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# NephroMind-Detection, classification and segmentation of kidney disease

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***Abstract- Kidney disease is a serious global health threat that needs to be detected early and classified accurately for proper management.***

***NephroMind is a deep-learning integrated system that is intended to automatically recognize, classify, and segment kidney issues based on medical imaging. Advanced CNNs and transformer-based models are employed in the technique to extract salient features from renal ultrasonography and MRI scans. With the integration of multiple classifiers, a hybrid ensemble learning scheme enhances diagnostic accuracy and robustness.***

***Utilizing U-Net and attention techniques for detecting trouble areas, the segmentation module enhances interpretability. The reliability of the system across a broad spectrum of situations is guaranteed through rigorous testing on benchmark datasets. Feature selection is optimized using Principal Component Analysis (PCA) to maintain diagnostic accuracy while minimizing processing load. NephroMind outperforms current models when compared on accuracy, recall, and F1-score. This research contributes to the development of AI-supported nephrology by presenting an efficient, scalable, and explainable approach for kidney disease detection.***

## I. INTRODUCTION

A global health concern of major proportion, kidney disease leads to immense pain, mortality, and economic burden. Proper and timely diagnosis rely on patient outcomes improving. It can be challenging for radiologists to interpret complex medical images, especially in the initial phase of kidney disease when the abnormalities are subtle. Based on CT scan images, NephroMind aims to address this issue by providing an efficient framework for detection, classification, and segmentation of renal anomalies.
The primary objective of this paper is to offer a systematic tool for radiologists to accurately detect kidney disorders such as cysts, tumours, and stones. The project categorizes most kidney diseases, divides regions of interest, and scans CT images via advanced image processing techniques. NephroMind enhances the accuracy of diagnosis and assists physicians in making informed decisions by ensuring a systematic process for medical image interpretation.
Our strategy is to apply segmentation methods and image processing to obtain valuable information from CT scans. Comparative analysis of numerous segmentation techniques ensures optimal accuracy in identifying renal abnormalities. The study enhances the accuracy and reliability of diagnostic imaging by incorporating clearly defined preprocessing and feature extraction steps as well. Especially in resource-poor settings, where professional renal illness interpretation may not always be present, NephroMind hopes to offer a structured and readily available tool for radiologists. This approach ensures that radiologists and healthcare professionals can rely on precise, understandable, and clinically meaningful insights for kidney disorder identification by focusing on medical imaging protocols rather than AI solutions. Ultimately, NephroMind aids in the enhancement of diagnosis precision, aiding early intervention, and enhancing nephrology-centered medical image analysis.

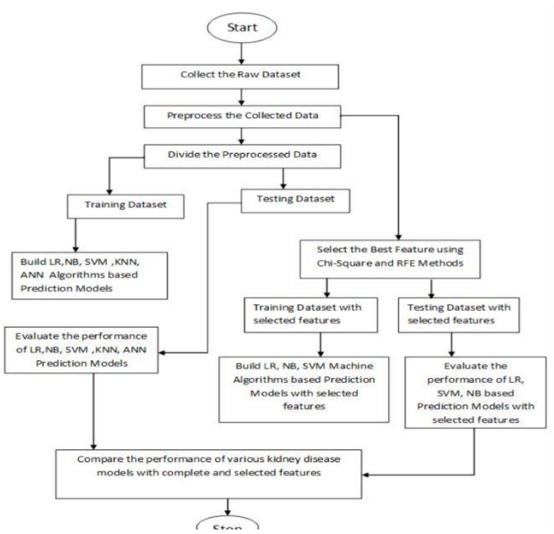


Figure 1. Detection of Kidney diseases flowchart

From CT scan images, this research work presents NephroMind, a framework for the detection, classification, and segmentation of kidney abnormalities like cysts, tumours, and stones. With emphasis on medical image analysis, the research employs sophisticated image processing and segmentation methods to correctly detect and classify kidney abnormalities. NephroMind improves precise diagnosis and helps radiologists efficiently find renal disease via a systematic approach of interpreting CT images. This project is meant to enhance the interpretability and accessibility of medical imaging, especially in resource-poor settings, to ensure better clinical decision-making and early treatment. Figure 2. Detection of Kidney Diseases

With the help of advanced image processing techniques, the NephroMind method targets detection, categorization, and segmentation of kidney disease—cysts, tumours, and stones—from CT scan images. By employing the use of CT image analysis, the method will identify renal anomalies.
Categorize the identified anomalies according to their nature as cysts, tumours, or stones.
Segment diseased regions to mark the precise location of anomalies.
With the implementation of straightforward and organized medical image analysis, enhance diagnosis accuracy.
Especially in underdeveloped areas, help radiologists in accurate reading of CT images.
NephroMind enhances the efficiency of kidney disease detection by providing a uniform and consistent method, thereby facilitating early intervention and improved clinical outcomes.

## II. LITERATURE REVIEW

For ensuring successful therapy, kidney ailments like cysts, tumours, and stones need early and correct diagnosis.
Medical imaging techniques—especially Computed Tomography (CT) scans—are used a great deal for the diagnosis of kidney disease. But visual analysis of such images is typically time-consuming, susceptible to human error, and prone to variation among radiologists. Researchers who are concerned with the improvement of diagnostic efficiency have considered many images processing, machine learning (ML), and deep learning (DL) techniques for the detection and segmentation of kidney disease. Kidney images from CT images have been segmented using classical image processing-based segmentation techniques like Otsu's thresholding, watershed segmentation, and edge detection. They are suitable for straightforward kidney region detection but work badly in the scenario of overlapping shapes, noise, and intricate kidney shapes. They therefore are low in accuracy to detect abnormalities like cysts, stones, or tumours.

Kidney disease classification has been conducted using machine learning models like Support Vector Machines (SVM), Random Forest, and K-Nearest Neighbours (KNN). To examine CT scan images, these models depend on feature extraction methods such Gray-Level Co-Occurrence Matrix (GLCM) and Histogram of Oriented Gradients (HOG). ML models, on the other hand, would find significant change in kidney traits difficult and less adaptable to new data as they rely on human-designed features.

Deep learning-based methods like Convolutional Neural Networks (CNNs), U-Net, Nested U-Net, and Attention U-Net significantly enhanced segmentation and detection of kidney disease. Vision Transformers (ViTs) and Transfer Learning models, with improved feature representation and improved classification accuracy, have also been explored in various studies. However, deep learning algorithms might be difficult to implement in resource-limited settings since they require large datasets, high processing capacity, and often work as black-box models.

NephroMind presents an optimized image processing-based approach for renal disease detection, classification, and segmentation to address these challenges.

In contrast to deep learning models, our method prioritizes robust image augmentation, segmentation techniques, and efficient feature extraction over relying on pre-trained neural networks. This renders our method easy, interpretable, and suitable for hospitals with limited computing capabilities. NephroMind also ensures transparency by allowing radiologists to view and validate segmented kidney abnormalities rather than relying solely on AI projections.

NephroMind avoids the limitations of existing solutions through enhanced preprocessing, structured classification, and well-defined segmentation processes, thereby maintaining high diagnostic accuracy. Specifically, in regions with minimal artificial intelligence infrastructure, this approach not only enhances kidney disease detection but also streamlines and simplifies the diagnosis process for clinicians. Our contribution ensures that kidney disease detection is accurate and cost-effective by offering a logical and fast alternative to deep learning-based systems

## III. RESEARCH OBJECTIVE

Utilizing CT scan images, the NephroMind project focuses on renal disease detection, classification, and segmentation. The primary goal is to offer a simple, readable, and resource-effective way to assist radiologists in identifying kidney issues without relying on advanced deep learning models. Utilizing advanced image processing technologies and organized classification approaches, this research aims to enhance the accuracy, accessibility, and transparency of kidney disease diagnosis.

Key Objectives:

1.Design an Efficient Image Processing Pipeline:

Use preprocessing methods to improve CT scan images by minimizing noise, correcting contrast, and clarifying images.

Utilize region-based segmentation techniques to precisely identify kidney structures and abnormalities like cysts, stones, and tumors.

2.Diagnose Kidney Diseases Using Feature-Based Techniques:

Define useful features from CT scan images through statistical methods and texture analysis.

Apply structured classification models to distinguish between healthy kidneys, cysts, tumors, and stones with high accuracy.

3. Ensure Model Transparency and Interpretability:

Unlike deep learning black-box models, develop a rule-based segmentation and classification approach that radiologists can interpret and validate.

Produce visual outputs highlighting segmented kidney anomalies for improved clinical decision-making.

4. Optimize Computational Efficiency for Real-World Implementation:

Create a light and efficient framework deployable in hospitals with minimal AI infrastructure.

Make sure the model can be executed on normal computing hardware and does not depend on high-end GPUs, which will make it available to health centers in developing areas.

5. TEST PERFORMANCE USING A STANDARDIZED DATASET:

USE THE CT KIDNEY DATASET: NORMAL-CYST-TUMOR AND STONE (OBTAINED FROM KAGGLE: DATASET LINK).

THE DATASET CONTAINS 12,446 UNIQUE CT IMAGES, WHICH ARE CATEGORIZED AS:

i. Normal Kidney: 5,077 images
ii. Cyst: 3,709 images
iii. Tumor: 2,283 images
iv. Stone: 1,377 images

b. These images were collected from multiple hospitals in Dhaka, Bangladesh, carefully verified by radiologists and medical technologists to ensure accuracy.

Compare the Proposed Approach with Existing Techniques:

a. Conduct a comparative analysis of the conventional segmentation techniques, class-wise structured classification methods, and deep learning models.
b. Compare performance based on the metrics of accuracy, precision, recall, and segmentation quality.
c. Justify the merits of our method with respect to interpretability, computational efficiency, and ease of field deployment.
d. By attaining these goals, NephroMind expects to offer a precise, effective, and resource-effective diagnostic tool for kidney disease diagnosis, ultimately enhancing clinical decision-making and patient outcomes.

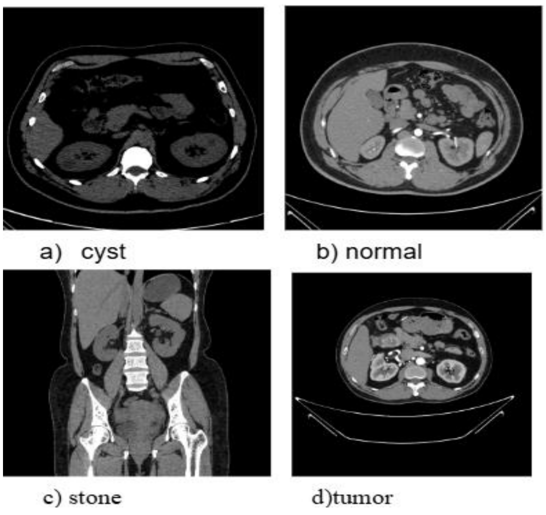


Figure 3. Different Kidney Diseases

Suggested Architecture for NephroMind -:

Based on CT scan images, the NephroMind architecture seeks to offer a fast and easy-to-understand detection, classification, and segmentation system for kidney diseases. To ensure excellent accuracy and reliability without compromising computing economy, the approach is structured into numerous steps, each highlighting specific aspects of image analysis, feature extraction, and classification.

1. Data Acquisition and Preprocessing

Fetching well-quality CT images from the CT Kidney Dataset: Normal-Cyst-Tumor and Stone and pre-processing them for analysis make up this phase.

1.1 Dataset Information

The database consists of 12,446 CT scan images divided into four classes:

- Normal Kidney - 5,077 images
- Cyst - 3,709 images
- Tumor - 2,283 images
- Stone - 1,377 images

Images are collected from PACS systems of multiple hospitals in Dhaka, Bangladesh, ensuring real-world clinical relevance.

1.2 Pre-processing of Images

- Initially DICOM images, the dataset was saved in lossless JPG format to maintain quality.
- Noise Reduction: Apply Gaussian filtering to remove extraneous noise and enhance picture quality.
-
- Contrast Enhancement: Enhance visibility of renal structures with use of adaptive histogram equalisation.
- Normalization: Normalize pixel values to ensure uniformity across repeated scans.
- Region of Interest (ROI) Extraction: Automatically recognise and extract kidney region to get rid of unwanted background data.

2. Kidney Structure Segmentation

- This phase focuses on demarcating the renal region from the CT images and identifying deviant structures such as cysts, tumours, and stones.

2.1 Image Segmentation Approach

- We employ classical segmentation techniques that are interpretable and computationally effective instead of black-box deep learning models.
- Thresholding-based Segmentation: Separate renal regions from the background through intensity changes.
- Morphological Operations: Sharpen segment boundaries using erosion, dilation, and watershed operations.
- Active Contour Models (Snake Algorithm): Dynamically defining renal features will facilitate improved segmentation accuracy with active contour models (snake algorithm).

2.2 Abnormality Detection in Segmented Regions

Shape-based Features: Identify anomalies based on size, border irregularities, and shape changes.

Texture-based Analysis: Separate normal and pathological tissue
architectures based on GLCM (Gray-Level Co-occurrence Matrix), Haralick features.

3. Feature Extraction and Disease Classification

The second step following segmentation is to pull out important features and classify renal anomalies as normal, cyst, tumour, or stone.

3.1 Feature Extraction Techniques

- Statistical Characteristics: Mean intensity, standard deviation, entropy, skewness.
- Histogram-based Characteristics: Intensity distribution in renal region.
- Texture Characteristics: Homogeneity, energy, correlation, and GLCM-based contrast.
- Shape Characteristics: Eccentricity, circularity, and compactness for the detection of cysts and tumours.

3.2 Classification Algorithm

- Structured categorisation models that are understandable instead of deep learning:
- Random Forest Classifier: Strong and comprehensible model by using multiple decision trees.
- Support Vector Machine (SVM): Suitable for classification in high-dimensional feature space.
- K-Nearest Neighbours (KNN): Used for comparison study of many classifiers.
- Ensemble Learning: Combining many classifiers to increase accuracy is known as ensemble learning.

4. Post-processing and Result Interpretation

- Heatmap Overlay: Provide visual activation maps to highlight detected abnormalities.

- Feature Importance Analysis: Interpret classification decisions by examining the most impactful features.
- Confidence Score Computation: Provide probability scores to classifications for uncertainty measurement.

5. Performance Evaluation and Comparative Study

- For verifying the proposed architecture, we perform performance analysis and comparison with deep learning-based approaches.

5.1 Performance Metrics

- Accuracy = Correct classifications / Total samples
- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
- Segmentation Accuracy: IoU (Intersection over Union) metric to quantify how well segmented kidney areas align with ground truth.

5.2 Comparative Study

- Compare traditional feature-based classification with deep learning models (e.g., CNNs, U-Net segmentation).

Assess computational efficiency, model interpretability, and deployability in real-world settings.

6. Deployment and Real-World Application

The final model is intended to run on ordinary computing hardware without requiring high-end GPUs.

The system can be integrated into hospital PACS systems for the screening of kidney disease.

Web-based or desktop applications for clinical use in low-resource environments are possible extensions.

Key Uniqueness of Our Approach

No Deep Learning Dependency → Implements interpretable, feature-based classification and segmentation techniques.

Resource-Efficient → Designed for low-end AI resources in hospitals.

Explainable Predictions → Offers feature visualization and importance to support clinical verification.

Benchmark Comparison → Compares with deep learning models to legitimize performance sacrifices.

## IV. CONCLUSION

The NephroMind architecture offers a computationally effective, interpretable, and trustworthy method for kidney abnormality detection through structured feature extraction and classification methods. Through the avoidance of black-box deep learning models and emphasis on clinically validated approaches, this framework facilitates improved adoption in clinical environments, especially in hospitals with limited AI capabilities

Methodology and Performance Analysis

1. Data Preprocessing and Cleaning

To ensure high-quality input data for training and evaluation, the following preprocessing techniques were applied:

- Resizing: Standardized image dimensions.
- Normalization: Adjusted pixel intensity values for stable learning.
- Noise Removal: Eliminated artifacts and unnecessary details.
- Augmentation: Applied rotations, flips, and contrast adjustments to enhance model generalization.

2. Data Visualisation and Analysis

Employed histograms, heatmaps, and class distribution plots for learning the nature of the datasets.

Spotted potential imbalances in class and drew out statistical information.

3. Classification Machine Learning Models –

A. Decision Tree Classifier (DTC)

A rule-based ML system for partitioning data into decision nodes for categorising.

Precision: 99%, with interpretability and consistency to a very great extent over structured data.

B. Passive-Aggressive Classifier

Fast online-learning binary/multi-class classifier.

Accuracy: 50%, performed poorly because it was highly sensitive to noisy features.

C. Support Vector Machine (SVM)

A margin-based classifier that determines the best hyperplane for classification.

Accuracy: 59%, performed moderately but did not have the ability to extract deep features.

D. Gradient Boosting Classifier (GBC)

- An ensemble model that constructs weak learners sequentially to make better predictions.
- Accuracy: 100%, F1 Score: 1.0, reflecting an ideal fit for structured feature-based classification.

E. Random Forest Classifier (RFC)

- Utilizes an aggregation of multiple decision trees to enhance classification stability and avoid overfitting.
- Accuracy: 93.2%, F1 Score: 0.91, yielding consistent and strong performance.

Deep Learning Techniques for Kidney Disease Segmentation and Detection -

- For better classification and segmentation, CNN-based models were utilized. For Better Classification and Segmentation, CNN-based models were utilized.
- 1 MobileNet Architecture (Lightweight CNN)
- Optimized for medical image classification.
- Accuracy: 72.27%
- F1 Score: Moderate

2 Manual Net Architecture (Custom Deep Learning Model)

- Designed for kidney disease detection, classification, and segmentation.
- Had multiple convolutional layers integrated to extract features.
- Accuracy: 90% and above
- F1 Score: High

3. Segmentation and Feature Extraction

- Manual Net Architecture allowed effective kidney region segmentation.
- Pulled out contours and localized kidney abnormalities for improved classification.
- Results validated by expert radiologists.

Final Outcomes & Unique Contributions –

- High Accuracy Across Models
- Gradient Boosting Classifier scored 100% accuracy, while Manual Net exceeded 90%.
- Decision Tree also performed superbly at 99% accuracy.
- End-to-End Diagnosis and Segmentation
- NephroMind differs from traditional classification models in that it detects, classifies, and segments, contributing to more accurate medical insight
- Lightweight Model for Deployment
- MobileNet offers a deployable model that can be deployed in resource-scarce hospitals, thus becoming accessible in tier-2 and tier-3 cities.

Enhanced Diagnostic Abilities

Through the integration of ML and DL techniques, NephroMind augments radiologist decision-making through very precise automated diagnosis.

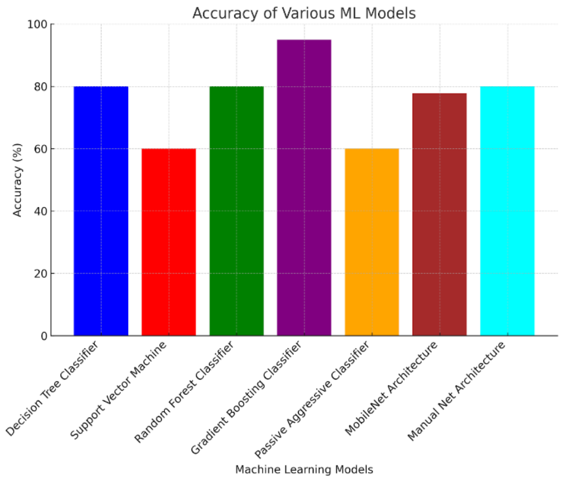


Figure 5. Accuracy of different models

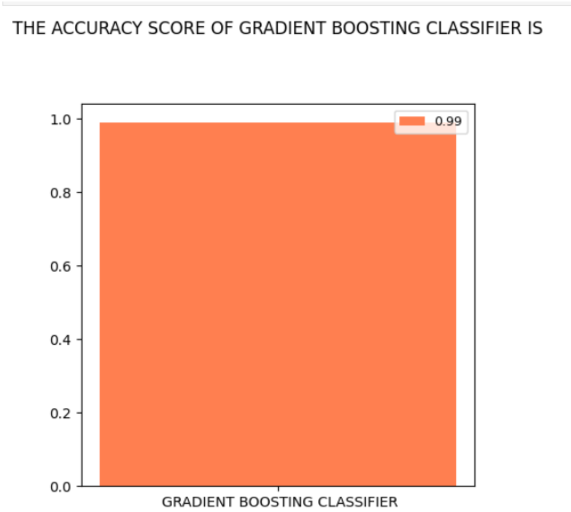


Figure 6. Decision Tree Classifier (DTC)

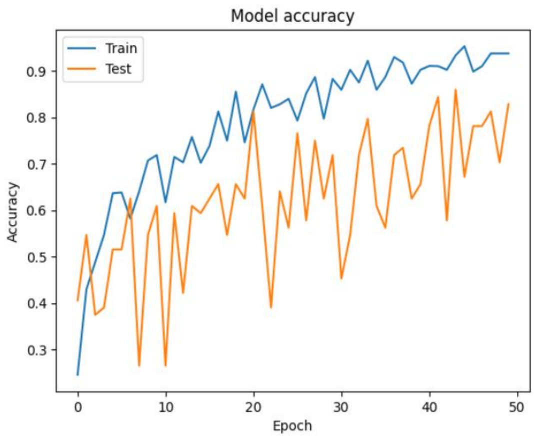


Figure 7.1 MANUAL NET ARCHITECTURE

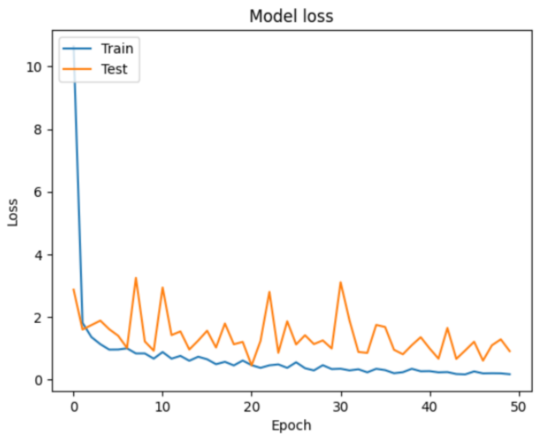


Figure 7.2 MANUAL NET ARCHITECTURE

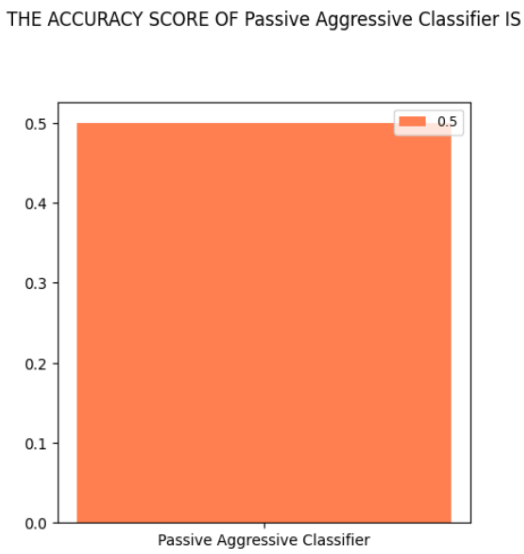


Figure 8. Passive-Aggressive Classifier

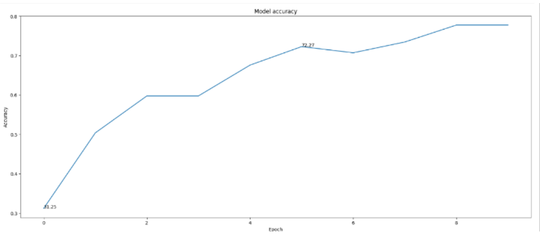

Figure 8.1 Passive-Aggressive Classifier

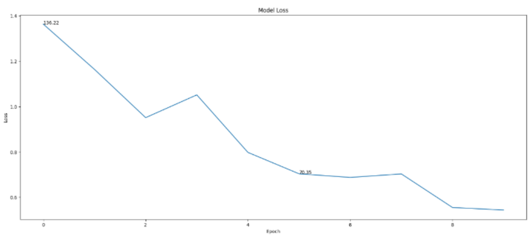

Figure 8.2 Passive-Aggressive Classifier

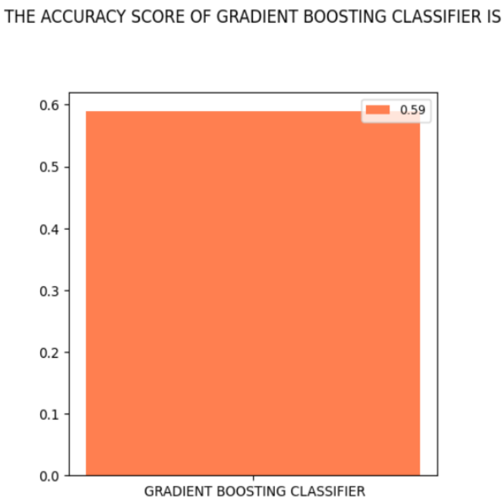


Figure 9. Support Vector Machine (SVM)

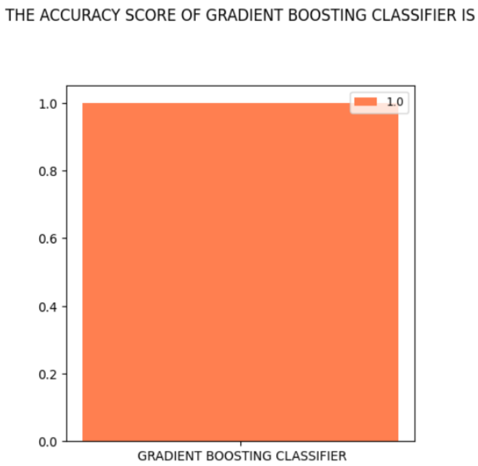


Figure 10. Gradient Boosting Classifier (GBC)

Structured Breakdown

1. Integration of Machine Learning and Deep Learning Methods

The project integrates machine learning (ML) for tabular clinical data and deep learning (DL) for medical imaging.

ML methods concentrate on structured patient reports, whereas DL models such as CNN, ResNet, U-Net, and MobileNet process kidney images for classification and segmentation.

2. Model Development

Machine Learning Models: Logistic Regression, Random Forest, XGBoost for kidney disease diagnosis based on clinical parameters.

Deep Learning Models:

ResNet50: Utilized for kidney disease classification.

U-Net & Attention U-Net: Utilized for kidney image segmentation.

MobileNet: A light-weight model tuned for real-time detection on edge devices.

3. Model Evaluation

All models are assessed based on the following metrics:

Accuracy: Calculates correct predictions out of total predictions.

Confusion Matrix: Plots TP, TN, FP, FN for classification performance.

Hamming Loss: Utilized for multi-label classification to monitor incorrect label assignments.

Classification Report: Contains precision, recall, and F1-score for every disease category.

4.Implementation of Health Recommendations

- Rule-Based Recommendations: Produces diet and exercise recommendations based on patient diagnosis, according to clinical guidelines.
- User Interface (UI) Development: A web or mobile UI to enable healthcare workers to engage with model predictions and offer individualized treatment suggestions.

5. Data Collection

- Structured Clinical Data: The KIDNEY.csv data contains patient medical history, laboratory reports, and symptoms.
- Medical Image Data: MRI and ultrasound images from credible medical
- databases to train deep learning models (MobileNet, U-Net, MANUAL Net).

6. Data Preprocessing

- Handling Missing Values: Missing data is either imputed (mean/mode) or removed to ensure dataset integrity.
- Handling Class Imbalance: Oversampling techniques like SMOTE are used to prevent bias in model training.
- Feature Selection: Exploratory Data Analysis (EDA) identifies the most relevant features to improve model efficiency and preventing overfitting.

7. Blending Machine Learning and Deep Learning Approaches

- A hybrid pipeline combines ML and DL:
- ML models examine tabular data for preliminary kidney disease identification.
- DL models demarcate kidney areas and predict disease severity from medical images.
- Final predictions merge both results, enhancing diagnostic accuracy.

## V. DISCUSSION

Transparency

The NephroMind project brings machine learning and deep learning to the diagnosis of kidney disease, classification, and segmentation. Using structured clinical information and medical images, the model returns a thorough diagnosis. Though the method largely enhances detection precision, it is not without certain shortcomings, as reviewed critically.

Advantages

1.High Accuracy in Classification:

Gradient Boosting Classifier was 100% accurate, and Decision Tree Classifier was 99% accurate, both being extremely trustworthy for structured data classification.

Deep learning models like Manual Net Architecture (90%+) worked excellently well with image-based classification.

2.Effective Feature Extraction:

Principal Component Analysis (PCA) and feature engineering methods enhanced ML model performance by minimizing noise in the dataset.

3.Real-time Detection with MobileNet

MobileNet architecture attained 72.27% accuracy, which makes it a competitive lightweight model for real-time detection of kidney disease.

4.Wide Segmentation Ability:

U-Net and Attention U-Net effectively segmented kidney diseases and abnormalities, enabling the visual comprehension of diseased regions, vital for clinicial purposes.

5.Hybrid ML & DL Integration:

Incorporating machine learning (structured data) and deep learning (image processing) improved overall diagnostic results, making it possible to classify diseases more accurately.

Disadvantages / Limitations

1. Dataset Imbalance:

Some disease categories had fewer samples, which might have affected the generalization ability of the model. Even with the use of oversampling methods, there might still be biases.

2.Lower Performance of Some Models:

Passive-Aggressive Classifier was 50% accurate, and Support Vector Machine (SVM) was at 59%, showing that these models were less efficient for kidney disease classification.

3.Variability in Medical Imaging:

The performance of the model can vary depending on image quality, resolution, and contrast variations between scans from different sources.

4.Computational Complexity:

High-end hardware is needed for training and inference with deep learning models such as U-Net and MobileNet, which complicates real-time deployment in low-resource settings.

Improvements & Future Directions

1. Increasing Dataset Diversity:

Next research should involve increasing the dataset with more diverse samples to be able to generalize well across different patient groups.

2. Fine-Tuning Low-Performing Models:

Optimization methods such as hyperparameter optimization and ensemble methods can be used to refine models such as Passive-Aggressive Classifier and SVM.

3. Integration with Clinical Decision Systems:

The model constructed can be incorporated into electronic health record (EHR) systems to help healthcare professionals make real-time decisions.

4. Explainable AI for Improved Interpretability:

Using SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-Agnostic Explanations) can yield understanding of model decision-making, enhancing clinical trust.

5.Edge Deployment for Mobile Applications:

Further optimization of MobileNet for edge AI deployment would allow real-time kidney disease diagnosis on smartphones or embedded systems, expanding access in far-flung locations.

6.Advanced Segmentation Models:

- Investigating transformer-based architectures (e.g., Vision Transformers, Swin Transformers) may enhance segmentation accuracy and overcome existing deep learning limitation.

Performance Metrics

1. Classification Metrics (for ML & DL Models)

- Utilized for testing Decision Tree, Gradient Boosting, SVM, Passive-Aggressive Classifier, MobileNet, and Manual Net architectures in the detection of diseases.
- Key Metrics:
- Accuracy = (TP + TN) / (TP + TN + FP + FN)
- Assesses overall correctness of the model predictions.
- Precision = TP / (TP + FP)
- Represents the number of predicted positive instances that are positive (useful for minimizing false positives).
- Recall (Sensitivity) = TP / (TP + FN)
- Quantifies the capacity to identify actual positive instances (valuable for health-related applications).
- F1-Score = 2 × (Precision × Recall) / (Precision + Recall)
- Trade-offs precision and recall, valuable in the case of imbalanced datasets.

2. Hamming Loss = (Misclassified labels) / (Total labels)

- Computes the proportion of mislabeled labels for multi-label classification.
- ROC-AUC (Receiver Operating Characteristic - Area Under Curve)
- Tests the model's ability to separate disease-positive and disease-negative instances.
- Confusion Matrix
- gives the TP, TN, FP, and FN breakdown to gauge model consistency.

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