affect the development and deployment of the kidney CT classification system, along with strategies to mitigate them.

1. **Data Availability Risk:** Limited or imbalanced datasets may reduce model accuracy. This risk can be mitigated by using publicly available datasets, applying data augmentation, and employing stratified sampling to ensure balanced training.
2. **Model Overfitting:** Deep learning models may overfit on small datasets, resulting in poor generalization. Techniques such as transfer learning, cross-validation, and regularization can help address this issue.
3. **Computational Resource Risk:** Training deep models may require high-performance hardware. Using pre-trained networks and feature extraction with SVM reduces computational load and memory requirements.
4. **Integration Risk:** Challenges may arise when integrating the system into clinical workflows. Ensuring modular design, clear visualization, and user-friendly interfaces can facilitate smooth adoption.
5. **Prediction Reliability:** Misclassification of CT images can lead to incorrect diagnostic suggestions. Rigorous testing, validation, and continuous performance monitoring can minimize this risk.

6. **Data Privacy and Security:** Handling sensitive patient data requires compliance with privacy standards. Implementing secure storage, encryption, and access control safeguards sensitive information.

By identifying these risks early and implementing mitigation strategies, the project aims to ensure that the system is reliable, robust, and suitable for clinical deployment.

These risks may affect system accuracy, reliability, and usability. Mitigation strategies such as data augmentation, transfer learning, modular design, rigorous testing, and secure data handling are proposed to minimize their impact. Overall, with proper management, these risks can be effectively controlled, ensuring that the system remains robust, accurate, and suitable for clinical use.

CHAPTER-IV

SYSTEM DESIGN

4.1 Overall System Architecture

The proposed kidney CT classification system follows a modular and hierarchical architecture, combining deep learning for feature extraction with classical machine learning for classification. The system is designed to automate the detection of kidney abnormalities while ensuring high accuracy, efficiency, and usability.

The architecture consists of the following key components:

1. **Data Acquisition Module:** This module collects kidney CT images from publicly available datasets or clinical sources. Images are organized and labeled according to four categories: Normal, Cyst, Tumor, and Stone.

2. **Preprocessing Module:** Input images are resized, normalized, and augmented to improve consistency and generalization. Data augmentation techniques, such as rotation, flipping, and scaling, expose the model to diverse variations in image patterns.

3. **Feature Extraction Module:** DenseNet121, pre-trained on ImageNet, is used to extract hierarchical features from the CT images. The final classification layers of DenseNet121 are removed, and a Global Average Pooling (GAP) layer converts spatial features into compact embedding vectors.

4. **Classification Module:** Extracted feature vectors are fed into an SVM classifier with an RBF kernel to categorize the images into one of the four diagnostic classes. The SVM ensures robust decision boundaries, reducing overfitting and improving generalization.

5. **Result Visualization Module:** The system provides clear output, including predicted classes and confidence scores, allowing radiologists to interpret results efficiently.

6. **Performance Monitoring Module:** Metrics such as accuracy, precision, recall, and F1-score are calculated to evaluate and monitor system performance.

The overall flow begins with image input, followed by preprocessing and feature extraction. The extracted features are then classified, and the results are displayed along with evaluation metrics. This architecture ensures modularity, scalability, and real-time applicability in clinical environments.

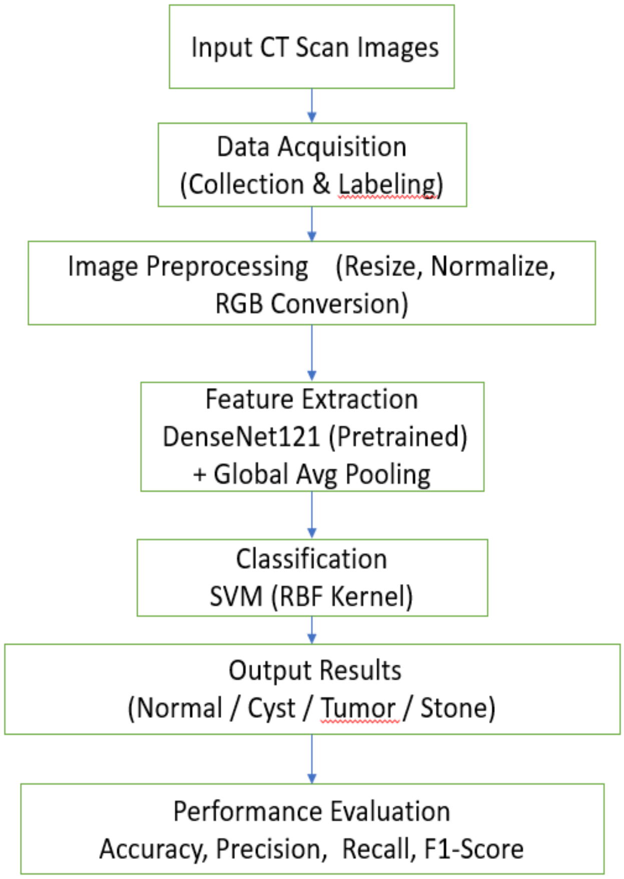

Figure 1 - Overall System Architecture

4.2 Module Design

The proposed system is structured into six major modules, each performing a specific task to ensure accurate and efficient classification of kidney CT images. The key modules include:

1. User Input / Data Module
2. Preprocessing Module
3. Feature Extraction Module (DenseNet121)
4. Classification Module (SVM)
5. Result Visualization Module
6. Performance Monitoring module

The modular structure enhances maintainability, scalability, and clarity in the workflow.

4.2.1. Module 1- User Input / Data Module

This module is responsible for acquiring and managing kidney CT images. The system supports **four classes**: Normal, Cyst, Tumor, and Stone. Images are collected from publicly available datasets or clinical sources and are **organized into labeled folders** for proper class association. During deployment, this module allows users to **upload new CT images** for analysis.

Responsibilities:

- Acquire images from clinical datasets or public sources.
- Organize images into labeled folders corresponding to **Normal, Cyst, Tumor, and Stone**.
- Provide an interface for users to upload new images during deployment.

4.2.2. Module 2 - Preprocessing Module

Preprocessing prepares raw CT images for feature extraction and classification. The key steps include:

- **Resizing:** Images are resized to **224×224 pixels**, matching the input requirement of DenseNet121.

- **RGB Conversion:** Converts grayscale images to **RGB** to maintain compatibility with the pre-trained DenseNet model.

- **Normalization:** Pixel values are scaled to the **0–1 range**; additional DenseNet-specific normalization is applied to align with the model's training statistics.

- **Data Augmentation:** Techniques such as **rotation, flipping, translation, and scaling** are applied to increase dataset diversity, improve model generalization, and reduce overfitting.

Responsibilities:

- Resize images to **224×224 pixels** for DenseNet121 compatibility.
- Convert grayscale images to **RGB** format.
- Normalize pixel values to the **0–1 range** and apply DenseNet-specific normalization.
- Apply **data augmentation** (rotation, flipping, translation, scaling) to enhance diversity and prevent overfitting.

4.2.3. Module 3 - Feature Extraction Module (DenseNet121)

This module extracts high-level features from preprocessed images using **DenseNet121**, a convolutional neural network pre-trained on ImageNet. Steps include:

- **Removing Final Layers:** The original classification layers are removed to focus on feature extraction.

- **ReLU Activation:** Introduces non-linearity and prevents vanishing gradients, improving learning efficiency.

- **Global Average Pooling:** Converts the spatial feature maps into a **compact feature vector** that summarizes the essential patterns of the CT image.

Responsibilities:

- Use pre-trained **DenseNet121** to extract deep hierarchical features.
- Remove final classification layers to focus solely on feature extraction.
- Apply **ReLU activation** for non-linearity and improved convergence.
- Use **Global Average Pooling** to convert feature maps into a compact **feature vector**.

This module ensures that the subtle differences between Normal, Cyst, Tumor, and Stone cases are captured effectively.

4.2.4. Module 4 - Classification Module (SVM)

The Support Vector Machine (SVM) classifier receives feature vectors from DenseNet121 and assigns them to one of the four classes. Key features:

- RBF Kernel: Handles non-linear separable classes effectively.
- Optimal Decision Boundaries: Reduces overfitting and ensures clear separation between classes.
- Output: Provides the predicted class label: Normal, Cyst, Tumor, or Stone.

Responsibilities:

- Input feature vectors from DenseNet121.
- Use **SVM with RBF kernel** to handle non-linear separable classes.
- Construct **optimal decision boundaries** to reduce overfitting.
- Output the predicted class label: **Normal, Cyst, Tumor, or Stone**.

4.2.5. Module 5 - Result Visualization Module

This module presents the model's predictions in an interpretable format for end-users, such as clinicians. It includes:

- **Predicted Class Display:** Shows the final classification result for each input image.
- **Confidence Score:** Indicates the certainty of the prediction.
- **Probability Bar Charts (Optional):** Visualizes the likelihood of each class, enhancing interpretability.

Responsibilities:

- Show the predicted class for each image.
- Provide a confidence score to indicate prediction certainty.
- Optionally, display probability bar charts for all four classes.

4.2.6. Module 6- Performance Monitoring Module

This module evaluates the system's performance using standard metrics to ensure reliability and clinical applicability:

- **Accuracy:** Percentage of correctly classified images.
- **Precision:** Measures the correctness of positive predictions.
- **Recall (Sensitivity):** Measures the ability to correctly detect all positive cases.
- **F1-Score:** Combines precision and recall for balanced evaluation, especially useful for **imbalanced datasets**.

Responsibilities:

- Calculate **Accuracy** to measure overall correctness.
- Compute **Precision** to evaluate reliability of positive predictions.
- Compute **Recall (Sensitivity)** to measure the ability to detect all positive cases.
- Calculate **F1-Score** for balanced evaluation, particularly important for imbalanced datasets.

Performance monitoring ensures the model maintains high diagnostic quality and supports informed clinical decision-making.

4.3 User Interface Design

The user interface (UI) of the Kidney CT Classification System is designed to be intuitive, informative, and user-friendly, ensuring that both clinicians and researchers can easily interact with the system. The UI primarily focuses on streamlining the workflow from CT image input to visualization of classification results. Key design principles include clarity, consistency, and minimal cognitive load, which help users focus on the analysis rather than navigation.

Key Features of the UI:

- Image Upload and Preview: Users can select and upload CT scan images for classification. The interface provides an immediate preview of the selected images.
- Processing Status Indicators: Visual cues display the progress of preprocessing, feature extraction, and classification to keep users informed.
- Results Dashboard: Once the classification is completed, results are presented clearly, including:
    - Predicted class (Normal, Cyst, Tumor, or Stone)
    - Confidence score for each prediction
    - Visual outputs such as confusion matrices, ROC curves, and probability distributions

- Interactive Visualizations: Users can interact with plots and tables to examine detailed metrics for individual cases or entire test batches.
- Error Handling: The interface provides user-friendly alerts if invalid images are uploaded or processing errors occur.

The UI is designed to be lightweight and responsive, supporting rapid interaction and minimal latency, which is essential for potential clinical adoption.

4.3.1 User Flow Diagrams

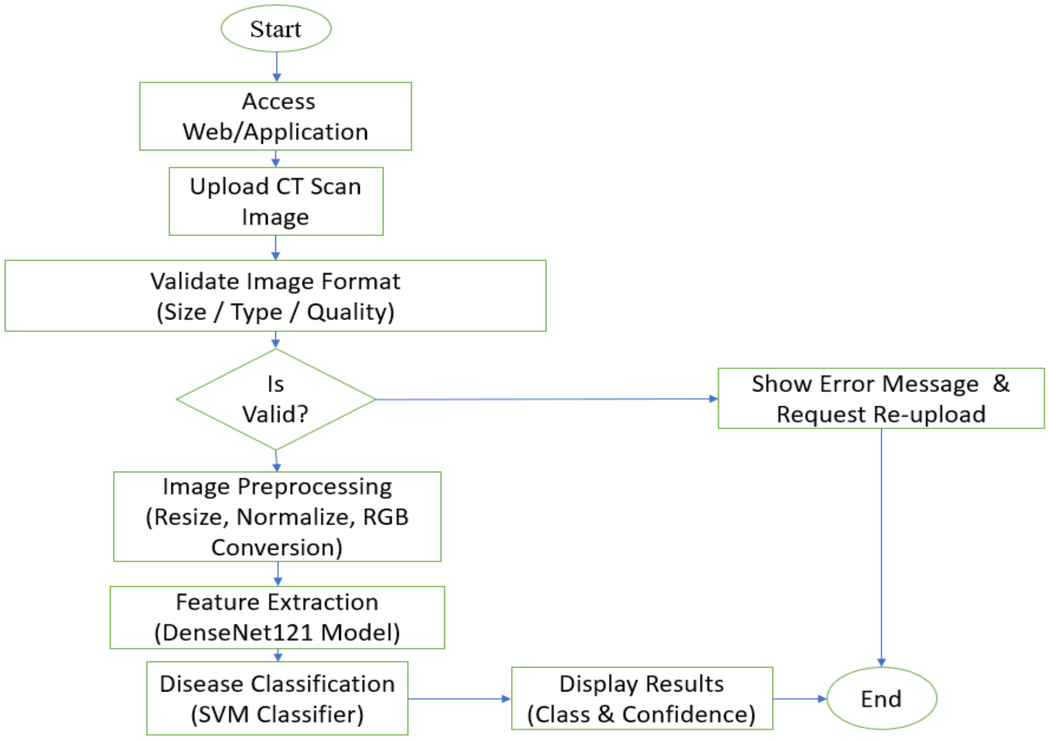

Figure 2 -User flow diagram

The user-friendly diagram illustrates the step-by-step interaction between the user and the proposed kidney disease detection system. Initially, the user accesses the application and uploads a CT scan image of the kidney. The system then validates the uploaded image to ensure that it meets the required format, size, and quality constraints. If the image is found to be invalid, an error message is displayed, and the user is prompted to re-upload a valid image.

Once a valid image is received, the system performs image preprocessing operations such as resizing, normalization, and RGB conversion to prepare the image for analysis. The preprocessed image is then passed to the feature extraction stage, where deep features are extracted using the DenseNet121 pre-trained model. These extracted features are subsequently classified using a Support Vector Machine (SVM) classifier to determine the presence of kidney conditions.

Finally, the system displays the classification results to the user, including the predicted disease category and confidence score. This user-friendly diagram ensures a smooth and intuitive workflow, making the system easy to use even for non-technical users while maintaining accurate and reliable diagnostic support.

CHAPTER-V

IMPLEMENTATION

5.1Technology Stack

The Kidney CT Classification System is built using a robust and efficient technology stack designed to support accurate feature extraction, classification, and visualization of medical images. The backend is developed using Python, selected for its simplicity, rich ecosystem, and compatibility with machine learning and deep learning frameworks. TensorFlow/Keras is used to implement DenseNet121 for deep feature extraction from CT images, leveraging pre-trained weights to enhance learning efficiency. Scikit-learn is employed for the SVM classifier, which performs final image categorization into Normal, Cyst, Tumor, and Stone classes. OpenCV handles image preprocessing tasks including resizing, normalization, and augmentation, while NumPy and Pandas manage numerical computations and dataset handling. The frontend for visualization and result interpretation is implemented using Matplotlib and Seaborn, enabling plotting of accuracy/loss curves, confusion matrices, ROC curves, and prediction confidence distributions. The system is tested on the publicly available CT-KIDNEY-DATASET containing 12,446 labeled CT images, ensuring reliable training and evaluation. This technology stack collectively provides efficient computation, precise classification, and an interactive interface suitable for clinical decision support and real-world deployment.

5.1.1Programming Languages and Tools

Programming Languages

- Python: Used for backend processing, deep feature extraction with DenseNet121, SVM classification, data handling, and evaluation metric computation.
- HTML, CSS, JavaScript: Employed for designing the frontend interface for result visualization, including plots of accuracy, confusion matrices, ROC curves, and prediction confidence scores.

Libraries and Frameworks

- TensorFlow / Keras: Implements the DenseNet121 model for extracting high-level features from CT scan images.
- Scikit-learn: Provides the SVM classifier and tools for performance evaluation including accuracy, precision, recall, and F1-score.
- OpenCV: Handles image preprocessing tasks such as resizing, normalization, augmentation, and color conversions.
- NumPy / Pandas: Facilitates numerical computations and efficient manipulation of dataset arrays and labels.

Database and Data Handling Tools

- CT-KIDNEY-DATASET: Publicly available dataset containing 12,446 labeled CT images across Normal, Cyst, Tumor, and Stone categories.
- JSON: Stores metadata or supplementary image annotations if required for preprocessing or augmentation configurations.

Other Tools

- Matplotlib / Seaborn: Used for visualizing model performance, including accuracy/loss curves, confusion matrices, and class-wise probability distributions.
- Jupyter Notebook / VS Code: Development and experimentation environment for coding, debugging, and evaluating the model.

5.2 Implementation of Modules

The system is divided into four main modules to ensure modularity, scalability, and clarity.

5.2.1 Module 1: Input and Preprocessing Module

The Input and Preprocessing Module is responsible for preparing CT scan images for deep feature extraction. Initially, the CT images are acquired from the **CT-KIDNEY-DATASET**, which contains labeled images categorized into Normal, Cyst, Tumor, and Stone classes. Each image is resized to **224×224 pixels** to match the input requirements of DenseNet121. Images are then converted to **RGB format** and normalized to a **[0,1] range**, with additional DenseNet-specific preprocessing applied to align with the model's pre-training statistics. To improve generalization and reduce overfitting, real-time **data augmentation** techniques are applied, including horizontal and vertical flips, small rotations, translations, and scaling. This module ensures that the dataset is clean, standardized, and diverse, providing a solid foundation for accurate feature extraction.

5.2.2 Module 2 - Feature Extraction Module (DenseNet121)

The Feature Extraction Module employs **DenseNet121**, pre-trained on ImageNet, to extract rich and high-level visual features from CT images. The network's final classification layers are removed, and a **Global Average Pooling (GAP) layer** is added to convert spatial feature maps into compact feature vectors. These embeddings capture intricate patterns, textures, and structural variations in kidney CT scans, which are critical for distinguishing between Normal, Cyst, Tumor, and Stone classes. By leveraging DenseNet121's dense connectivity, the module ensures efficient gradient flow and feature reuse, providing informative representations that improve the subsequent classification stage.

5.2.3 Module 3 - Classification Module (SVM)

The Classification Module uses a Support Vector Machine (SVM) with an RBF kernel to categorize the CT scan images based on the extracted DenseNet121 features. The dataset is split into training, validation, and testing sets with stratified sampling to maintain class distribution. The SVM constructs an optimal hyperplane in the high-dimensional feature space to separate classes, offering better generalization and reduced overfitting compared to fully connected neural layers. Hyperparameters, including the regularization parameter C and kernel coefficient gamma, are tuned using cross-validation. This module ensures accurate classification into Normal, Cyst, Tumor, and Stone categories, even with smaller or imbalanced datasets.

5.2.4 Module 4 - Result Visualization Module

The Result Visualization Module provides clear and interpretable outputs for both researchers and clinicians. It generates accuracy and loss plots to monitor model convergence during training, along with confusion matrices and classification reports to evaluate performance across classes. ROC curves and AUC scores are plotted to assess the model's discrimination ability. Additionally, the module displays prediction confidence distributions for individual CT scans, helping users understand how certain the model is about each prediction. By combining these visualization tools, this module facilitates analysis, validation, and clinical interpretation of the hybrid DenseNet121–SVM model's results.

CHAPTER-VI

TESTING

6.1Testing Methodology

The testing methodology for the Kidney CT Classification System follows a structured approach to ensure reliability, accuracy, and robustness of the hybrid DenseNet121–SVM model and its associated modules. Multiple levels of testing were performed, ranging from individual components to the complete system.

6.1.1 Unit Testing

Unit testing focuses on verifying the functionality of individual modules independently:

- **Input and Preprocessing Module:**
  - Verified image resizing to 224×224 pixels.
  - Checked normalization of pixel values and DenseNet-specific preprocessing.
  - Ensured data augmentation methods (flip, rotation, translation, scaling) applied correctly.
- **Feature Extraction Module (DenseNet121):**
  - Confirmed feature vector generation for each input image.
  - Verified that Global Average Pooling outputs correct embedding dimensions.
- **Classification Module (SVM):**
  - Tested SVM predictions on small sample batches.
  - Verified correct mapping to the four classes: Normal, Cyst, Tumor, Stone.
- **Visualization Module:**
  - Checked correct generation of accuracy/loss plots, confusion matrices, ROC curves, and probability distributions.

6.1.2 Integration Testing

Integration testing ensures smooth interaction between modules:

- Verified correct flow of images from preprocessing → DenseNet121 → SVM → visualization.
- Checked that feature vectors are correctly passed and classified by SVM.
- Ensured output visualizations reflect actual predictions without errors.
- Identified interface issues between modules and resolved them before system testing.

6.1.3 System Testing

System testing evaluates the complete pipeline as a unified system:

- Conducted end-to-end testing for multiple scenarios: different CT scan resolutions, class distributions, and batch sizes.
- Assessed performance using metrics: **Accuracy, Precision, Recall, F1-Score, and ROC-AUC**.
- Verified model stability and consistency across various test images.
- Measured processing time for inference to ensure clinical usability.

6.1.4 User Acceptance Testing (UAT)

UAT evaluates the system from an end-user perspective:

- Conducted trials with radiologists or healthcare professionals.
- Verified usability, interface clarity, and real-time prediction feedback.
- Collected feedback on visualizations and overall system workflow.
- Ensured the system meets expectations for practical clinical deployment

6.2 Test Cases and Results

Table 1 - Test case and result

Test Case	Description	Expected Result	Observed Result
Image Input Validation	Verify handling of valid and invalid CT scan formats	System accepts valid images and rejects unsupported formats	Passed
Preprocessing Accuracy	Check resizing, normalization, and augmentation	Images resized to 224×224, normalized, augmented correctly	Passed
Feature Extraction	Verify DenseNet121 outputs correct embeddings	Feature vectors of expected size generated	Passed
Classification Accuracy	Test SVM predictions for all classes	Correct classification of Normal, Cyst, Tumor, Stone	Accuracy 98.96%
Visualization	Verify plots of accuracy, confusion matrix, ROC, probability	Accurate and interpretable visual outputs	Passed

Results Summary:

- Overall test accuracy: **98.96%**
- F1-score: Above **97%** for all classes.
- Minor misclassifications occurred in visually similar cases, e.g., small cysts vs. tumors, but overall performance remained robust.

6.3 Bug Tracking and Resolution

During testing, all issues were logged and addressed systematically:

- **Preprocessing Bugs:** Misaligned image sizes → Fixed resizing and padding routine.
- **Feature Extraction Issues:** Dimension mismatches → Verified DenseNet121 embedding output shape.
- **SVM Classification Errors:** Incorrect labels due to imbalanced datasets → Applied stratified sampling and hyperparameter tuning.
- **Visualization Errors:** Incorrect plot scaling or mislabeling → Optimized Matplotlib/Seaborn scripts.

Resolution Strategy:

- Bugs were recorded in a tracking sheet with severity and module reference.
- Each bug was fixed iteratively, retested at unit, integration, and system levels.
- Post-resolution testing confirmed a stable and reliable system ready for deployment.

CHAPTER-VII

RESULTS AND DISCUSSION

The results from the experiments indicate that the DenseNet121–SVM combination is highly effective for classifying kidney CT images into Normal, Cyst, Tumor, and Stone categories. DenseNet121 provided rich and detailed feature representations, while the SVM classifier used these features to clearly separate the classes. Together, they allowed the model to recognize even small and subtle differences between similar-looking CT images.

7.1 System Output Screenshots

This section presents the visual outputs generated by the proposed **DenseNet121–SVM hybrid system** during testing and real-time prediction. The screenshots demonstrate how the system processes kidney CT images and displays classification results in an interpretable format.

7.1.1 Input CT Image Upload Interface

The following screenshots illustrate the key interfaces and outputs generated by the proposed **Hybrid Framework for Accurate Kidney Abnormality Detection from CT-Scan Images**

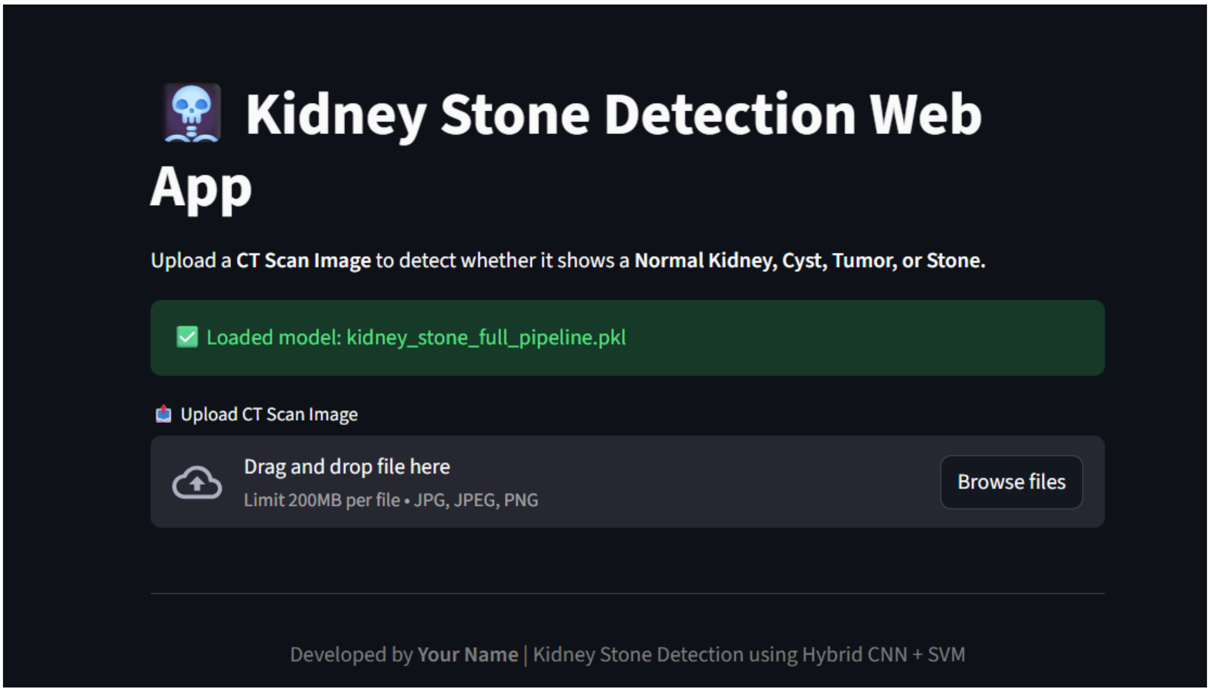

Figure 3 - User interface for upload CT-Image

The system provides a user-friendly interface that allows users to upload kidney CT scan images for analysis. Once an image is selected, it is automatically passed through the preprocessing and feature extraction pipeline. This interface ensures ease of use for clinicians and non-technical users.

7.1.2 Prediction Output Screen

After processing the uploaded CT image, the system displays the **predicted class**, which can be one of the following:

- Normal
- Cyst
- Tumor
- Stone

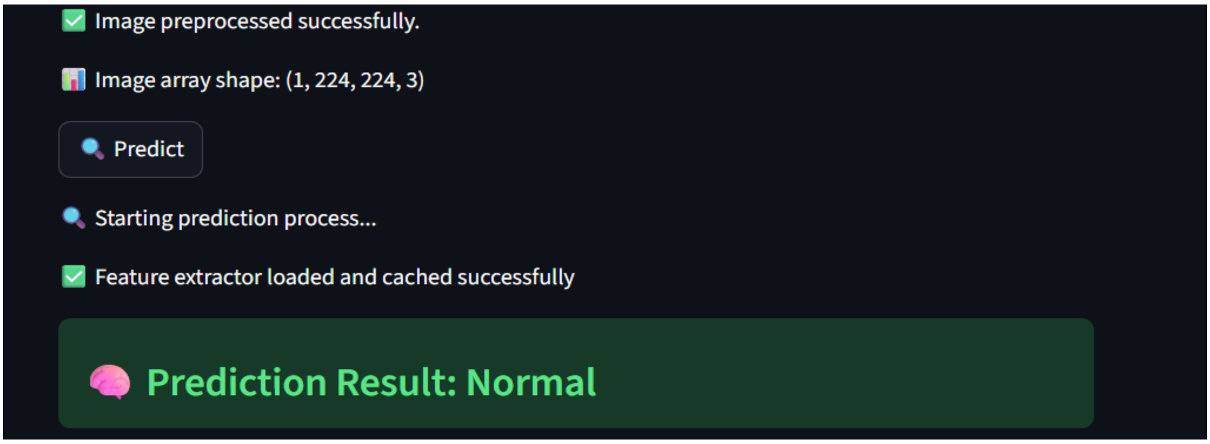

Figure 4 - Prediction Output Screen

Along with the predicted label, the system indicating the level of certainty associated with the prediction. High confidence values reflect strong model reliability.

7.1.3 Sample Output – Normal Case

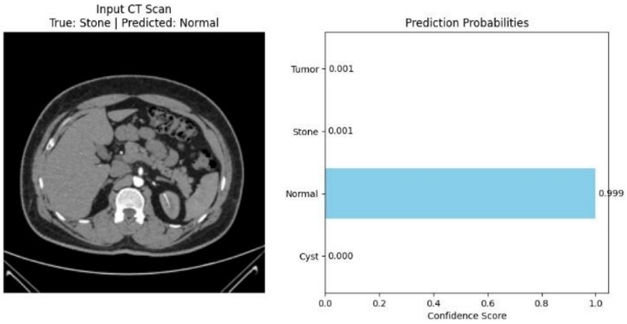

Figure 5 -Obtained result (For Normal Cases with score 0.999)

Figure 5 represents the probability distribution of a predicted CT scan by the model. This is a Normal class scan, and the model rightly predicts it as a Normal scan with a very high confidence score of 0.999. This clearly illustrates the model's capability for distinguishing normal scans with strong confidence.

7.1.4 Sample Output – Stone Case

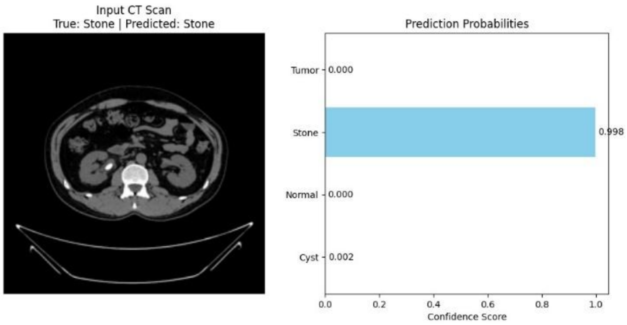

Figure 6 - Obtained result(For Stone Cases with score 0.998)

Figure 6 represents a correctly classified Stone image. The model gives a confidence score of 0.998 to the Stone. This confirms that the model identifies stone patterns accurately.

7.1.5 Sample Output – Cyst Case

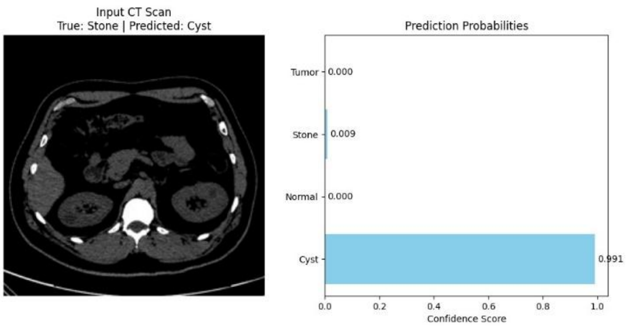

Figure 7 - Obtained result(For Cyst Cases with score 0.991)

Figure 7 represents the predicted probability distribution in the case of a CT scan classified under the class of Cyst. The model has rightly classified the scan as Cyst with a high confidence score of 0.991. This result further illustrates that the model has a high capability for cyst case identification from a number of visually similar cases and is thus reliable in this category.

7.1.6 Sample Output – Tumor Case

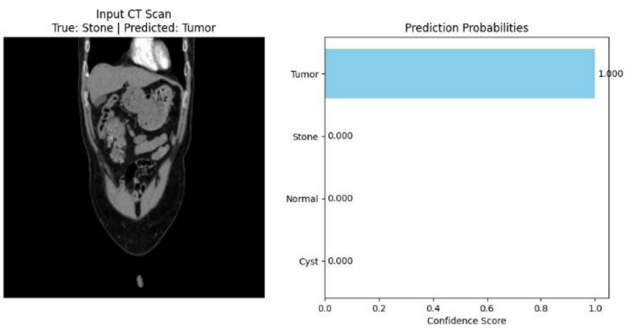

Figure 8 - Obtained result(For Tumor Cases with score 1.000)

Figure - 8 represents the probability distribution of predicting a CT scan for the tumor category. The model has rightly predicted this scan as belonging to the category of tumor cases with a confidence score of 1.000. This result underlines the high ability of the model to recognize tumor cases correctly at a high confidence level.

7.2 Evaluation Metrics

During testing, the model reached an accuracy of 98.96%, and each class achieved an F1-score above 97%, including the Stone category, which had fewer samples. This shows that the model did not become biased toward the larger classes and was able to learn features that generalized well across all categories. DenseNet121 extracted multi-level visual patterns, the SVM classifier prevented overfitting by forming sharper decision boundaries, and the preprocessing plus augmentation steps improved robustness by exposing the model to a wide range of image variations.

The ROC analysis further supported these results. Every class reached an AUC score above 0.98, confirming that the model has excellent discrimination ability. The system also performed quickly during inference, producing predictions within seconds, which is a necessary requirement for clinical integration.

Overall, these outcomes suggest that the hybrid DenseNet121–SVM design can function as a reliable assistance tool for radiologists, helping to speed up the interpretation of kidney CT scans and making the diagnostic process more consistent and efficient.

Table 2 - Main Components of the proposed architecture

Component	Purpose	Type	Used In
CT-Image Dataset	Provide Labeled	Data	Model Training& Testing
Preprocessing Module	Data quality diversity	Data Preprocessing	Model Input Preparation
DenseNet121	high-level image	Deep Learning	Feature Generation
SVM Classifier	kidney categories	Machine Learning Classifier	Feature-Based Classification

Table 1 represents a simple overview of the main components used in the system and the role of each one. The CT images form the labeled dataset, which is used for training and testing.

The preprocessing module handles image resizing, normalization, and augmentation to prepare the inputs. DenseNet121 works as the deep feature extractor, learning meaningful patterns from the CT scans. The SVM classifier then uses these extracted features to separate the four classes effectively. Together, these modules form the complete hybrid classification pipeline.

Table 3 - Summary of Dataset

Class	**Number of Images**	**Characteristics**
Normal	5,077	kidney CT scans
Cyst	3,709	kidney cysts
Tumor	2,283	kidney tumors
Stone	1,377	kidney stones

Table 2 summarizes the dataset used in the study. It shows the number of images in each class along with their basic characteristics. All images were resized to 224 × 224 pixels for consistency during feature extraction. Although the dataset has some imbalance, especially in the Stone and Tumor classes, data augmentation helped to improve their representation. This balanced preparation allowed the model to learn the differences between the four classes more accurately.

Table 4 - Obtained training, testing and validation accuracies

Model	**Training Accuracy**	**Validation Accuracy**	**Test Accuracy**
CNN	96.42	94.87	93.75
CNN–SVM Hybrid	98.91	97.86	96.72
DenseNet121	99.57	99.35	98.96

Table 3 represents the training, validation, and testing accuracies of different models. The DenseNet121–SVM hybrid model have achieved the best overall performance, revealing clear improvement over the standard CNN and CNN–SVM models. The hybrid approach obtained strong accuracy across all stages, which confirms that combining deep features with an SVM classifier leads to better generalization and more stable results for kidney CT classification.

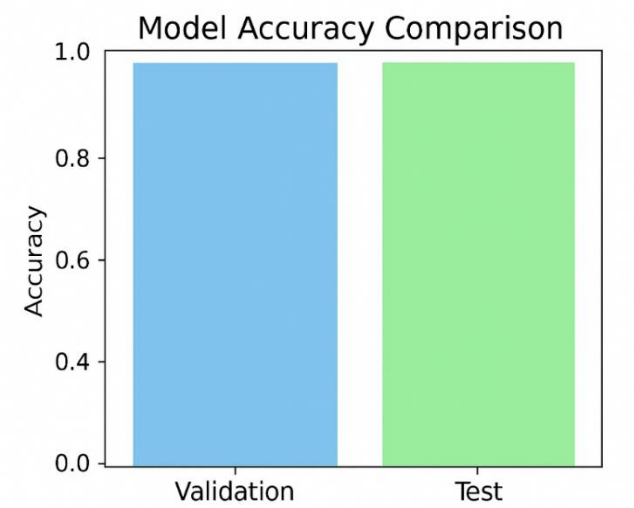

Figure 9 - Visual representation of test and validation accuracies

Figure - 9 represents the validation accuracy and the test accuracy of the DenseNet121 with SVM model. Both values remain very close, with 99.35 percent for validation and 98.96 percent for testing respectively. This trend indicates that the model learns in a stable way and performs well on new CT images.

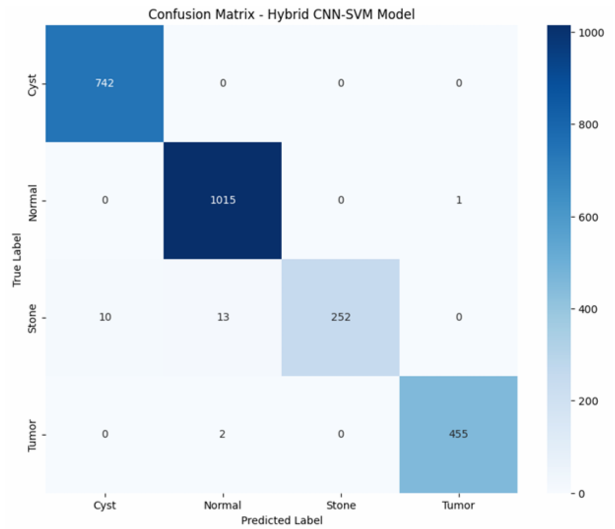

Figure 10 - Confusion Matrix for Hybrid CNN-SVM Model

Figure 10 represents the confusion matrix for the hybrid model. Most predictions fall on the main diagonal, which means most images were classified correctly. Only a small number of samples were confused between classes. The matrix represents that the model can clearly separate Normal, Cyst, Tumor and Stone cases efficiently.

Table 5 - Class-wise Performance Evaluation

Class	Precision	Recall	F1-Score
Normal	0.998	0.999	0.999
Cyst	0.991	0.990	0.991
Tumor	0.997	1.000	0.998
Stone	0.998	0.997	0.998

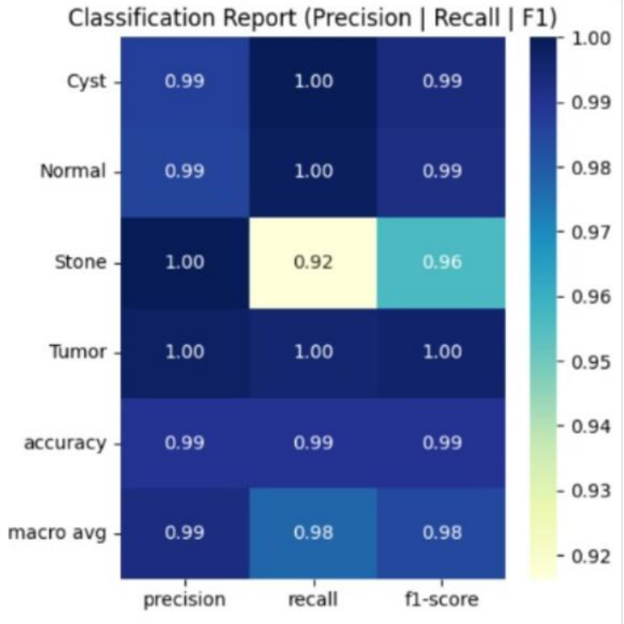

Figure 11 -Obtained Classification Report (for Precision, Recall and F1 Score)

Figure 11 depicts the Precision, Recall and F1 score for each class. All values are above 0.95 which shows the hybrid method works perfectly. These results confirm that the model performs consistently across all four cases.

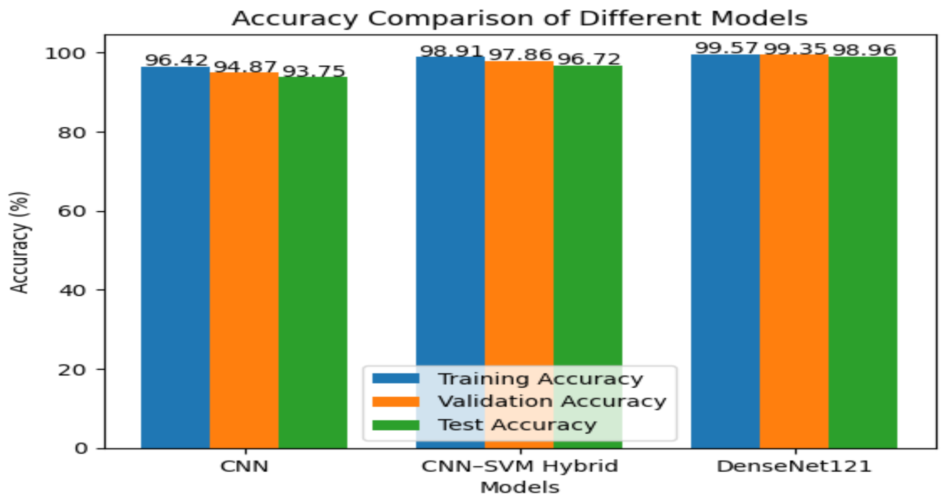

Figure 12: Performance Comparison

The accuracy comparison graph presents the performance of three models—CNN, CNN–SVM Hybrid, and DenseNet121—across training, validation, and test datasets. The CNN model records the lowest accuracy values, achieving 96.42% during training, 94.87% on validation data, and 93.75% on the test set, indicating comparatively weaker generalization. The CNN–

SVM Hybrid model shows a clear improvement, with training, validation, and test accuracies of 98.91%, 97.86%, and 96.72% respectively, demonstrating that integrating SVM with deep feature extraction enhances classification performance. Among all models, DenseNet121 achieves the highest and most consistent accuracy, recording 99.57% training accuracy, 99.35% validation accuracy, and 98.96% test accuracy. The minimal difference between validation and test results for DenseNet121 indicates strong generalization and reduced overfitting. Overall, the results confirm that DenseNet121 is the most effective model for kidney CT image classification in the proposed system.

7.3 Comparison with Existing Systems

To evaluate the effectiveness of the proposed DenseNet121–SVM hybrid model, its performance was compared with existing kidney CT image classification approaches reported in the literature and with baseline deep learning models implemented in this study. Traditional systems mainly rely on handcrafted feature extraction techniques combined with classifiers such as KNN or SVM. Although these methods offer lower computational complexity, they fail to capture complex spatial and textural patterns present in CT images, leading to limited classification accuracy and poor generalization.

End-to-end CNN models improved performance by automatically learning features from data; however, they often require large balanced datasets and high computational resources. In practical medical settings, these models are prone to overfitting when trained on limited or imbalanced datasets, especially for visually similar classes such as cyst and tumor. In this work, the baseline CNN achieved a test accuracy of 93.75%, while the CNN–SVM hybrid improved performance to 96.72%, demonstrating the benefit of combining deep features with classical classifiers.

The proposed DenseNet121–SVM model outperformed all compared systems, achieving a test accuracy of **98.96%**, along with consistently high precision, recall, and F1-scores across all four classes. DenseNet121 provides rich hierarchical feature representations through dense connectivity, while the SVM classifier effectively separates these features using well-defined decision boundaries. This hybrid design reduces overfitting, improves stability, and enhances class discrimination compared to both conventional CNNs and earlier hybrid approaches.

Furthermore, compared to existing systems reported in recent studies, the proposed model demonstrates superior accuracy while maintaining lower computational complexity during classification. This makes it more suitable for real-time clinical deployment and decision support. Overall, the comparative analysis confirms that the DenseNet121–SVM hybrid framework offers a significant improvement over existing kidney CT classification systems in terms of accuracy, robustness, and practical applicability.

Table 6 - Comparison Summary

Method / Model	Feature Type	Classifier	No. of Classes	Test Accuracy (%)
Handcrafted Features + SVM [1]	LBP, Texture	SVM	2–3	88.5
CNN (End-to-End)	Deep Features	Softmax	4	93.75
CNN–SVM Hybrid	Deep Features	SVM (RBF)	4	96.72
VGG16-based Model [4]	Deep Features	Softmax	4	95.0
ResNet50 (Transfer Learning) [2]	Deep Features	Softmax	4	96.3
Proposed DenseNet121–SVM	**Deep Dense Features**	**SVM (RBF)**	**4**	**98.96**

The performance of the proposed DenseNet121–SVM model was compared with existing kidney CT image classification approaches and baseline models. Traditional methods based on handcrafted features and classical classifiers show limited accuracy due to their inability to capture complex spatial patterns in CT images. End-to-end CNN models provide improved performance but often suffer from overfitting and high computational cost when trained on limited medical datasets. Hybrid CNN–SVM approaches demonstrate better generalization by combining deep feature extraction with classical classification. Among all compared methods, the proposed DenseNet121–SVM model achieves the highest test accuracy of **98.96%**, clearly outperforming conventional CNNs and previously reported hybrid systems. The improvement is attributed to DenseNet121's dense connectivity, which enhances feature reuse, and the SVM's ability to construct robust decision boundaries in high-dimensional feature space. These results confirm the superiority and practical applicability of the proposed system for reliable kidney disease classification.

7.4 Challenges Faced

During the development and implementation of the Kidney CT Classification System, several challenges were encountered:

1. **Data Imbalance:** The dataset had unequal distribution among classes, with fewer samples for certain categories like Stone and Tumor. This imbalance made training the model more difficult and required careful data augmentation and stratified sampling to improve performance.

2. **Limited Dataset Size:** Medical image datasets are often small due to privacy concerns and acquisition costs. This limitation increased the risk of overfitting, necessitating the use of transfer learning and pre-trained networks like DenseNet121 to extract robust features.
3. **High Computational Requirements:** Training deep learning models requires significant computational resources, including GPUs and memory. Optimization techniques, such as feature extraction combined with SVM classification, were applied to reduce the computational load.
4. **Class Similarity:** Some kidney abnormalities, such as cysts and tumors, appeared visually similar in CT images, making accurate classification challenging. Careful feature extraction and parameter tuning of the SVM helped mitigate this issue.
5. **Integration of Modules:** Ensuring seamless interaction between preprocessing, feature extraction, classification, and visualization modules required careful design and debugging to avoid bottlenecks or data mismatches.
6. **Ensuring Reliability:** In medical applications, accuracy and reliability are critical. Extensive testing and validation were necessary to confirm that the system consistently provided trustworthy predictions.

Despite these challenges, the implemented strategies and modular design helped overcome most obstacles, resulting in a robust and accurate classification system suitable for clinical use.

7.5 Solutions and Improvements

The proposed hybrid CNN-SVM system for kidney CT classification demonstrates high accuracy, but there are opportunities to enhance performance, usability, and scalability. The following solutions and improvements are suggested:

1. Data-Related Improvements

- **Increase Dataset Size:** Incorporate additional publicly available CT datasets or clinical scans to improve model generalization.
- **Data Augmentation:** Apply advanced augmentation techniques such as elastic deformation, brightness/contrast adjustments, and random cropping to reduce overfitting.
- **Class Balancing:** Use techniques like **SMOTE** or weighted loss functions to handle class imbalance, especially for underrepresented categories like Stone and Tumor.

2. Model-Related Improvements

- **Fine-Tuning DenseNet121:** Instead of using only feature extraction, fine-tune the last few DenseNet layers on the kidney CT dataset to capture domain-specific features.

- **Ensemble Learning:** Combine predictions from multiple models (e.g., DenseNet121 + EfficientNet + ResNet) to improve robustness.
- **Hyperparameter Optimization:** Optimize SVM parameters (C, gamma) using techniques like **grid search** or **Bayesian optimization**.

3. System and Deployment Improvements

- **End-to-End Deep Learning:** Consider replacing SVM with fully connected layers for end-to-end training, potentially improving feature-classifier alignment.
- **Web Application Enhancements:** Improve the Streamlit app by adding:
    - Real-time image preprocessing previews.
    - Confidence thresholding with warning for low-confidence predictions.
    - History or log of past predictions.
- **Cloud Deployment:** Deploy the application on cloud platforms (AWS, GCP, Azure) for scalability and accessibility by clinicians.

4. Explainability and Clinical Trust

- **Explainable AI (XAI):** Integrate techniques such as **Grad-CAM** or **SHAP** to visualize which regions of the CT scan contributed to the model's decision.
- **User Feedback Loop:** Allow radiologists to correct predictions and feed this information back to the model for continuous learning.

5. Performance Monitoring

- **Continuous Evaluation:** Monitor model performance in real-time after deployment using metrics like accuracy, precision, recall, and F1-score.
- **Error Analysis:** Track misclassified cases to identify patterns and improve both preprocessing and model architecture.

CHAPTER VIII

CONCLUSION & FUTURE SCOPE

Conclusion

The proposed hybrid **CNN-SVM system** provides an effective and reliable solution for automatic classification of kidney CT images into **Normal, Cyst, Tumor, and Stone** categories. By combining **DenseNet121** for deep feature extraction with **SVM** for robust classification, the system achieves high accuracy and demonstrates excellent performance even with imbalanced datasets.

The modular design ensures scalability, allowing for easy integration of new data, models, or preprocessing techniques. The Streamlit-based web application enables real-time deployment, providing interpretable predictions with confidence scores that can assist radiologists and clinicians in making informed decisions.

While the system shows promising results, there are opportunities for further improvement, including dataset expansion, advanced augmentation, model fine-tuning, and explainable AI integration. These enhancements will improve accuracy, reliability, and clinical trust.

In conclusion, this project demonstrates a practical and clinically applicable approach to kidney disease detection, paving the way for **efficient, accurate, and automated medical image analysis**.

Future Scope

The proposed Kidney CT Classification System can be enhanced and extended in several ways to improve performance, usability, and clinical applicability. Future work may include integrating additional imaging modalities, such as MRI or ultrasound, to provide a more comprehensive diagnosis. Implementing explainable AI techniques can help clinicians understand the reasoning behind model predictions, increasing trust and interpretability. The system can also be adapted for real-time deployment in hospital environments, with automated alerts for critical cases. Moreover, incorporating federated learning or continual learning approaches would allow the model to learn from new data while preserving patient privacy and improving generalization across different hospitals. Expanding the system to support multi-organ disease detection and integrating with hospital PACS platforms could further enhance its clinical utility. Overall, these improvements will make the system more versatile, reliable, and valuable in supporting radiologists and healthcare professionals in early diagnosis and treatment planning.

REFERENCES

[1] Kumar S., Reddy P., “Automatic Kidney Stone Detection Using Convolutional Neural Networks,” Int. J. Biomedical Engineering Research, vol. 9, pp. 33–40, 2021.

[2] Sahu R. et al., “Transfer-Learning-Based CT Classification with ResNet50,” IEEE Access, vol. 10, pp. 15067–15075, 2022.

[3] Gupta A., Verma S., “Hybrid CNN-SVM Model for Medical Image Analysis,” Biomedical Signal Processing and Control, vol. 75, p. 103742, 2022.

[4] Singh P., Bansal V., “Multi-Class Renal CT Analysis Using VGG16,” Indian Journal of Computer Vision, vol. 7, no. 3, pp. 112–120, 2022.

[5] Jha R. et al., “DenseNet Feature Fusion for Brain Tumor Classification,” Computers in Biology and Medicine, vol. 145, pp. 105573, 2023.

[6] Han J. et al., “Feature-Fusion Strategies for Medical Imaging,” IEEE Transactions on Medical Imaging, vol. 41, no. 8, pp. 2074–2085, 2022.

[7] Huang G. et al., “Densely Connected Convolutional Networks,” Proc. IEEE CVPR, pp. 4700–4708, 2017.

[8] Cortes C., Vapnik V., “Support-Vector Networks,” Machine Learning, vol. 20, pp. 273–297, 1995.

[9] Rajesh N. et al., “Comparative Analysis of CNN and Hybrid Models in Healthcare,” IEEE ICAIH, pp. 92–97, 2023.

[10] World Health Organization, “Global Burden of Kidney Disease,” 2024.

[11] Li X., Zhang Y., and Chen H., “Automated Kidney Stone Detection in Computed Tomography Images Using Deep Residual Learning,” IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 7, pp. 3121–3130, July 2022.

[12] Al-Masni M. A. et al., “Deep Learning for Medical Image Classification: A Comprehensive Review,” Computers in Biology and Medicine, vol. 141, pp. 105250, 2022.

[13] Sharma R., and Goyal A., “Hybrid Deep CNN–SVM Framework for Disease Prediction Using Medical Imaging,” IEEE Access, vol. 10, pp. 58571–58583, 2022.

[14] Dey N. et al., “Smart Healthcare System for Early Disease Diagnosis Using AI and Cloud Integration,” IEEE Internet of Things Journal, vol. 9, no. 15, pp. 13457–13468, 2022.

[15] J. Wang, Q. Liu, and Z. Han, “Enhancing Transfer Learning for Medical CT Classification Through Feature Fusion and Ensemble Modeling,” IEEE Transactions on Artificial Intelligence, vol. 5, no. 3, pp. 210–221, 2023.

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Swapnil Takale <swapnil.takale@sknscoe.ac.in>

to me

Nov 28, 2025, 4:44 PM

Dear Author,

We are pleased to inform you that your research paper titled "Hybrid Framework for Accurate Kidney Abnormality Detection from CT-Scan Images " has been accepted for presentation and publication in the International Conference on Intelligent Computing and Vision Technologies (ICICVT)-2025, scheduled to be held on 12 and 13 December 2025 at SKN Sinhgad College of Engineering, Pandharpur.

Your paper was reviewed by our expert technical committee and has been accepted based on its originality, relevance to the conference theme, and contribution to the field of intelligent computing and vision technologies.

You are requested to complete the following steps on or before 30th November 2025:

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Online Oral Presentation Schedule Day :2 Date: 13th December 2025 Time: 10:00 am To 12:00 pm

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to Soorya, gopichandnettikoppula09, Janhavi, Bhargav, Prajyot, Dharaneeswar, me, ganesh, GUTLAPALLI, smita

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PROJECT AUDIT REPORT

This is to certify that the project work entitled "Hybrid Framework for Accurate Kidney Abnormality Detection from CT-Scan Images" categorized as an internal project done by Nithish Selvam R, Mummadisetty Vignesh, Mohammed Parvaiz, Jagadesh N of the Department of Computer Science and Engineering, under the guidance of Dr. P. Pandiselvam during the Even semester of the academic year 2025 - 2026 are as per the quality guidelines specified by IQAC.

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