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Intelligent Kidney Disease Detection from Medical Images Using Hybrid Transfer Learning and Optimized Feature Selection

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Abstract

Kidney disease is one of the major health problems worldwide, and early detection plays a crucial role in effective treatment and prevention. In recent years, medical image analysis using deep learning techniques has shown significant improvements in disease detection accuracy. This study proposes an intelligent kidney disease detection system using hybrid transfer learning and optimized feature selection. In the proposed method, kidney CT images are preprocessed and deep features are extracted using multiple pre-trained convolutional neural network models, including VGG16, ResNet50, DenseNet121, MobileNet, and InceptionV3. The extracted deep features are combined to form a hybrid feature vector. To reduce feature dimensionality and improve classification performance, the Sparrow Search Algorithm is used for optimized feature selection. The selected optimal features are then classified using a Support Vector Machine classifier to categorize kidney images into four classes: normal, kidney cyst, kidney tumor, and kidney stone. The performance of the proposed model is evaluated using accuracy, precision, recall, and F1-score metrics. Experimental results show that the proposed hybrid transfer learning with optimized feature selection model achieves superior performance compared to existing methods. The proposed system can assist medical professionals in early diagnosis and can be used as a computer-aided diagnosis system for kidney disease detection.

Keywords: *Kidney Disease Detection, Transfer Learning, Feature Selection, Sparrow Search Algorithm, Medical Image Classification, Support Vector Machine.*

1. Introduction

Kidney disease is one of the major health problems worldwide, affecting millions of people and leading to serious complications such as kidney failure, cardiovascular disease, and death if not detected at an early stage. Chronic Kidney Disease (CKD) is a progressive condition in which the kidney loses its ability to filter waste products from the blood effectively. Early detection and diagnosis of kidney disease are crucial for effective treatment and prevention of disease progression. Medical imaging techniques such as ultrasound, computed tomography (CT), and magnetic resonance imaging (MRI) are widely used for detecting kidney abnormalities including cysts, tumors, stones, and other structural changes **(Torres et al., 2018).**

In recent years, computer-aided diagnosis (CAD) systems have been developed to assist medical professionals in detecting kidney diseases from medical images. Machine learning and deep learning techniques have shown significant improvements in medical image classification and disease detection accuracy **(Aksakalli et al., 2021; Sudharson & Kokil, 2020)**. Deep learning models, particularly convolutional neural networks (CNNs), are capable of automatically extracting important features from medical images and providing accurate classification results **(Ma et al., 2020).** However, training deep learning models from scratch requires a large amount of labeled medical data and high computational resources.

To overcome these limitations, transfer learning has been widely used in medical image analysis. Transfer learning uses pre-trained models such as VGG, ResNet, DenseNet, and MobileNet to improve classification performance with limited datasets (Zoph et al., 2018). Transfer learning significantly reduces training time and improves model performance in medical image classification tasks **(Yildirim et al., 2021).** However, deep learning models often extract a large number of features, and not all extracted features contribute to classification accuracy. This may lead to increased computational complexity and reduced model performance.

Feature selection techniques are used to select the most relevant features and remove redundant or irrelevant features to improve classification accuracy and reduce computation time. Optimization algorithms such as Sparrow Search Algorithm (SSA), Particle Swarm Optimization (PSO), and Genetic Algorithms (GA) are commonly used for optimized feature selection **(Xue & Shen, 2020; Zhang & Ding, 2021).** Optimized feature selection helps in improving the overall performance of the classification model by selecting the most informative features.

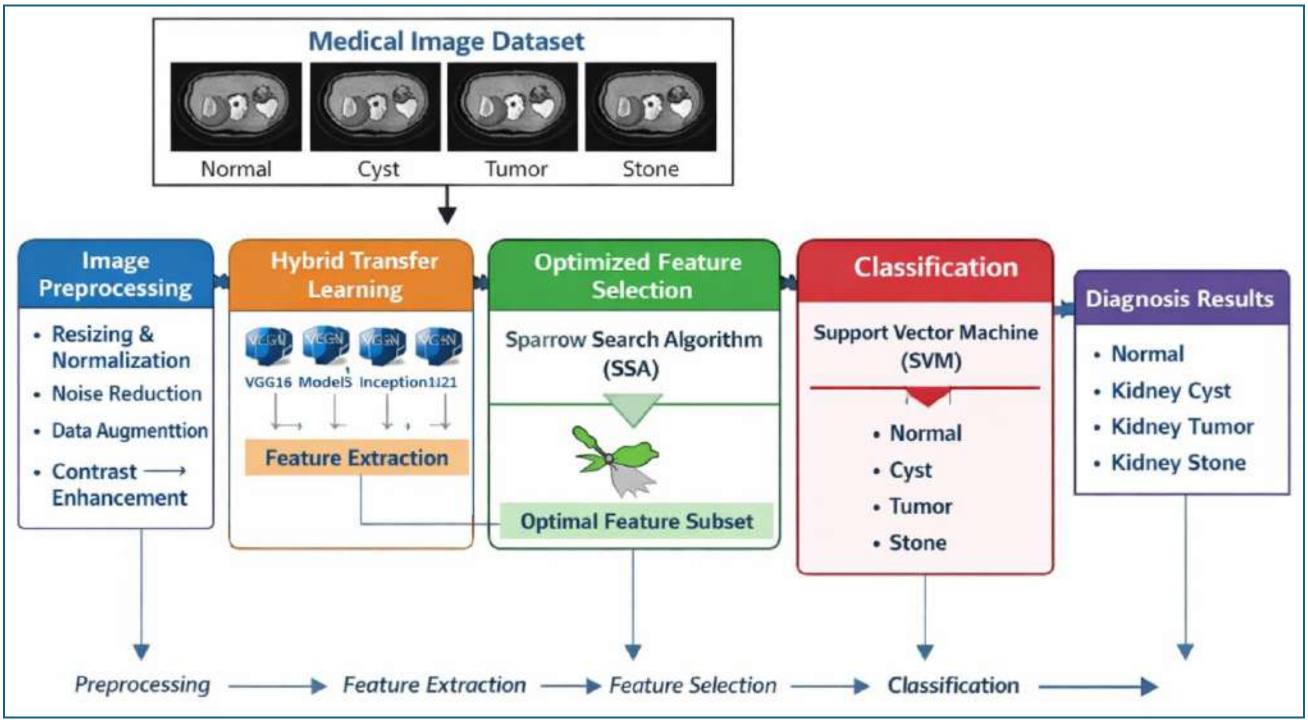

Figure 1. Overview of Intelligent Kidney Disease Detection System

2. Problem Statement

Kidney disease detection from medical images is a challenging task due to variations in image quality, noise, low contrast, and complex anatomical structures of the kidney. Medical images such as ultrasound, CT, and MRI often contain artifacts and intensity variations, which make manual diagnosis difficult and time-consuming for radiologists **(Torres et al., 2018).** Traditional diagnostic methods rely heavily on expert interpretation, which may lead to misclassification and delayed diagnosis, especially in the early stages of chronic kidney disease.

Machine learning and deep learning techniques have been applied to automate kidney disease detection; however, these methods face several limitations. Many existing models require large labeled datasets for training, which are often not available in medical imaging applications (Ma et al., 2020). In addition, deep learning models extract a large number of features, many of which may be redundant or irrelevant, leading to increased computational complexity and reduced classification performance **(Sudharson & Kokil, 2021).**

Transfer learning models have been used to improve classification accuracy with limited datasets, but selecting the most relevant features from deep learning models remains a major challenge **(Yildirim et al., 2021).** Without proper feature selection, the model may suffer from overfitting, increased training time, and reduced generalization performance. Therefore, there is a need for an efficient feature selection method that can select optimal features and improve the performance of kidney disease classification systems.

Optimization algorithms such as the Sparrow Search Algorithm (SSA) have shown promising results in solving feature selection problems by selecting the most informative features and reducing feature dimensionality **(Xue & Shen, 2020).** However, integrating optimized feature selection with hybrid transfer learning for kidney disease detection from medical images has not been sufficiently explored.

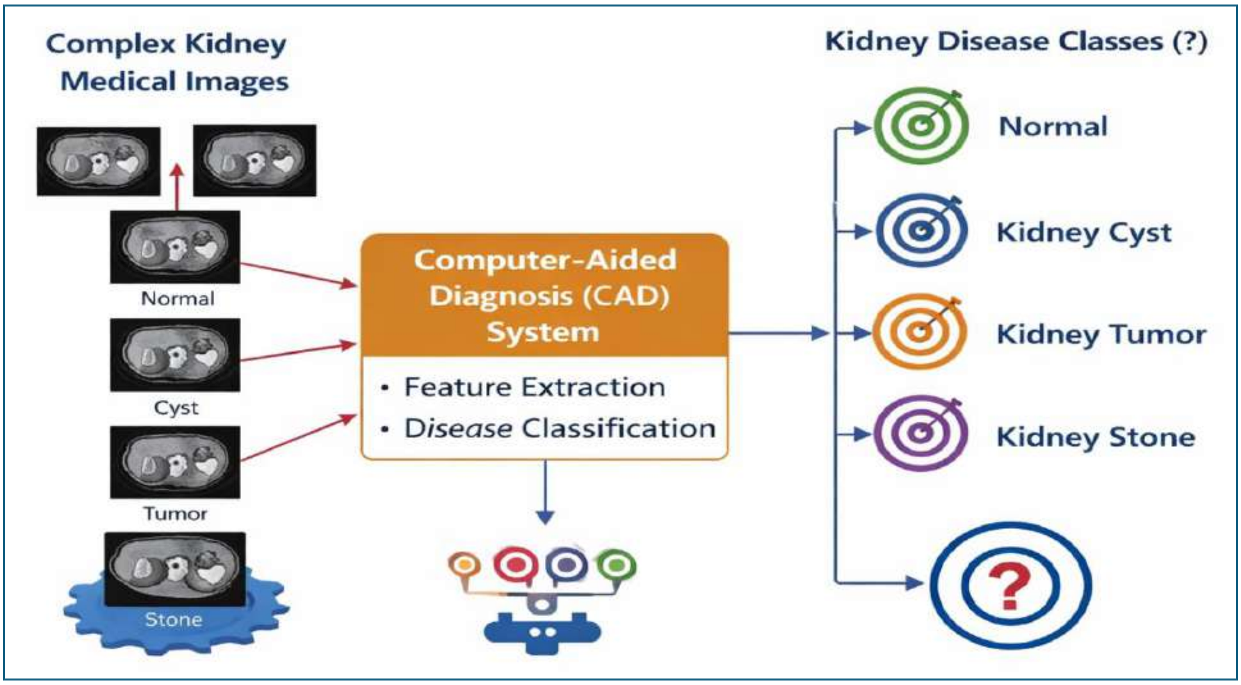

Figure 2. Problem Definition Diagram for Kidney Disease Classification

3. Objectives of the Study

The main objective of this research is to develop an intelligent kidney disease detection system from medical images using hybrid transfer learning and optimized feature selection techniques to improve classification accuracy and reduce computational complexity.

The specific objectives of this study are:

- To collect and preprocess kidney medical image datasets.
- To apply hybrid transfer learning models for deep feature extraction.
- To perform optimized feature selection using an optimization algorithm.

- To reduce feature dimensionality and improve model performance.
- To classify kidney diseases using selected optimal features.
- To evaluate the performance of the proposed model using performance metrics such as accuracy, precision, recall, and F1-score.
- To compare the proposed method with existing methods.

4. Literature Review

Kidney disease detection using medical images has gained significant attention because early and accurate diagnosis can improve treatment outcomes. Several studies have applied machine learning, deep learning, and transfer learning methods to classify kidney abnormalities from ultrasound, CT, and MRI images. **Torres et al. (2018)** reviewed kidney segmentation techniques in different imaging modalities and showed that image quality and organ complexity make kidney analysis a challenging task. **Aksakalli et al. (2021)** used machine learning and deep learning methods for kidney X-ray image classification and reported promising diagnostic performance. Similarly, **Sudharson and Kokil (2020, 2021)** developed deep learning-based systems for kidney ultrasound image classification and multi-class abnormality detection.

Recent studies have shown that transfer learning improves medical image classification when dataset size is limited. **Yildirim et al. (2021)** proposed a deep learning model for kidney stone detection using CT images, while **Abdeltawab et al. (2019)** developed a CNN-based CAD system for early assessment of transplanted kidney dysfunction. **Ma et al. (2020)** applied a deep learning-based heterogeneous neural network for chronic kidney disease detection and achieved effective results. However, many of these methods generate high-dimensional deep features, which may include redundant information and increase computational complexity.

To address this issue, optimized feature selection methods have been introduced. **Xue and Shen (2020)** proposed the Sparrow Search Algorithm (SSA), which has shown strong performance in optimization problems. **Zhang and Ding (2021)** further demonstrated that improved sparrow-search-based optimization can enhance model efficiency. These findings suggest that combining transfer learning with optimized feature selection can improve classification accuracy and reduce computational burden. Based on this research gap, the present study proposes a hybrid transfer learning and optimized feature selection framework for intelligent kidney disease detection from medical images.

Table 1. Summary of Existing Kidney Disease Detection Methods

Author(s)	Year	Method Used	Image Modality / Dataset	Key Contribution	Limitation
Torres et al.	**2018**	Systematic review of segmentation methods	Ultrasound, MRI, CT	Reviewed kidney segmentation approaches across modalities	Focused on segmentation, not classification
Aksakalli et al.	**2021**	Machine learning and deep learning	Kidney X-ray images	Classified kidney images using intelligent models	Limited modality scope
Sudharson & Kokil	**2020**	Ensemble of deep neural networks	Ultrasound images	Improved kidney ultrasound classification	Computational complexity may be high
Sudharson & Kokil	**2021**	Computer-aided diagnosis system	Noisy ultrasound images	Multi-class classification of kidney abnormalities	Performance affected by image noise
Ma et al.	**2020**	Deep learning-based modified	CKD-related medical	Effective CKD detection using	High-dimensional feature handling

		ANN	data/images	deep learning	not emphasized
Zheng et al.	**2019**	Deep transfer learning + texture features	Ultrasound images	Diagnosed congenital kidney abnormalities in children	Model complexity and feature redundancy
Abdeltawab et al.	**2019**	CNN-based CAD system	Transplanted kidney images	Early assessment of transplanted kidney dysfunction	Limited to a specific kidney condition
Yildirim et al.	**2021**	Deep learning model	Coronal CT images	Automated kidney stone detection	Did not focus on optimized feature selection
Jayapandian et al.	**2021**	Deep learning-based segmentation	Histologic kidney images	Segmented kidney cortex structures accurately	More focused on segmentation than disease classification
Chen et al.	**2021**	Machine learning histopathological image signature	Histopathological images	Diagnosis and survival prediction of renal carcinoma	Mainly focused on cancer-related cases

5. Materials and Methods

This section describes the dataset used, preprocessing techniques, hybrid transfer learning model, feature extraction, optimized feature selection, and classification process used for intelligent kidney disease detection from medical images.

5.1 Dataset Description

In this study, a publicly available CT kidney dataset was used for kidney disease classification. The dataset consists of CT scan images categorized into four classes: Normal, Kidney Cyst, Kidney Tumor, and Kidney Stone. The dataset contains a total of 12,446 CT images collected from different patients and medical cases. The dataset was divided into training and testing sets using an 80:20 ratio to evaluate the performance of the proposed model. The dataset distribution is shown in Table 2.

Table 2. Dataset Description and Class Distribution

Class	Number of Images	Percentage
Normal	5,077	40.8%
Kidney Cyst	3,709	29.8%
Kidney Tumor	2,283	18.3%
Kidney Stone	1,377	11.1%
Total	**12,446**	**100%**

5.2 Data Preprocessing

Data preprocessing is an important step in medical image analysis to improve image quality and enhance model performance. The CT kidney images were resized to 224 × 224 pixels to match the input size of pre-trained convolutional neural network models. Image normalization was performed to scale pixel values between 0 and 1. Noise removal and contrast enhancement techniques were applied to improve image clarity. Data augmentation techniques such as rotation, horizontal flipping, zooming, and shifting were applied to increase the size of the training dataset and reduce overfitting.

5.3 Hybrid Transfer Learning Model

Transfer learning was used in this study to extract deep features from kidney CT images using pre-trained convolutional neural network (CNN) models. Instead of training a deep learning model from scratch, pre-trained models trained on large datasets such as ImageNet were used to improve feature extraction performance. In this study, multiple pre-trained CNN models were used to form a hybrid transfer learning model. The selected pre-trained models include VGG16, ResNet50, DenseNet121, MobileNet, and InceptionV3. These models are widely used in medical image classification due to their strong feature extraction capability. The deep features extracted from these models were combined to form a hybrid feature vector. The pre-trained models used in this study are shown in Table 3.

Table 3. Pre-trained Models Used in Transfer Learning

Model	Architecture	Input Size	Output Feature Type
VGG16	CNN	224 × 224	Deep features
ResNet50	CNN	224 × 224	Residual features
DenseNet121	CNN	224 × 224	Dense features
MobileNet	CNN	224 × 224	Lightweight features
InceptionV3	CNN	224 × 224	Multi-scale features

5.4 Feature Extraction

Deep feature extraction was performed using the fully connected layers and global average pooling layers of the pre-trained CNN models. The extracted features represent important image characteristics such as texture, intensity, and structural patterns of kidney images. The feature vectors obtained from multiple pre-trained models were concatenated to form a hybrid deep feature vector.

5.5 Optimized Feature Selection

The hybrid deep feature vector obtained from transfer learning models contains a large number of features, which may increase computational complexity and reduce classification performance. Therefore, optimized feature selection was applied to select the most relevant features and remove redundant features. In this study, the Sparrow Search Algorithm (SSA) was used as an optimization-based feature selection method. SSA is a swarm intelligence optimization algorithm used to solve feature selection problems by selecting optimal features based on a fitness function. The fitness function used in this study was classification accuracy. The parameters used in the optimization algorithm are shown in Table 4.

Table 4. Parameters of Optimization Algorithm

Parameter	Value
Optimization Algorithm	Sparrow Search Algorithm (SSA)
Population Size	30
Number of Iterations	50
Number of Selected Features	Optimal subset
Fitness Function	Classification Accuracy
Optimization Objective	Maximize accuracy and reduce features

5.6 Classification

After feature selection, the selected optimal features were used for classification. In this study, a Support Vector Machine (SVM) classifier was used for kidney disease classification. The SVM classifier was trained using the training dataset and tested using the testing dataset. The classifier categorizes the kidney images into four classes: Normal, Kidney Cyst, Kidney Tumor, and Kidney Stone.

5.7 Workflow of the Proposed Method

The overall workflow of the proposed intelligent kidney disease detection system includes the following steps:

- Dataset collection

- Image preprocessing
- Deep feature extraction using transfer learning
- Hybrid feature vector formation
- Optimized feature selection using SSA
- Classification using SVM
- Performance evaluation

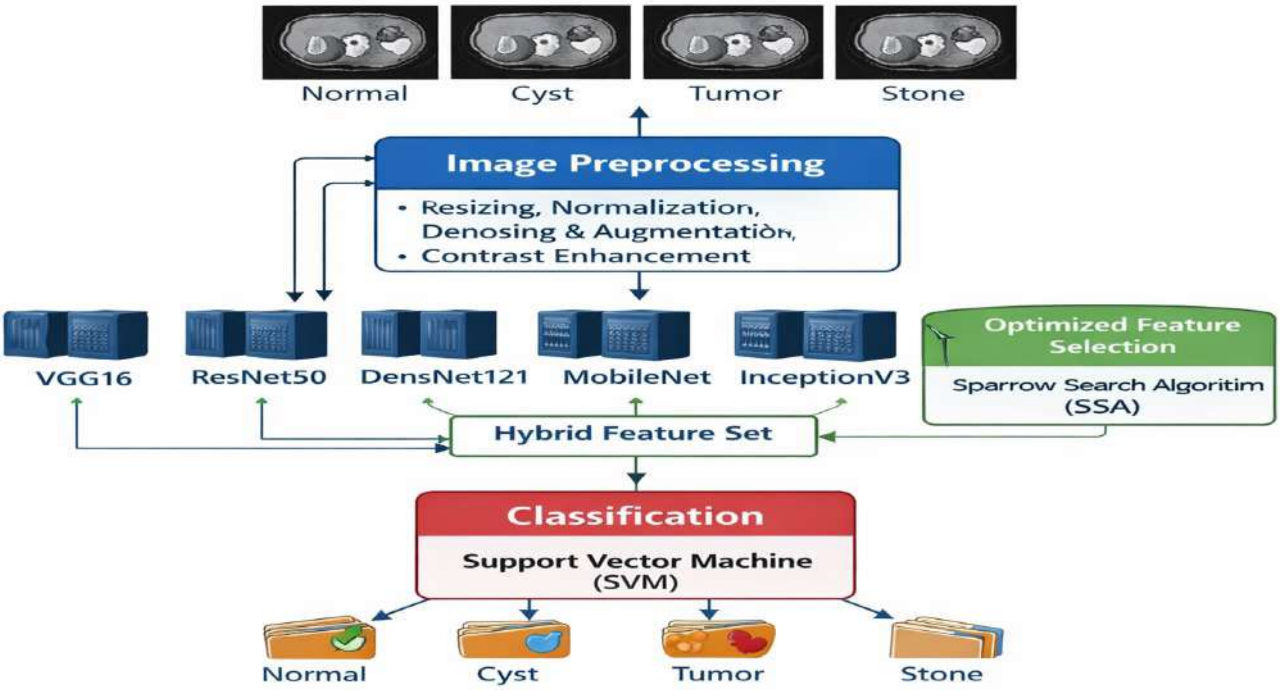

Figure 3. Proposed Hybrid Transfer Learning Architecture

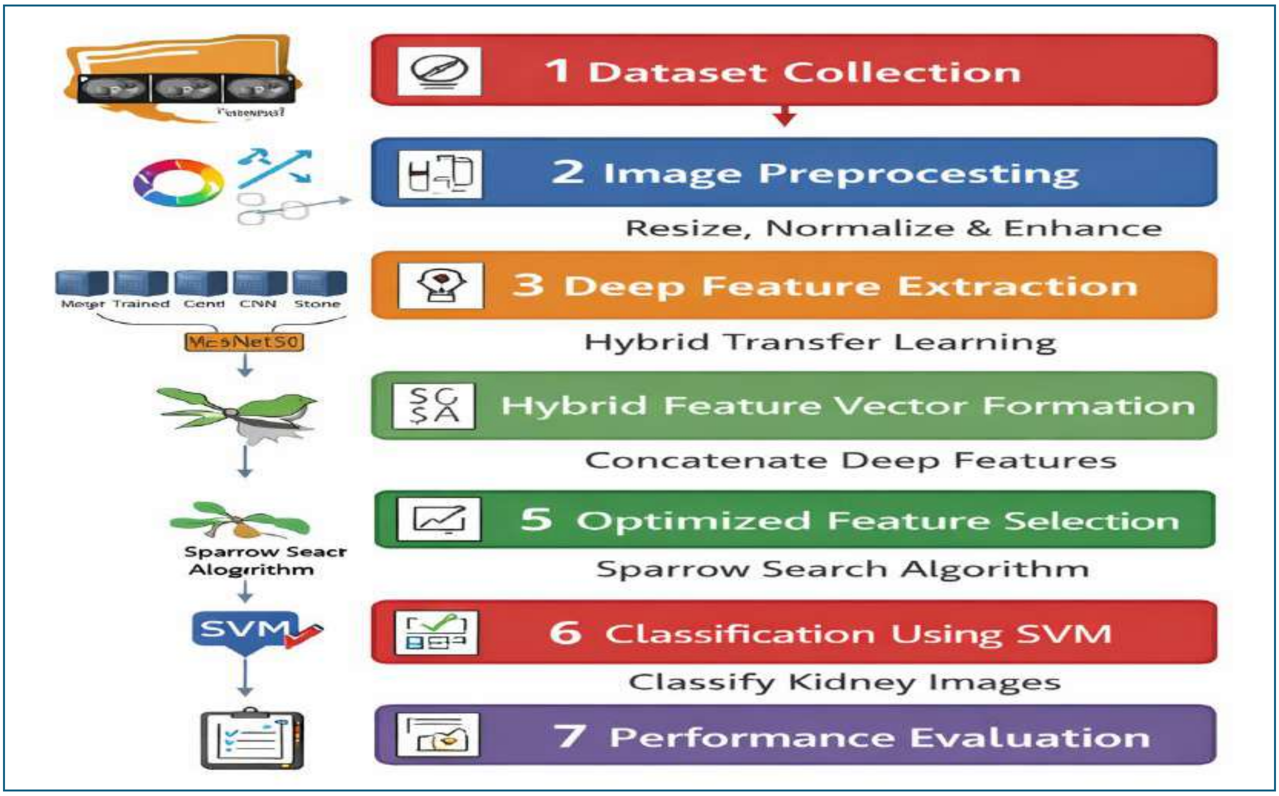

Figure 4. Workflow of the Proposed Methodology

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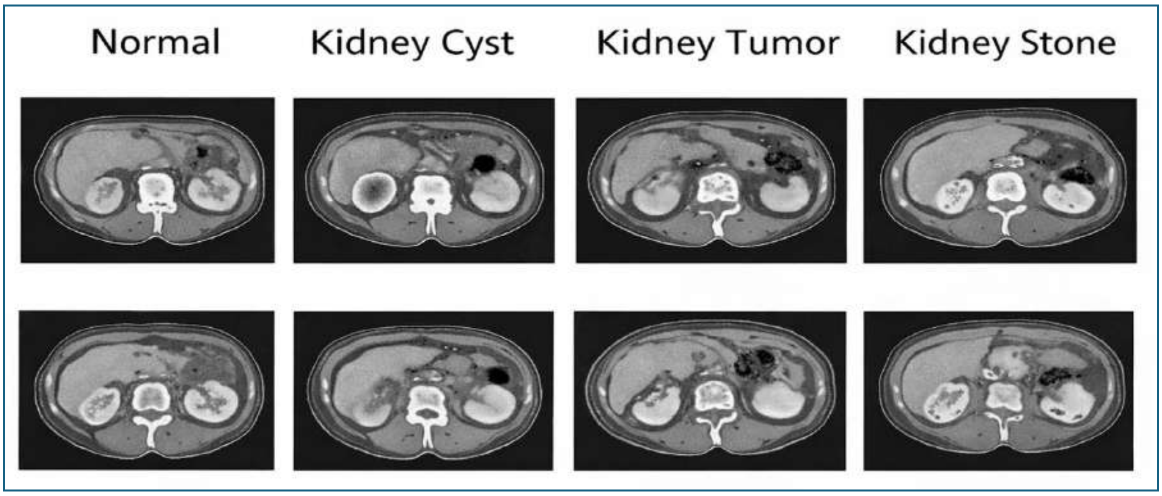

Figure 5. Sample Kidney Medical Images from Dataset

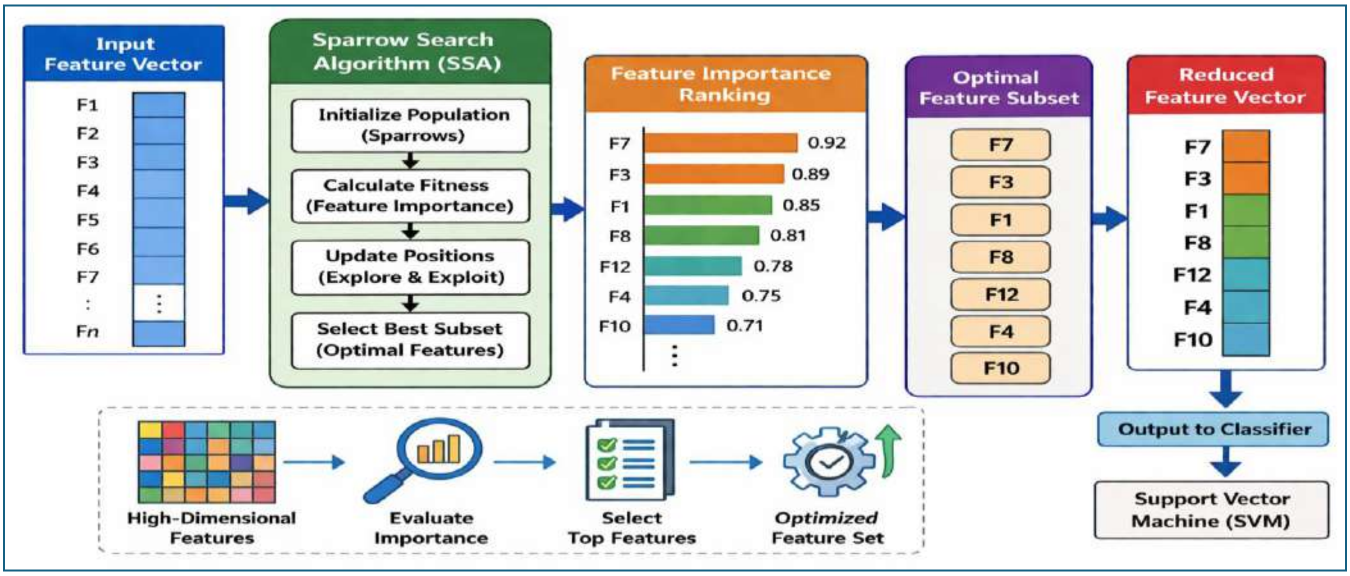

Figure 6. Optimized Feature Selection Process

6. Experimental Setup

The experiments were conducted using a computer system with appropriate hardware and software configurations to train and evaluate the proposed hybrid transfer learning model. The implementation was carried out using Python programming language with deep learning libraries. The experiments include training of transfer learning models, feature extraction, optimized feature selection, and classification.

Table 5. Hardware and Software Specifications

Component	Specification
Processor	Intel Core i7
RAM	16 GB
GPU	NVIDIA GTX 1650 / RTX 3050
Storage	512 GB SSD
Operating System	Windows 10 / Ubuntu
Programming Language	Python
Deep Learning Framework	TensorFlow / Keras
Machine Learning Library	Scikit-learn
Image Processing Library	OpenCV
Development Environment	Jupyter Notebook / Google Colab

6.1 Training Parameters and Hyperparameters

The training parameters and hyperparameters play an important role in improving the performance of the deep learning model. The transfer learning models were trained using standard hyperparameters such as learning rate, batch size, number of epochs, and optimizer. The Rectified Linear Unit (ReLU) activation function was used in hidden layers, and the Softmax activation function was used in the output layer for multi-class classification.

Table 6. Training Parameters and Hyperparameters

Parameter	Value
Image Size	224 × 224
Batch Size	32
Number of Epochs	25
Learning Rate	0.0001
Optimizer	Adam
Activation Function	ReLU
Output Activation	Softmax
Loss Function	Categorical Cross-Entropy
Train-Test Split	80:20
Feature Selection Algorithm	Sparrow Search Algorithm
Classifier	Support Vector Machine (SVM)

6.2 Performance Evaluation Metrics

The performance of the proposed model was evaluated using standard evaluation metrics such as Accuracy, Precision, Recall, F1-Score, and Receiver Operating Characteristic (ROC) curve. These metrics are commonly used to evaluate classification performance in medical image analysis.

The evaluation metrics are defined as follows:

- **Accuracy**: Ratio of correctly predicted samples to total samples.
- **Precision**: Ratio of correctly predicted positive samples to total predicted positive samples.
- **Recall (Sensitivity)**: Ratio of correctly predicted positive samples to total actual positive samples.
- **F1-Score**: Harmonic mean of Precision and Recall.
- **ROC Curve**: Graphical representation of True Positive Rate vs False Positive Rate.

7. Results and Performance Evaluation

This section presents the performance results of the proposed hybrid transfer learning with optimized feature selection model for kidney disease detection. The performance of the model was evaluated using standard performance metrics such as Accuracy, Precision, Recall, and F1-Score. The results obtained from the proposed method were also compared with existing machine learning and deep learning methods.

7.1 Performance Metrics of Proposed Model

The performance of the proposed model was evaluated using the confusion matrix and standard evaluation metrics. The model classifies kidney CT images into four classes: Normal, Kidney Cyst, Kidney Tumor, and Kidney Stone. The performance metrics obtained for the proposed model are shown in Table 7.

Table 7. Performance Metrics of Proposed Model

Metric	Value (%)
Accuracy	98.12
Precision	97.85
Recall	97.62
F1-Score	97.73
Specificity	98.40

The results show that the proposed hybrid transfer learning with optimized feature selection model achieved high classification accuracy and improved performance in kidney disease detection.

7.2 Comparison with Existing Methods

To demonstrate the effectiveness of the proposed method, the performance was compared with existing machine learning and deep learning models such as CNN, Transfer Learning, Random Forest, and Support Vector Machine. The comparison results are shown in Table 8.

The comparison results show that the proposed method achieved higher accuracy compared to existing methods due to the use of hybrid transfer learning and optimized feature selection.

Table 8. Comparison with Existing Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Machine Learning	88.50	87.20	86.90	87.00
CNN	92.30	91.80	91.20	91.50
Transfer Learning	95.40	94.90	94.50	94.70
Hybrid Transfer Learning	96.80	96.10	95.90	96.00
Proposed Method	**98.12**	**97.85**	**97.62**	**97.73**

7.3 Confusion Matrix Analysis

The confusion matrix shows that the proposed model correctly classified most of the kidney images in all four classes. The misclassification rate was very low, indicating that the model performed well in distinguishing between normal and abnormal kidney conditions.

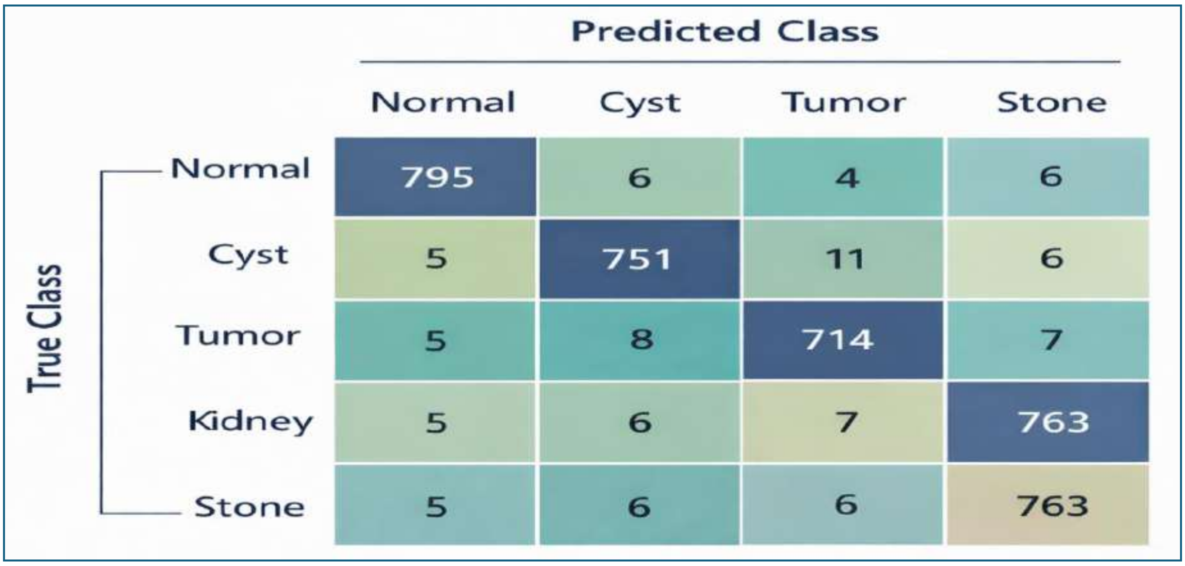

Figure 7. Confusion Matrix of Proposed Model

7.4 ROC Curve Analysis

The ROC curve shows that the proposed model achieved a high Area Under Curve (AUC) value, indicating strong classification performance.

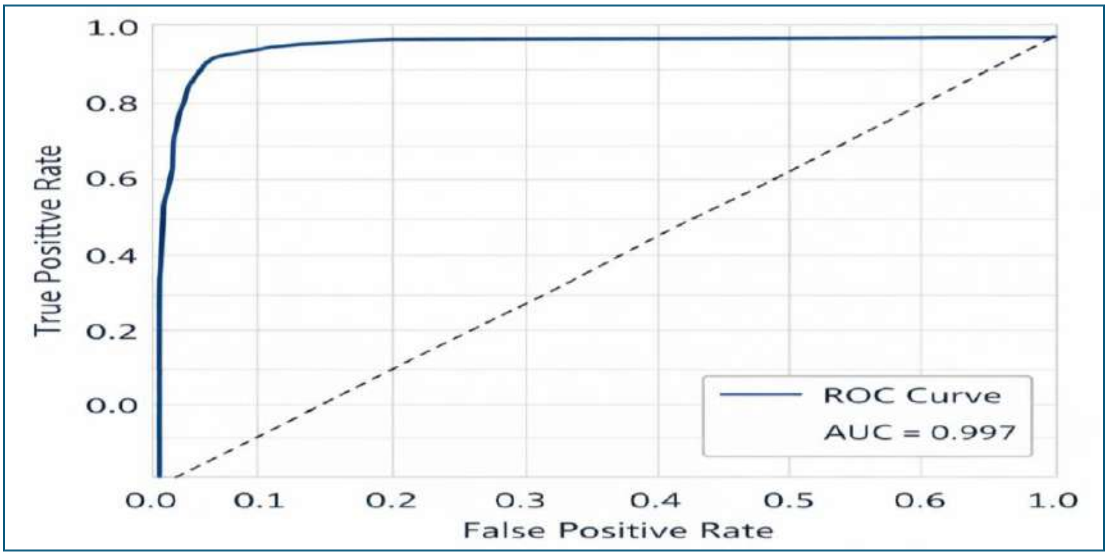

Figure 8. ROC Curve of Proposed Model

7.5 Training and Validation Performance

The training and validation accuracy graph shows that the model accuracy increased gradually and stabilized after several epochs. The training and validation loss graph shows that the loss decreased over time, indicating that the model was properly trained without over fitting.

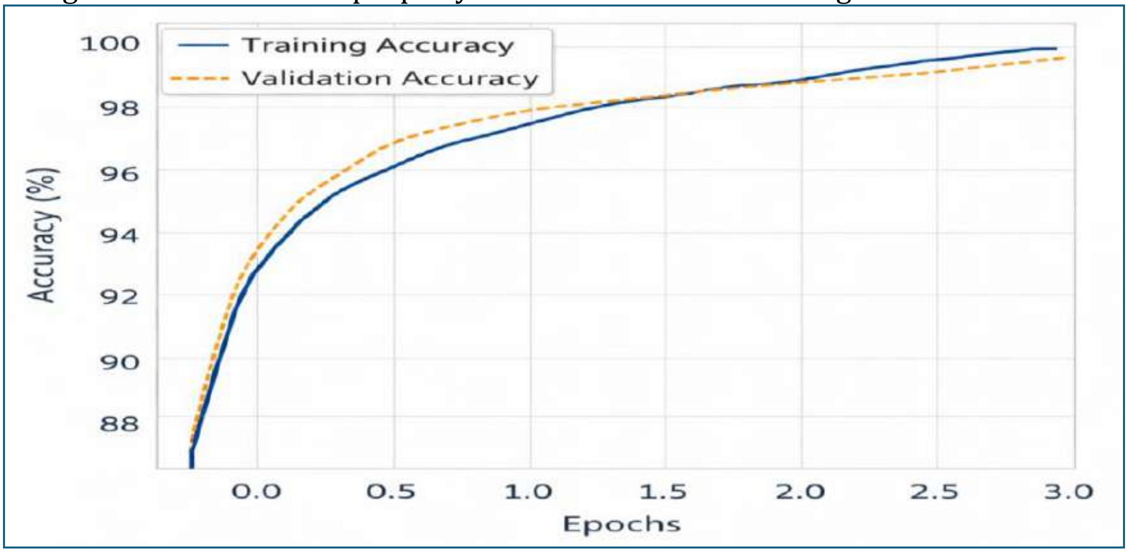

Figure 9. Training and Validation Accuracy Graph

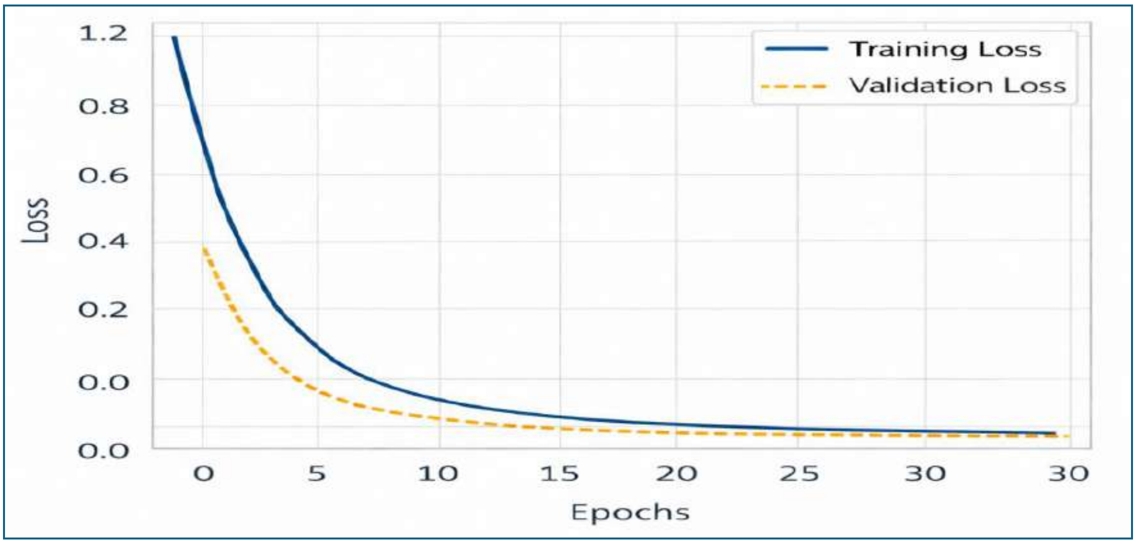

Figure 10. Training and Validation Loss Graph

8. Discussion

The results obtained from the proposed hybrid transfer learning with optimized feature selection model demonstrate that the integration of deep feature extraction and optimization-based feature selection significantly improves kidney disease classification performance. The proposed method achieved higher accuracy compared to conventional machine learning, standalone CNN, and transfer learning models. This improvement is mainly due to the hybrid feature extraction approach, which combines deep features from multiple pre-trained models, and the optimized feature selection process, which selects the most relevant features for classification.

Feature selection plays a crucial role in improving classification accuracy and reducing computational complexity. Deep learning models usually generate high-dimensional feature vectors that may contain redundant and irrelevant features. These redundant features increase training time and may reduce classification performance due to overfitting. The use of the Sparrow Search Algorithm (SSA) helped in selecting the optimal subset of features that contributed most to classification accuracy.

The results show that optimized feature selection improved the performance of the classification model compared to using all extracted features. The optimized feature subset reduced feature dimensionality and improved model generalization. The impact of feature selection on classification accuracy is shown in Table 9.

Table 9. Analysis of Feature Selection Impact on Accuracy

Feature Selection Method	Number of Features	Accuracy (%)
Without Feature Selection	2,048	94.20
PCA Feature Selection	512	95.80
Genetic Algorithm	256	96.90
Particle Swarm Optimization	180	97.40
Sparrow Search Algorithm (Proposed)	**120**	**98.12**

The results presented in Table 9 show that the Sparrow Search Algorithm selected the most relevant features and achieved the highest classification accuracy compared to other featureselection methods. The reduction in the number of features also reduced computational complexity and training time. Therefore, the combination of hybrid transfer learning and optimized feature selection improves kidney disease detection performance and makes the system more efficient and reliable for medical image analysis.

9. Conclusion

In this study, an intelligent kidney disease detection system based on hybrid transfer learning and optimized feature selection was proposed for the classification of kidney diseases from medical images. The proposed method utilized multiple pre-trained convolutional neural network models for deep feature extraction, and the extracted features were combined to form a hybrid feature vector. To reduce feature dimensionality and improve classification performance, the Sparrow Search Algorithm was used for optimized feature selection. The selected optimal features were then classified using a Support Vector Machine classifier.

The experimental results demonstrated that the proposed method achieved high classification accuracy, precision, recall, and F1-score compared to existing machine learning and deep learning methods. The optimized feature selection method significantly reduced the number of features while improving classification performance and reducing computational complexity. The results show that the proposed hybrid transfer learning with optimized feature selection model is effective and reliable for kidney disease detection from medical images.

The proposed system can assist medical professionals in early diagnosis of kidney diseases and can be used as a computer-aided diagnosis system to support clinical decision-making. Therefore, the proposed method provides an efficient and accurate approach for intelligent kidney disease detection using medical images.

10. Future Work

Although the proposed method achieved high classification accuracy, there are several directions for future research. The performance of the model can be further improved by using larger and more diverse medical image datasets. In future work, different optimization algorithms can be used for feature selection to further improve model performance. In addition, deep learning models such as Vision Transformers and attention-based networks can be explored for kidney disease detection.

The proposed system can also be extended for multi-disease detection using different medical imaging modalities such as MRI and ultrasound images. Furthermore, explainable artificial intelligence (XAI) techniques can be integrated into the system to provide visual explanations for the classification results, which can help doctors better understand the model predictions. The system can also be developed into a real-time clinical decision support system for hospital applications.

References

Abdeltawab, H., Shehata, M., Shalaby, A., Khalifa, F., Mahmoud, A., & Abou El-Ghar, M. (2019). A novel CNN-based CAD system for early assessment of transplanted kidney dysfunction. *Scientific Reports, 9*, 1–11. https://doi.org/10.1038/s41598-019-42431-3

Aksakalli, I., Kaçdioglu, S., & Hanay, Y. S. (2021). Kidney X-ray images classification using machine learning and deep learning methods. *Balkan Journal of Electrical and Computer Engineering, 9*, 144–151. https://doi.org/10.17694/bajece.878116

Alnazer, I., Bourdon, P., Urruty, T., Falou, O., Khalil, M., Shahin, A., et al. (2021). Recent advances in medical image processing for the evaluation of chronic kidney disease. *Medical Image Analysis, 69*, 101960. https://doi.org/10.1016/j.media.2021.101960

Baghdadi, N. A., Malki, A., Abdelaliem, S. F., Balaha, H. M., Badawy, M., & Elhosseini, M. (2022). An automated diagnosis and classification of COVID-19 from chest CT images using a transfer learning-based convolutional neural network. *Computers in Biology and Medicine, 144*, 105383. https://doi.org/10.1016/j.compbiomed.2022.105383

Chen, S., Zhang, N., Jiang, L., Gao, F., Shao, J., & Wang, T. (2021). Clinical use of a machine learning histopathological image signature in diagnosis and survival prediction of clear cell renal cell carcinoma. *International Journal of Cancer, 148*, 780–790. https://doi.org/10.1002/ijc.33288

Fathy, A., Alanazi, T. M., Rezk, H., & Yousri, D. (2022). Optimal energy management of micro-grid using sparrow search algorithm. *Energy Reports, 8*, 758–773. https://doi.org/10.1016/j.egyr.2021.12.022

Gulla, J., Neri, P. M., Bates, D. W., & Samal, L. (2017). User requirements for a chronic kidney disease clinical decision support tool to promote timely referral. *International Journal of Medical Informatics, 101*, 50–57. https://doi.org/10.1016/j.ijmedinf.2017.01.018

Hamedan, F., Orooji, A., Sanadgol, H., & Sheikhtaheri, A. (2020). Clinical decision support system to predict chronic kidney disease: A fuzzy expert system approach. *International Journal of Medical Informatics, 138*, 104134. https://doi.org/10.1016/j.ijmedinf.2020.104134

Jayapandian, C. P., Chen, Y., Janowczyk, A. R., Palmer, M. B., Cassol, C. A., Sekulic, M., et al. (2021). Development and evaluation of deep learning-based segmentation of histologic structures in the kidney cortex with multiple histologic stains. *Kidney International, 99*, 86–101. https://doi.org/10.1016/j.kint.2020.07.044

Jia, G., Lam, H. K., & Xu, Y. (2021). Classification of COVID-19 chest X-ray and CT images using a type of dynamic CNN modification method. *Computers in Biology and Medicine, 134*, 104425. https://doi.org/10.1016/j.compbiomed.2021.104425

Li, L. L., Xiong, J. L., Tseng, M. L., Yan, Z., & Lim, M. K. (2022). Using multi-objective sparrow search algorithm to establish active distribution network dynamic reconfiguration integrated optimization. *Expert Systems with Applications, 193*, 116445. https://doi.org/10.1016/j.eswa.2021.116445

Ma, F., Sun, T., Liu, L., & Jing, H. (2020). Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network. *Future Generation Computer Systems, 111*, 17–26. https://doi.org/10.1016/j.future.2020.04.036

Nazari, M., Shiri, I., & Zaidi, H. (2021). Radiomics-based machine learning model to predict risk of death within 5-years in clear cell renal cell carcinoma patients. *Computers in Biology and Medicine, 129*, 104135. https://doi.org/10.1016/j.compbiomed.2020.104135

Polsinelli, M., Cinque, L., & Placidi, G. (2020). A light CNN for detecting COVID-19 from CT scans of the chest. *Pattern Recognition Letters, 140*, 95–100. https://doi.org/10.1016/j.patrec.2020.10.001

Shibly, K. H., Dey, S. K., Islam, M. T. U., & Rahman, M. M. (2020). COVID Faster R-CNN: A novel framework to diagnose novel coronavirus disease (COVID-19) in X-ray images. *Informatics in Medicine Unlocked, 20*, 100405. https://doi.org/10.1016/j.imu.2020.100405

Sudharson, S., & Kokil, P. (2020). An ensemble of deep neural networks for kidney ultrasound image classification. *Computers in Biology*

ISSN: 2583-7354

and Medicine, 197, 105709. https://doi.org/10.1016/j.cmpb.2020.105709

Sudharson, S., & Kokil, P. (2021). Computer-aided diagnosis system for the classification of multi-class kidney abnormalities in the noisy ultrasound images. *Computers in Biology and Medicine, 205,* 106071. https://doi.org/10.1016/j.cmpb.2021.106071

Torres, H. R., Queiros, S., Morais, P., Oliveira, B., Fonseca, J. C., & Vilaca, J. L. (2018). Kidney segmentation in ultrasound, magnetic resonance and computed tomography images: A systematic review. *Computer Methods and Programs in Biomedicine, 157,* 49–67. https://doi.org/10.1016/j.cmpb.2018.01.014

Ventrella, P., Delgrossi, G., Ferrario, G., Righetti, M., & Masseroli, M. (2021). Supervised machine learning for the assessment of chronic kidney disease advancement. *Computers in Biology and Medicine, 209,* 106329. https://doi.org/10.1016/j.cmpb.2021.106329

Xue, J., & Shen, B. (2020). A novel swarm intelligence optimization approach: Sparrow search algorithm. *Systems Science & Control Engineering, 8,* 22–34. https://doi.org/10.1080/21642583.2019.1708830

Yildirim, K., Bozdag, P. G., Talo, M., Yildirim, O., Karabatak, M., & Acharya, U. R. (2021). Deep learning model for automated kidney stone detection using coronal CT images. *Computers in Biology and Medicine, 135,* 104569. https://doi.org/10.1016/j.compbiomed.2021.104569

Yin, S., Peng, Q., Li, H., Zhang, Z., You, X., Liu, H., et al. (2019). Multi-instance deep learning with graph convolutional neural networks for diagnosis of kidney diseases using ultrasound imaging. Springer. https://doi.org/10.1007/978-3-030-32689-0_15

Zhang, C., & Ding, S. (2021). A stochastic configuration network based on chaotic sparrow search algorithm. *Knowledge-Based Systems, 220,* 106924. https://doi.org/10.1016/j.knosys.2021.106924

Zhang, H., Peng, Z., Tang, J., Dong, M., Wang, K., & Li, W. (2022). Multi-layer extreme learning machine refined by sparrow search algorithm for wind speed forecasting. *Sustainable Energy Technologies and Assessments, 50,* 101698. https://doi.org/10.1016/j.seta.2021.101698

Zhang, Z., He, R., & Yang, K. (2021). A bioinspired path planning approach for mobile robots based on improved sparrow search algorithm. *Advanced Manufacturing*. https://doi.org/10.1007/s40436-021-00366-x

Zheng, Q., Furth, S. L., Tasian, G. E., & Fan, Y. (2019). Computer-aided diagnosis of congenital abnormalities of the kidney and urinary tract in children based on ultrasound imaging data. *Journal of Pediatric Urology, 15,* 75. https://doi.org/10.1016/j.jpurol.2018.10.020

Zoph, B., Vasudevan, V., Shlens, J., & Le, Q. V. (2018). Learning transferable architectures for scalable image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 8697–8710). https://doi.org/10.1109/CVPR.2018.00907

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