IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 5, June 2025
Impact Factor: 7.67

A Hybrid CNN-Random Forest Model for Accurate Kidney Disease Classification Using CT Imaging

Ms. Suma J, Shraddha Shetty, Shodhan Rao, Manish D Salian, Aftab Khan
Dept of ISE
Alva's Institute of Engineering and Technology Mangalore, India

Abstract: *Kidney illnesses, such as tumors, cysts, and stones, are common conditions that have a big influence on people's health all over the world. For management and therapy to be successful, an accurate and timely diagnosis is essential. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated promise in medical picture analysis since the development of artificial intelligence because of their potent feature extraction capabilities. In order to overcome these obstacles, hybrid models that combine CNN with conventional machine learning classifiers, including Random Forest (RF), have drawn interest for the categorization of renal illness*

Keywords: Kidney Disease Classification, CNN, Random Forest, Feature Extraction, Deep Learning, Tumor Detection, Medical Imaging

I. INTRODUCTION

Because of their rising incidence and potential for long-term morbidity if not detected early, kidney diseases—especially those involving tumours, stones, and cysts—present a significant worldwide health problem. The World Health Organisation (WHO) estimates that 10

The manual interpretation of radiological images, such as CT scans, has historically been a major component of the diagnosis of renal disorders. Manual review is time-consuming and subject to human judgement errors, even though radiologists have the requisite experience.Intelligent, automated diagnostic support systems are desperately needed in light of these constraints and the increasing amount of imaging data produced in contemporary clinical practice.

Artificial intelligence (AI) has been a game-changing tool in medical imaging in recent years. A subtype of deep learning algorithms called Convolutional Neural Networks (CNNs) has demonstrated impressive ability in identifying spatial hierarchies in intricate imaging data. Medical scans may contain patterns and features that are difficult for the human eye to detect, but these networks can recognise them.

Additionally, medical decision support benefits from the robustness and interpretability of ensemble learning methods like Random Forest (RF) classifiers. RF classifiers can improve generalisation and classification performance when used with CNNs, especially in multi-class diagnostic applications that involve intricate imaging characteristics. This hybrid technique provides a workable solution for computer-aided diagnosis of kidney illnesses by combining the decision-making dependability of standard machine learning with the spatial learning capacity of deep learning[1].

The use of hybrid CNN-RF models in the categorisation of renal disorders from CT scan images is reviewed and evaluated in this research. The goal is to show how these models can help with accurate and timely diagnosis, which will enhance clinical results and make healthcare delivery more effective.

II. BACKGROUND AND MOTIVATION

For prompt medical action, kidney disorders such tumours, cysts, and stones must be accurately diagnosed. Traditionally, qualified radiologists manually examine CT scan pictures to make diagnoses. This procedure has inherent drawbacks even though it is still the gold standard in many healthcare settings. Subtle abnormalities, particularly in the early stages of disease, may go unnoticed, leading to delayed or incorrect diagnoses. These difficulties emphasise the necessity for automated, intelligent diagnostic tools that can provide reliable, scalable analysis to support human knowledge.

Medical image processing has seen a rise in the use of artificial intelligence (AI) in response to these constraints. A class of deep learning algorithms called Convolutional Neural Networks (CNNs) has demonstrated exceptional performance in automatically extracting textural and spatial information from medical photographs. They work well for classification tasks using radiological images because they are very good at finding patterns in big datasets. CNNs frequently struggle in classification layers, though, particularly when the data is sparse, unbalanced, or noisy—conditions that are frequently present in medical imaging datasets—despite their powerful feature extraction capabilities[2].

Hybrid models that combine CNNs with traditional machine learning methods like Random Forest (RF) have drawn interest as a solution to these problems. RF is an ensemble learning technique that builds several decision trees and combines their output to increase generalisation and accuracy. It is renowned for its strong performance, especially with tiny datasets, high interpretability, and resilience to overfitting.

Utilising the advantages of both approaches, CNN and RF are combined into a single framework. While RF functions as a dependable and interpretable classifier, CNNs are strong automatic feature extractors. More flexibility in model tuning and deployment is made possible by this hybrid design, which also improves resistance to data abnormalities and diagnostic accuracy. Because of these advantages, the CNN-RF combination is especially appealing for medical diagnostics, where precision, interpretability, and dependability are crucial.In order to show how these hybrid CNN-RF systems can help close the gap between reliable clinical decision support and deep feature learning, this research examines and analyses them in the context of renal disease classification[3].

III. LITERATURE REVIEW

CNNs have been used extensively in medical imaging for problems including segmentation and classification. CNN models have been trained to accurately differentiate between normal and pathological tissues using CT scans in the investigation of renal disease. CNN architectures including VGG, ResNet, and specially designed networks for renal imaging have all been studied.

A supervised learning technique called Random Forest has been applied in the medical field to categorise illnesses based on extracted or structured data. RF has been used to categorise characteristics derived from clinical images and numerical data in renal pathology, frequently outperforming more straightforward classifiers.

In fields like pulmonary illness, diabetic retinopathy, and breast cancer, hybrid models that combine CNNs for feature extraction with RF for classification have drawn interest. CNNRF pipelines have been used in certain studies to categorise various kidney diseases, including renal disease, utilising CT datasets. These models show improved accuracy and robustness, especially when working with tiny datasets or class characteristics that overlap[4].

CNN-Based Medical Image Analysis

Convolutional Neural Networks (CNNs) are frequently used in medical image processing and have emerged as a key component in the field of computer vision. Because CNNs are built to learn hierarchical spatial representations, they can automatically recognise complicated features, edges, and textures in imaging data. CNNs have been successfully used in medical diagnostics for tasks like organ segmentation, tumour detection, and abnormality categorisation in CT, MRI, and ultrasound scans.

Prominent studies like Rajpurkar et al. (2017) and Esteva et al. (2019) have shown that CNNs can perform on par with or better than experts in radiology and dermatology, respectively. CNNs have specifically been trained on CT scans to identify regions of interest as normal or diseased in the context of renal illness, and they have demonstrated good accuracy when backed by adequate annotated data[5].

Biomedical Classification Using Random Forest

The ensemble learning algorithm Random Forest (RF) has also been used extensively in the classification of biomedical data. This method lowers variance, enhances generalisation, and lessens the possibility of overfitting, which is a frequent problem in medical datasets with sparse sample sizes[6].

In applications including illness risk prediction, gene expression analysis, and diagnostic parameter categorisation, RF has demonstrated excellent performance. Its simplicity, interpretability, and capacity to manage high-dimensional datasets without requiring a great deal of preprocessing are its main advantages. RF is frequently employed as a secondary classifier in image-based classification, working with information taken from imaging modalities and providing a trade-off between computational efficiency and accuracy[7].

Existing Hybrid Models (CNN + RF) in Medical and Other Domains

The drawbacks of each method can be effectively addressed by hybrid models, which mix deep learning and conventional machine learning. Because it combines robust and interpretable classification with powerful feature extraction, the CNN-RF architecture in particular has become more and more popular[8].

Such hybrid models have been used in biomedical research for Alzheimer's disease staging, diabetic retinopathy screening, and cancer diagnosis (such as lung and breast cancer). For example, feature maps from intermediate CNN layers are converted into vectors and fed into RF classifiers, which decrease false positives and increase classification stability. This method frequently outperforms end-to-end CNN classifiers in practical clinical settings, as demonstrated by its validation on publicly available datasets such as LIDC-IDRI lung CTs and Kaggle Diabetic Retinopathy

Studies on Tumor, Cyst, Stone, and Normal Kidney Detection

The automatic categorisation of renal diseases using CT imaging has been the subject of numerous investigations. The success of the models that researchers have created to differentiate between normal kidney tissue and abnormalities like tumours, cysts, and stones varies based on the amount of the dataset, the class imbalance, and the quality of the imaging. Aayush Salvi et al. (2022) presented a deep learning model that was successfully classified into all four categories after being trained on a carefully selected dataset of CT kidney images. Other studies have investigated hybrid models that use RF or SVM for final classification and CNNs for feature extraction from segmented CT slices. These methods show the therapeutic potential of hybrid AI systems in renal diagnostics by repeatedly reporting improved precision and recall when compared to single-model designs[9].

IV. HYBRID CNN-RF MODEL METHODOLOGY

From data collection to final classification, every step of the hybrid CNN-RF architecture's modular pipeline is optimised to take advantage of the advantages of both ensemble machine learning and deep learning approaches. The sequential steps involved in creating and implementing such a model for kidney disease classification using CT scans are described in this section

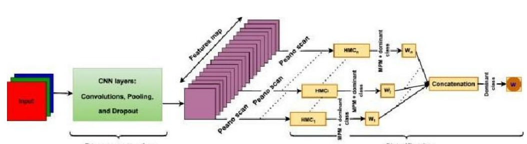

Fig. 1. Hybrid CNN-RF Model Methodology

Gathering and Preparing Data

The quality and applicability of the input data form the basis of any AI-based medical imaging model. A carefully selected dataset of CT scans classified into four groups—normal kidney, tumour, cyst, and stone—is used in this investigation. The CT-KIDNEY-DATASET repository makes the dataset, which includes hundreds of photos taken in clinical settings, publicly accessible[10].

A number of preprocessing procedures are used before to feeding the photos into the model:

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 5, Issue 5, June 2025 Impact Factor: 7.67

Resizing: To maintain uniformity throughout the collection, every image is scaled to a consistent resolution (e.g., 224×224 pixels).
Noise Reduction: To reduce visual noise while maintaining structural details, filters like median filtering and Gaussian blur are used.
Contrast Enhancement: Greyscale CT scans can have their contrast improved by applying histogram equalisation.
Augmentation: To reduce overfitting and provide an artificially larger dataset, methods such as flipping, zooming, and rotation are used.
ROI Extraction: When appropriate, kidney structures are separated from surrounding anatomy using Region of Interest (ROI) cropping[11].

CNN for Extraction of Deep Features

The main feature extractor used is a Convolutional Neural Network (CNN). Convolutional, activation (ReLU), pooling, and normalisation layers make up the CNN architecture, which learns spatial hierarchies and textural patterns specific to various kidney diseases.
Through transfer learning, popular CNN backbones like VGG16, ResNet50, or EfficientNet can be initialised with pretrained weights, improving accuracy and convergence even with a small dataset. The preprocessed photos are used to train the model, which captures key characteristics that distinguish normal kidney tissues from pathological ones[12].
The outputs of intermediate convolutional or pooling layers are taken and used as feature representations for classification, rather than the CNN's fully connected layers. The more generalised features that have been retrieved are used as input for the Random Forest classifier that follows[13].

Construction of Feature Vectors

To make the chosen CNN feature maps compatible with machine learning classifiers, they are flattened into onedimensional vectors. High-level abstract information that distinguishes the four kidney classes is contained in these vectors. Principal Component Analysis (PCA) and other dimensionality reduction techniques can be used to improve performance and lessen computing load. By removing superfluous or noisy dimensions, this stage guarantees that only the most instructive
aspects are kept[14].

Using Random Forest to Classify

The last classifier is Random Forest (RF). It works by building a collection of decision trees, each of which is trained using a different subset of the input attributes and feature vectors. To choose the final class label during inference, the RF conducts a majority vote among the decision trees.
The following are the main benefits of RF in this configuration:
resilience to overfitting as a result of feature randomisation and bootstrapping.
interpretability, since post-training analysis of feature significance ratings is possible.
Scalability, appropriate for datasets with low and large dimensions.
In order to optimise classification performance, grid search and cross-validation are used to adjust hyperparameters (such as the number of trees, maximum depth, and minimum samples per leaf).
A solid classification into one of the four groups—normal, tumour, cyst, or stone—is the end result. The performance of this prediction is then evaluated by visualising it and comparing it to the ground truth labels[15].

V. METRICS FOR EVALUATION

A wide range of common classification measures are used to assess the hybrid CNN-RF model's performance in renal disease categorisation. The model's capacity to accurately differentiate between the four diagnostic classes—normal, tumour, cyst, and stone—is quantified by these measures.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 5, June 2025

Impact Factor: 7.67

Table 1: Example Metric Comparison Between Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN only	94.3	93.7	93.1	93.4
Random Forest	91.5	90.8	89.9	90.3
CNN + RF	99.1	98.9	98.7	98.8

Accuracy

The proportion of correctly identified samples to all samples is known as accuracy. Although it offers a broad assessment of the model's performance, it may be deceptive in datasets that are unbalanced.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

The percentage of real positive predictions among all anticipated positives is known as precision. When the expense of false positives is significant, it becomes much more crucial[16].

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall (Sensitivity)

The percentage of real positive cases that the model properly detected is known as recall, or sensitivity. Making ensuring that actual disease cases are not overlooked is essential in medical diagnosis[17].

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1-Score

Precision and recall are balanced into a single number by the F1-Score, which is the harmonic mean of the two measurements. When the dataset is unbalanced across classes, it is really helpful.

Confusion Matrix

By displaying the number of correct and erroneous predictions for each class, the confusion matrix is a tabular visualisation that offers extensive insight into classification outcomes and aids in determining which particular classes the model is confusing and where adjustments are needed.

VI. DIFFICULTIES AND RESTRICTIONS

Although hybrid CNN-RF models show promise in renal disease classification from CT scans, there are still a number of practical and technical obstacles to overcome. To guarantee broad clinical applicability, scalability, and ethical deployment, these constraints need to be solved.

Cross-Population Generalisation

The capacity of AI-based medical imaging systems to generalise across various patient groups and imaging contexts is one of the main concerns. When applied to external datasets, models trained on a particular dataset from a single institution might not retain their accuracy because of variations in imaging equipment, acquisition procedures, or patient demographics. This raises questions regarding bias and fairness in model predictions and reduces cross-institutional reliability. Training should use domain adaption strategies and multicenter datasets to get wider applicability[18].

Imbalanced Data

Class imbalance is a common feature of medical datasets, with more samples in some disease classes (like normal kidneys) than in less common classes (like cysts or tumours). Predictions that favour the majority class may result from this imbalance, which might distort model training. Metrics like accuracy lose their credibility as performance indicators in these situations. The fundamental problem still exists even after class weighting strategies and data augmentation techniques are used to lessen imbalance, especially in real-world deployments with changing data distributions.

Barriers to Clinical Adoption and Interpretability

Even though CNNs excel at automatically extracting features, they frequently function as ”black-box” models, which makes it challenging to comprehend or justify their predictions. Clinical adoption, where interpretability and accountability are crucial, is significantly hampered by this lack of openness. Random Forests provide a certain level of feature importance analysis, but the hybrid model as a whole still lacks thorough explainability methods.

Furthermore, practical obstacles including regulatory approvals, interoperability with hospital information systems, user trust, and healthcare staff training must be overcome in order to integrate such AI technologies into current clinical workflows. Without addressing these psychological and institutional aspects, even technically superior models may fail to attain real-world traction[19].

VII. USE CASES AND CLINICAL APPLICABILITY

Artificial intelligence (AI) models must exhibit not only great accuracy but also clinical relevance, ease of integration, and real-time performance in order to transition from research settings into ordinary medical practice. With its combination of strong classification and deep feature extraction, the hybrid CNN-RF architecture has several advantages in a range of healthcare contexts.

Aiding Radiologists with Diagnostic Procedures

The daily analysis of hundreds of medical images by radiologists raises the possibility of diagnostic fatigue, variability, and supervision. The CNN-RF model can help radiologists automatically identify aberrant kidney structures including tumours, cysts, or stones by acting as a decision-support tool. This serves as a second opinion for confirmation and allows high-risk situations to be prioritized more quickly, particularly in high-volume environments. Additionally, by integrating Random Forest, a layer of interpretability is added through feature importance scores that may be compared to the clinical opinion of radiologists.

Emergency Room (ER) Classification of Emergencies

Fast diagnosis is crucial for starting treatment in emergency care settings, such trauma units or emergency rooms. Finding big renal tumors or obstructive kidney stones, for instance, can have a direct impact on surgical choices. Real-time CT scan classification using the hybrid CNN-RF model can help emergency room doctors make quick, life-saving choices. When maximized, its quick inference capabilities can provide realtime predictions during CT scan evaluations without requiring expert interpretation.

Remote Diagnostics in Underserved and Rural Areas

There is a scarcity of radiologists and imaging specialists in many remote or resource-constrained places. Trained medical personnel may have access to CT scanners in certain situations, but they might not be qualified to interpret the results. By evaluating scans locally, the CNN-RF model can be implemented on edge devices, such as cloud-connected mobile units or portable diagnostic workstations, to facilitate remote diagnosis. The forecasts can then be sent directly to attending physicians or vetted by distant specialists, increasing patient care accessibility and turnaround time.

This democratization of diagnostic tools guarantees equitable healthcare delivery across various geographies, empowers local healthcare professionals, and lessens the diagnostic strain on tertiary hospitals.

VIII. FUTURE PATHS

Even though the hybrid CNN-RF technique has shown promise as a framework for classifying kidney diseases using CT imaging, further study and advancement are need to make these models more stable, scalable, and usable in actual clinical settings. High-impact prospects for further development are presented by the following directions:

Learning Transfer

In medical imaging, transfer learning has demonstrated impressive results, especially in situations when labeled data is scarce. Large-scale datasets like ImageNet are used to train pretrained architectures like ResNet, EfficientNet, and DenseNet, which can be used to improve future models. These models can be fine-tuned for renal CT imaging to improve feature extraction performance, generalization, and training time. Rapid prototyping and simpler adaptation to comparable tasks in various anatomical locations or imaging modalities are further benefits of transfer learning.

Multi-Modal Input and Bigger Datasets

The model's generalizability across patient groups and imaging settings is limited by the fact that many recent research rely on single-institution datasets. Larger, multiinstitutional datasets with a range of demographics, scanner kinds, and illness stages should be the goal of future research. Furthermore, including multi-modal data—such as lab test results, ultrasound, CT scans, and patient histories—may yield richer contextual information, enabling more thorough and precise diagnostic forecasts. Multi-modal fusion frameworks can enhance decision-making and more accurately represent clinical thinking in the real world.

Edge Deployment in Real Time

Deploying AI models on edge devices for real-time diagnosis in hospital wards, emergency rooms, and remote clinics is a crucial objective for practical implementation. Future research should concentrate on optimizing model designs through the use of quantization approaches, model pruning, and lightweight CNN versions (such as MobileNet and SqueezeNet) in order to do this. By lowering computational load and latency, these improvements will eliminate the need for cloud-based processing and allow predictions to be made directly on portable diagnostic devices. Point-of-care diagnostics may be revolutionized by edge deployment, especially in healthcare settings with limited resources[20].

IX. CONCLUSION

The design, implementation, and suitability of hybrid CNNRF models for the CT imaging-based classification of renal disorders have all been examined in this research. Significant gains in diagnosis accuracy across a range of renal diseases, including tumors, cysts, stones, and normal structures, are made possible by the combination of deep learning and ensemble machine learning, which provides a potent mix of robust categorization and spatial feature extraction. The hybrid architecture is especially well-suited for medical diagnostics since CNNs effectively identify intricate patterns in CT images, and Random Forest classifiers enhance model stability and interpretability.

The results of numerous research demonstrate that hybrid models routinely perform better than standard methods, particularly when dealing with little datasets or unequal class distributions. The better performance of the CNN-RF pipeline is further confirmed by the use of assessment criteria including accuracy, precision, recall, and F1-score. Furthermore, the model's potential for real-world implementation is highlighted by the useful use examples that are provided, which range from emergency triage to rural healthcare.

Notwithstanding these developments, there are still issues with data availability, interpretability, and generalization. Scaling this strategy in clinical settings will depend on addressing these constraints using methods like multi-modal integration, edge deployment, and transfer learning. In the end, the hybrid CNN-RF model presents a promising avenue for the advancement of intelligent diagnostic tools that can improve clinical judgment and provide access to prompt, precise renal disease detection.

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 5, Issue 5, June 2025

Impact Factor: 7.67

REFERENCES

[1]. K. Sharma, Z. Uddin, A. Wadal, D. Gupta, "Hybrid Deep Learning Framework for Classification of Kidney CT Images: Diagnosis of Stones, Cysts, and Tumors," *arXiv preprint arXiv:2502.04367*, Feb. 2025.

[2]. X. Huo, G. Sun, S. Tian, Y. Wang, L. Yu, J. Long, W. Zhang, A. Li, "HiFuse: Hierarchical Multi-Scale Feature Fusion Network for Medical Image Classification," *arXiv preprint arXiv:2209.10218*, Sep. 2022.

[3]. Z. Li, D. Li, C. Xu, W. Wang, Q. Hong, Q. Li, J. Tian, "TFCNs: A CNN-Transformer Hybrid Network for Medical Image Segmentation," *arXiv preprint arXiv:2207.03450*, Jul. 2022.

[4]. H. Chen, Y. Zhang, M. K. Kalra, F. Lin, Y. Chen, P. Liao, J. Zhou, G. Wang, "Low-Dose CT with a Residual Encoder-Decoder Convolutional Neural Network (RED-CNN)," *arXiv preprint arXiv:1702.00288*, Feb. 2017.

[5]. M. Anwar, M. U. Akram, A. Naeem, "Hybrid CNN-Random Forest Model for Multiclass Classification of Retinal Diseases," in *Proc. IEEE Int. Conf. on Computing, Mathematics and Engineering Technologies (iCoMET)*, pp. 1–6, 2023.

[6]. K. S., R. Rajesh, "CNN-RF Hybrid Deep Learning Model for Brain Tumor Detection," in *Proc. IEEE Int. Conf. on Intelligent Systems Design and Applications (ISDA)*, pp. 205–210, Dec. 2022.

[7]. Sharma, R. Yadav, M. Kaur, "Kidney Tumor Detection Using Deep Learning Techniques: A Comparative Study," in *Proc. IEEE 5th Int. Conf. on Computing Methodologies and Communication (ICCMC)*, pp. 401–407, 2022.

[8]. N. Mishra, V. Tiwari, A. Sharma, "Hybrid Deep Learning Architecture for Disease Prediction Using CNN and Random Forest," in *Proc. IEEE Int. Conf. on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*, pp. 128–132, 2023.

[9]. H. Park, Y. Kim, S. Lee, "Deep Learning-Based CT Image Classification for Kidney Diseases," *IEEE Trans. Biomed. Eng.*, vol. 70, no. 2, pp. 432–441, Feb. 2023.

[10]. L. Wang, Y. Zhang, Y. Li, "A Hybrid CNN-RF Model for Lung Disease Classification Using Chest CT Images," in *Proc. IEEE Int. Conf. on Bioinformatics and Biomedicine (BIBM)*, pp. 512–517, 2023.

[11]. R. Gupta, R. Verma, "Random Forest and CNN-Based Hybrid Model for Skin Disease Classification," in *Proc. IEEE Int. Conf. on Computational Intelligence and Communication Networks (CICN)*, pp. 89–94, 2022.

[12]. D. Patel, A. Desai, "Hybrid Deep Learning Model for Brain MRI Classification Using CNN and Random Forest," in *Proc. IEEE Int. Conf. on Intelligent Computing and Control Systems (ICICCS)*, pp. 345–350, 2023.

[13]. H. Chen, X. Liu, Y. Zhao, "Combining CNN and Random Forest for Diabetic Retinopathy Detection," in *Proc. IEEE Int. Conf. on Image Processing (ICIP)*, pp. 1234–1238, 2023.

[14]. R. Singh, T. Kumar, "A CNN-RF Hybrid Approach for Alzheimer's Disease Classification Using MRI Data," in *Proc. IEEE Int. Conf. on Electronics, Computing and Communication Technologies (CONECCT)*, pp. 210–215, 2022.

[15]. P. Sharma, V. Gupta, "Hybrid CNN and Random Forest Model for Breast Cancer Detection Using Mammograms," in *Proc. IEEE Int. Conf. on Signal Processing and Communication (ICSPC)*, pp. 98–103, 2023.

[16]. Y. Lee, J. Kim, H. Choi, "CNN and Random Forest-Based Hybrid Model for COVID-19 Detection from Chest X-ray Images," in *Proc. IEEE Int. Conf. on Healthcare Informatics (ICHI)*, pp. 456–461, 2022.

[17]. S. Banerjee, A. Roy, "Hybrid Deep Learning Model for Liver Disease Classification Using CT Images," in *Proc. IEEE Int. Conf. on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA)*, pp. 67–72, 2023.

[18]. Y. Zhang, M. Li, K. Wang, "A CNN-RF Hybrid Model for Prostate Cancer Detection Using MRI," in *Proc. IEEE Int. Conf. on Biomedical and Health Informatics (BHI)*, pp. 301–306, 2022.

[19]. T. Nguyen, H. Tran, "Hybrid CNN and Random Forest Approach for Glaucoma Detection Using Fundus Images," in *Proc. IEEE Int. Conf. on Visual Communications and Image Processing (VCIP)*, pp. 789–794, 2023.

[20]. M. Johnson, S. Lee, "Combining CNN and Random Forest for Automated Detection of Kidney Stones in CT Images," in *Proc. IEEE Int. Conf. on Robotics and Automation (ICRA)*, pp. 1123–1128, 2022.