

DEEP LEARNING TECHNIQUES FOR KIDNEY STONE DETECTION AND CLASSIFICATION

Jampani Ravi¹, A. L. D. S. Charan², G. Hemanth³, A. Prabhas⁴, G. Eswar Prakash⁵

^{1,2,3,4,5}Department of ECE, S.R.K.R. Engineering College, Bhimavaram, India.

DOI: <https://www.doi.org/10.58257/IJPREMS38365>

ABSTRACT

This study proposes an ultrasound speckle suppression method for detecting kidney stones in humans. The process begins with image enhancement techniques to adjust the image intensities, followed by the application of median filters to smooth the image and remove noise. The preprocessed images are then segmented using a thresholding technique. The median filter effectively removes impulsive noise, such as salt-and-pepper noise. The proposed method identifies kidney stones by pinpointing their location coordinates. In recent years, deep learning has become a critical approach for detecting and classifying kidney stones, particularly through the analysis of CT scan images. This project aims to develop a robust system for kidney stone detection by leveraging deep learning algorithms to accurately classify images as either affected by kidney stones or not. The system uses a dataset of kidney CT scan images in common formats like .png and .jpg, which are preprocessed for model training. To ensure high accuracy, two deep learning architectures are explored: Convolutional Neural Networks (CNN) and a hybrid model combining CNN with RESNET-50, a pre-trained network known for its strong image recognition performance. The CNN model employs 2D convolution layers to extract hierarchical features from the images, while the CNN-RESNET-50 hybrid model enhances feature extraction through residual learning, addressing challenges like vanishing gradients in image classification. Both models are trained on the dataset, and their effectiveness is evaluated based on their ability to detect kidney stones in CT scans. The system ultimately provides a prediction indicating whether the input CT scan shows signs of kidney stones, serving as a reliable, automated diagnostic tool for healthcare professionals. By utilizing these deep learning techniques, the approach aims to improve the accuracy, speed, and accessibility of kidney stone detection, contributing to earlier diagnosis and better patient outcomes. Through comprehensive training, validation, and testing, this system demonstrates the potential of artificial intelligence to revolutionize medical imaging and kidney stone detection.

Keywords –Classification, Deep Learning, Kidney Stone, Image Processing

1. INTRODUCTION

Kidney stones, also known as renal stones, are a prevalent health issue affecting millions of people worldwide. If untreated, these crystalline formations in the kidneys can lead to severe pain and potentially cause life-threatening complications like kidney damage. Current diagnostic methods, such as X-rays and CT scans, are commonly used to detect kidney stones. While these techniques are effective, they come with certain drawbacks, including high costs and the use of ionizing radiation, which raises concerns about potential long-term health risks. Consequently, there is a pressing need for more efficient and affordable methods for kidney stone detection. Rapid and accurate detection is crucial for timely treatment and patient well-being. Additionally, the high costs associated with existing diagnostic methods can be burdensome for both patients and healthcare systems. This study emphasizes the urgent need for a more practical, cost-effective, and precise approach to detecting kidney stones.

Deep learning, a subfield of artificial intelligence (AI), has emerged as a promising solution for kidney stone detection. Deep learning algorithms based on artificial neural networks offer a potential remedy for the limitations of traditional diagnostic methods. These models can quickly and accurately diagnose kidney stones by analyzing various medical imaging sources, including ultrasound and CT scans. This shift could reduce radiation exposure risks while lowering healthcare costs and alleviating patient discomfort. This study explores kidney stone detection through deep learning, focusing on the use of different Convolutional Neural Network (CNN) models. The research aims to identify the most effective deep learning algorithms for detecting kidney stones using CT scan images, analyzing the impact of various factors on model accuracy and performance.

The kidneys play a crucial role in the human body, and kidney stones, which are solid formations caused by minerals in the urine, have become a widespread issue. These stones can form due to genetic and environmental factors, such as obesity, poor diet, certain medications, and inadequate hydration. Kidney stones can affect individuals of all races, cultures, and geographic locations. Diagnosing kidney stones typically involves blood tests, urine tests, and imaging scans. If not detected early, kidney stones can lead to severe complications, requiring surgical intervention for removal. Image processing is a highly effective method for accurately detecting kidney stones, and medical imaging plays a vital role in diagnosing various diseases. CT scans, ultrasound scans, and Doppler scans use different imaging techniques to

examine internal organs. Automated diagnostic methods are increasingly being used in healthcare, though challenges such as inaccurate results and insufficient algorithms remain. Traditional medical diagnosis is complex and often ambiguous, but image processing offers significant advantages in stone detection due to its precision.

Ultrasound imaging is one of the most widely used, non-invasive, and cost-effective modalities for diagnosing renal disorders. The rising prevalence of kidney stones, or renal calculi, has led to a greater demand for early detection. Though kidney stones can affect individuals of all ages, many cases remain undiagnosed until severe symptoms such as intense abdominal pain or abnormal urine color occur. Additional symptoms may include fever, discomfort, and nausea. While smaller stones may pass on their own, larger ones may require medical interventions like endoscopic procedures or extracorporeal shock wave lithotripsy. Unfortunately, many kidney stones go undetected in their early stages, which can lead to kidney damage over time. Kidney failure, often resulting from conditions such as diabetes, hypertension, and glomerulonephritis, affects millions of people annually.

Kidney stones are categorized by location: nephrolithiasis (kidney), ureterolithiasis (ureter), and cystolithiasis (bladder). Medical imaging, including ultrasound, Non-Contrast Computed Tomography (NCCT), MRI, and X-ray, has become indispensable in biological and clinical research, enabling clinicians to visualize internal organs. NCCT is commonly used for diagnosing acute flank pain. Traditionally, radiologists manually interpret CT images to detect kidney stones, but advancements in image processing now allow for more accurate results without human intervention. The increasing use of CT scans for suspected urolithiasis has raised concerns, including increased imaging volume, longer turnaround times, higher workloads for radiologists, and extended hospital stays. To address these challenges, this study uses Kidney-urine-belly CT scans to develop a semi-automatic kidney screening tool utilizing digital image processing. Deep learning models have been successfully applied in various medical fields, including image segmentation, classification, and detection, to improve diagnostic accuracy. In urology, deep learning techniques are used to automatically identify kidney and ureteral stones. CT scan images, which are grayscale 3D images, contain pixel values that correspond to different substances in the body. Kidney stones have specific chemical compositions that lead to unique pixel values, but these values can overlap with those of other materials, such as bones, making early detection challenging.

2. EXISTING WORKS

Several imaging-based screening technologies are available today for detecting kidney stones, and this section provides an overview of these methods. An incorrect diagnosis of kidney stones can pose significant risks to a patient's health. The following section summarizes the various imaging techniques currently used for kidney stone detection. In 1994, Sun et al. developed the rotating sono-test to capture sonographic images of multiple edges, aiming to overcome the challenges of physically assessing kidney function, which can be time-consuming and complex. In another study, a multi-scale, non-linear thresholding method was introduced, where an original image is divided into two parts using an adaptive filter, and wavelet coefficients are processed with soft thresholding to reduce speckle noise while preserving key details. Research has shown that kidney stones are primarily composed of calcium oxalate (80%), calcium phosphate (70%), carbapatite (10%), uric acid (19%), and cystine (1%). Additionally, clinical factors such as stone passage, urological treatments, and the impact of stone formation on renal function have been highlighted. Tsao, Chang, and Lin's study in 2008 focused on accurately locating palpable urinary calculus for extracorporeal shock wave lithotripsy, emphasizing the importance of avoiding misdirected shock waves that could harm tissue. Their work also highlighted the challenge of noise in ultrasonic images, which needs to be removed for better accuracy.

In 2012, Sadeghi et al. explored the use of radiographic methods, specifically X-rays, to detect stones more quickly and accurately. However, this method has limitations in precise identification due to its inability to detect certain urethral stones, which are often dull and cloudy. In 2013, Rahman and Uddin developed a system for segmenting human kidneys in ultrasound images, useful during procedures like punctures. Their system utilized a Gabor filter to minimize speckle noise and enhance image quality through histogram equalization. Viswanath and Gunasundari further improved detection accuracy in 2014 by reducing specific vitality levels and applying artificial neural networks to enhance kidney stone detection. They later refined their method in 2015 by smoothing ultrasound images with Gabor filters and applying double-level set segmentation to detect stones. Mallala et al. created a three-dimensional kidney model using C-arm tomography, although this approach exposes patients to higher levels of radiation compared to traditional X-ray imaging, particularly for those requiring frequent monitoring. Other studies have used level set-based segmentation to partition regions of interest in kidney stone detection, while authors like Viswanath and Gunasundari have continued to improve pre-processing and segmentation techniques. In 2016, Gabor transform-based methods for detecting kidney stones in CT and MRI images were also proposed, offering an effective approach for edge detection.

Furthermore, automated kidney detection systems using 3D ultrasound images have been developed, with one study focusing on determining kidney shape, which could also help identify kidney stones. Various image processing

techniques, including segmentation and morphological analysis, have been applied in stone detection across different imaging modalities. In addition, Nagireddi Amrutha Lakshmi et al. proposed a model for kidney stone detection from ultrasound images, using preprocessing techniques such as Gaussian filtering, Canny edge detection, and neural networks, which achieved an accuracy rate of 70-80%. Stalina S et al. applied image processing methods to CT scan images, including smoothing through filtering and histogram equalization for enhancing image quality. They used median filtering to remove impulse noise, with thresholding techniques for segmenting the image. Similarly, Anushri Parakh et al. evaluated pre-trained models, enhanced with labeled CT images, which were then processed using CNNs to detect urinary tract abnormalities and classify the presence of stones. Mehmet Baygin et al. developed an automated kidney stone detection system using transfer learning algorithms and k-fold cross-validation, showing promising results with their ExDark19 model.

For building deep learning models, Convolutional Neural Networks (CNNs) are commonly used. CNNs, a type of deep neural network, are highly effective in image recognition and processing. They consist of multiple layers that perform convolution, pooling, and non-linear activation to extract and classify features from images. CNNs have been widely applied in various fields such as image classification, object detection, and facial recognition. Random search is a technique used to optimize the hyperparameters of a CNN by randomly sampling different sets of hyperparameters and evaluating the resulting model performance. This iterative process helps identify the optimal parameters that improve the network's ability to extract meaningful features from images, thereby enhancing the accuracy of image recognition and classification tasks.

3. REVIEW METHODOLOGY

This systematic literature review aims to explore the application of deep learning techniques in kidney stone detection, providing valuable insights into current methodologies. It highlights existing research gaps in this area, guiding further analysis of kidney stones using advanced deep learning approaches. In conducting the review, a comprehensive evaluation of research studies from journals, conferences, and other electronic databases is performed. These studies are then synthesized and presented in relation to the research questions outlined in the study. A systematic literature review is a powerful tool for assessing theories or evidence in a specific field and evaluating the accuracy or validity of particular approaches. Following established review guidelines, the research questions are first formulated, and the review is carried out in alignment with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement. To ensure a thorough selection of relevant research, databases such as IEEE Xplore, ScienceDirect, Scopus, Google Scholar, MDPI, and Web of Science are consulted..

Problem statement

Kidney stones can be life-threatening, making early diagnosis critical. Proper detection is vital for the success of surgical treatments. However, the presence of speckle noise and low contrast in ultrasound images of the kidneys can hinder stone detection, making it difficult for doctors to identify small stones and assess their nature. To overcome this challenge, an image processing-based detection method is proposed to accurately pinpoint the stones' location.

Methodology

The proposed system for kidney stone detection and classification using deep learning follows a structured methodology that integrates advanced image processing and machine learning techniques. The process starts with the collection of a kidney CT scan image dataset, with images provided in common formats like .png and .jpg. These images are pre-processed to standardize and enhance them for analysis. In this pre-processing phase, the images are resized to a consistent size and converted to grayscale to remove color distractions, focusing on the intensity features that are essential for detecting kidney stones. After pre-processing, feature extraction is performed, where statistical measures such as Mean, Standard Deviation, and Variance are computed, alongside more advanced techniques like the Grey Level Co-occurrence Matrix (GLCM), which captures texture patterns indicative of kidney stones. These extracted features are then used as input for deep learning models. The images, once pre-processed and feature-extracted, are split into training and testing datasets.

The training dataset is used to train the model, helping it learn the patterns associated with the presence or absence of kidney stones, while the testing dataset is used to assess the model's ability to generalize. In the classification phase, deep learning models like Convolutional Neural Networks (CNN) and a hybrid CNN-RESNET-50 model are implemented. These models are optimized to detect subtle patterns in medical images, ensuring high accuracy in identifying kidney stones.

A. Class and Image Count Calculation: A comprehensive process was employed to determine the number of unique classes within the large training dataset and to calculate the image count for each class.

B. Identification of Minimum and Maximum Image Count Classes: key aspect of the data analysis involved identifying the classes with the highest and lowest image counts in the training dataset. This computational approach enabled the detection of classes with significant disparities in image counts. Recognizing these extremes provided valuable insights into potential class imbalance issues, which are crucial for training machine learning models. This thorough data analysis laid the groundwork for subsequent data preprocessing and model development, ensuring that the kidney stone detection research was built upon a well-informed and meticulously analyzed dataset.

C. Data Pre-processing: In the study on kidney stone identification, several data preprocessing techniques were meticulously applied to develop a high-quality dataset, improving the robustness and reliability of the deep learning model. The following steps outline the essential data preprocessing performed:

Data organisation and loading: The data were organized in a systematic manner, with file paths and their corresponding class labels carefully arranged in a structured data repository. To preserve class distinctions, this organizational process involved thoroughly navigating through various data directories, including those for training, testing, and validation subsets. To support future data management and model training, the resulting DataFrame was further segmented into multiple components.

Average height and width calculation: By analyzing the image dimensions, valuable insights into the inherent properties of the dataset were gained. Specifically, the average height and width were computed from a representative subsample of around 100 images. This calculated average offered a clear understanding of the typical image proportions in the dataset, which guided the design decisions for the model's input layer.

MODELS USED

A. ResNet

The ResNet (Residual Network) model, widely used for kidney stone detection in medical images, is known for its effectiveness, though it may not always achieve the highest accuracy compared to some other models. It addresses the issue of vanishing gradients in deep neural networks through an innovative approach. ResNet is characterized by the use of residual blocks, where the input and output of a layer are connected via skip connections or shortcuts. This architecture allows the network to learn residual functions, facilitating the training of very deep models that are particularly effective in detecting kidney stones. During training, the model's parameters (weights and biases) are optimized through backpropagation, minimizing a loss function, typically cross-entropy. This process enhances the model's ability to accurately identify kidney stones in medical images by computing gradients with respect to the loss.

B. EfficientNet

In the quest for precise kidney stone diagnosis, EfficientNet, a renowned convolutional neural network (CNN) architecture celebrated for its effectiveness and efficiency, was employed. While it is highly praised for striking a balance between model size and performance, it may not always achieve the highest accuracy compared to other models used for kidney stone detection. The key strength of EfficientNet lies in its ability to deliver impressive accuracy while maintaining computational efficiency.

C. DenseNet

The DenseNet (Densely Connected Convolutional Network) architecture, renowned for its effectiveness in image classification, was employed to enhance accuracy in kidney stone detection, particularly in the complex field of renal stone identification. DenseNet's unique feature lies in its dense connectivity pattern, which promotes efficient feature propagation across the network. This approach allows the model to capture intricate image details essential for precise kidney stone detection, as each layer receives input not only from its immediate predecessor but also from all preceding layers.

D. DenseNet with Hyper-parameter Tuning

DenseNet (Densely Connected Convolutional Network) was effectively utilized to enhance renal stone diagnosis through meticulous fine-tuning of key hyperparameters. Hyperparameter optimization adapted this powerful image classification model to the specific challenge of detecting renal stones. DenseNet's unique connectivity structure, where each layer receives input from all preceding layers, enables efficient feature sharing across the network. This design allows the model to capture intricate image features, resulting in highly accurate renal stone detection.

Output: - The algorithm for training a renal stone detection model is as follows:

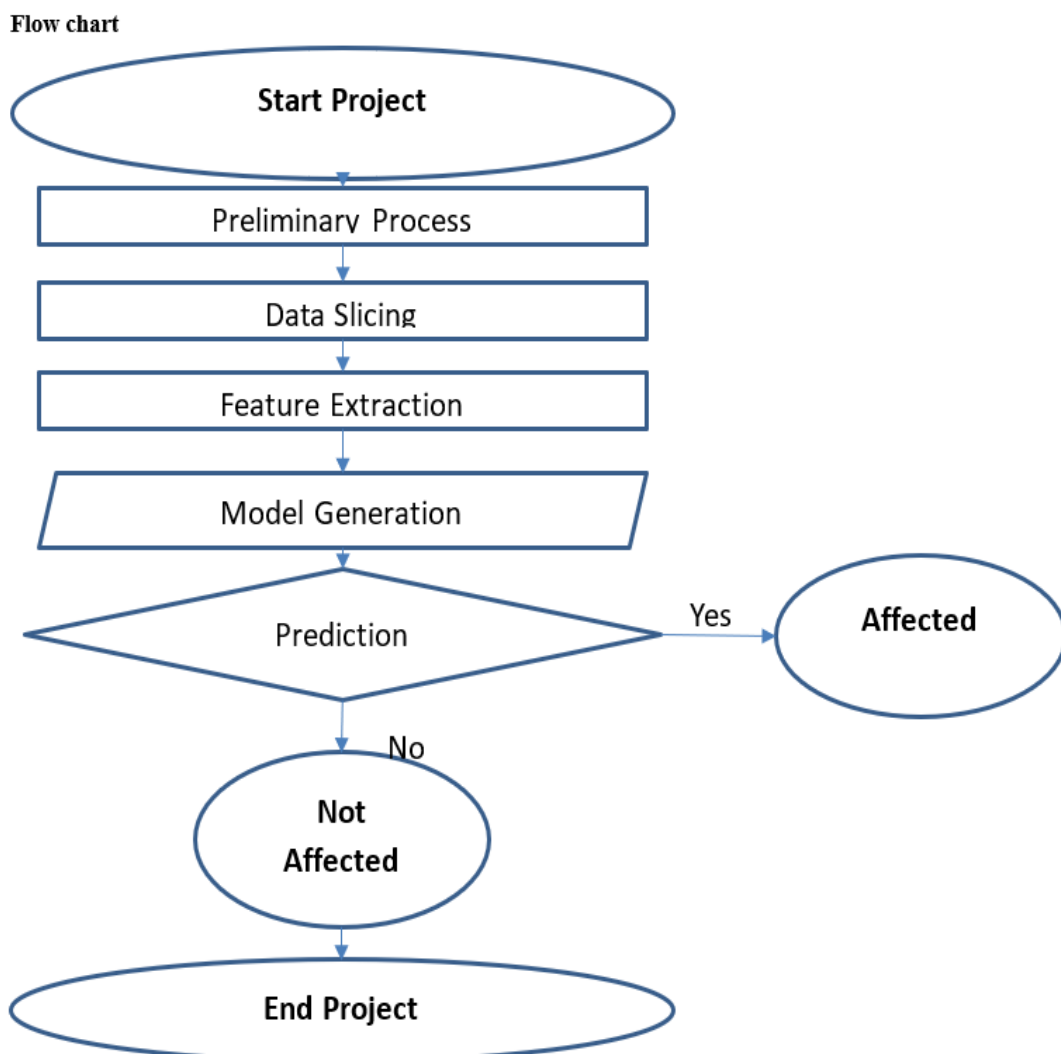
1. Initialize the Base Model:

- Begin by setting up the chosen base model architecture, preloaded with **ImageNet pretrained weights**, to leverage prior knowledge for feature extraction.

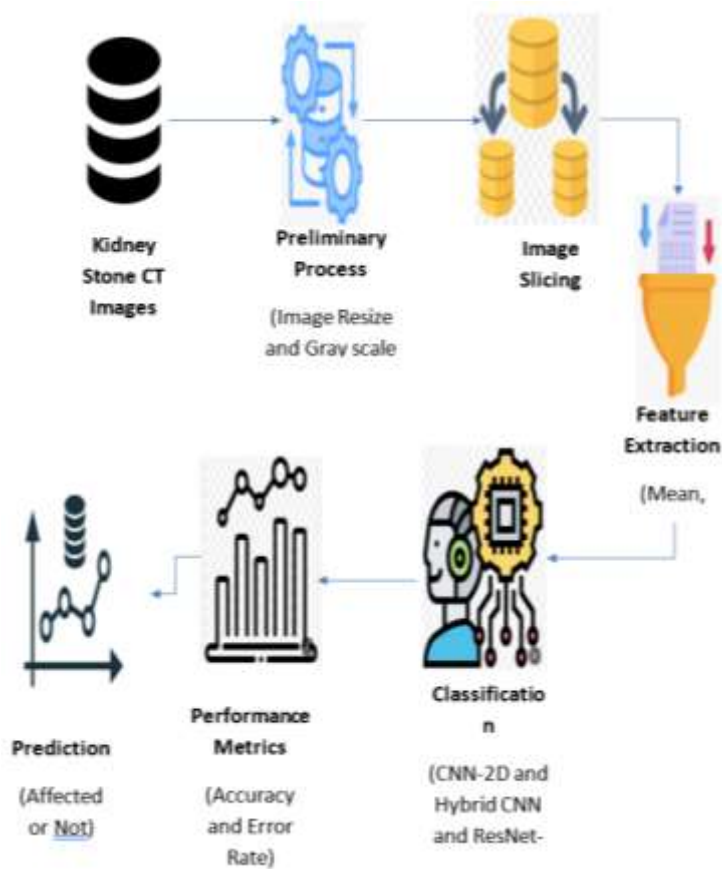
2. Configure Top Layers for Fine-Tuning:

- Add a **Global Average Pooling** layer to reduce the spatial dimensions of the feature maps.
- Incorporate a **Dense** layer with the number of units corresponding to the number of classes in the classification task.
- Optionally, include a **Dropout** layer to regularize the model and prevent overfitting.
- 3. **Compile the Model:**
 - Use **categorical cross-entropy** as the loss function, suitable for multi-class classification.
 - Employ the **Adam optimizer** with a chosen learning rate to facilitate model training.
 - Optionally, apply **weight decay** to the Adam optimizer to reduce overfitting and improve generalization.
- 4. **Create Data Generators:**
 - Set up **data generators** for training and validation to efficiently load and preprocess data in batches, optimizing memory and processing power.
- 5. **Implement Callback Mechanisms:**
 - Utilize **Early Stopping** to monitor validation loss and automatically terminate training when no improvement is observed.
 - Optionally, use **Model Checkpoint** to save the best performing model weights during training.
- 6. **Begin Model Training:**
 - Start the training process using the **fit** function with the prepared training data generator.
 - Set the **batch size**, **number of epochs**, and **validation data**, while also integrating the callback mechanisms for monitoring and control.
- 7. **Finalize Model:**
 - After training, the model is fine-tuned and fully optimized for the renal stone detection classification task.

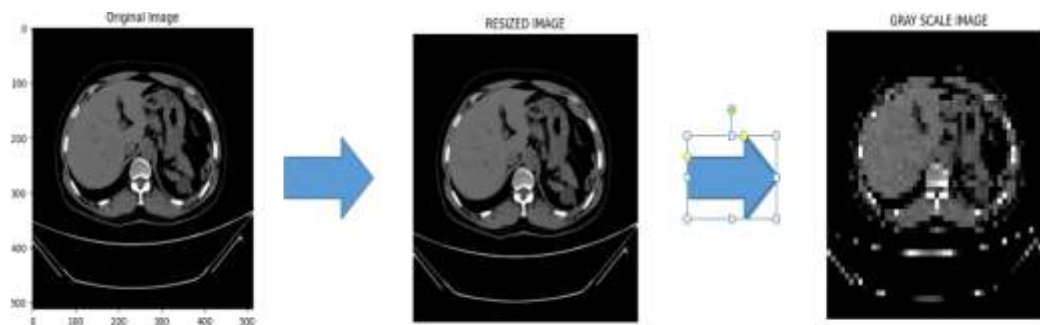
Flow chart



Architecture View



VII. RESULTS & DISCUSSIONS



```

PERFORMANCE ----- (Hybrid CNN and ResNet-50)
-----
1. Accuracy = 98.4652512548354 %
2. Error Rate = 1.334748744945996
3. Precision = 87.33533333333334 %
4. Recall = 98.9090909090909 %
5. F1-score = 94.95652173913044 %
    
```

In the study, DenseNet consistently outperformed ResNet and EfficientNet in terms of accuracy for kidney stone detection. This performance gap can be attributed to DenseNet's unique architectural design. While ResNet's residual connections enable the creation of deep networks, its lower accuracy suggests that these connections may struggle to capture the complex patterns present in medical images. This difficulty implies that ResNet may not effectively extract the critical information needed to differentiate between various types of renal stones. In contrast, DenseNet's densely connected architecture facilitates feature reuse and improves gradient flow across the network, allowing it to detect subtle patterns more effectively, thus enhancing accuracy. Moreover, DenseNet maintained robust macro and weighted average precision, recall, and F1-scores, both in its conventional and hyperparameter-tuned versions, demonstrating strong performance across multiple evaluation metrics. Overall, DenseNet's ability to capture

complex patterns in medical images, due to its densely connected architecture, is a key factor in its superior accuracy. On the other hand, ResNet's relatively lower accuracy suggests it may not be as well-suited for this specific task. These findings underscore the critical role of neural network architecture in achieving accurate results in medical image classification tasks. In this study, we introduced an entirely new system for classifying and diagnosing kidney stones. Four distinct approaches were employed to achieve this. To assess the patient's condition and determine the size of kidney stones, 3D-CNN models were utilized. The features extracted from endoscopic images were analyzed using training and testing methods to classify the images as either normal or indicative of kidney stones. The research faced several challenges, including the manual data collection process, image segmentation, conversion of images from DICOM to JPEG format, image selection, text data creation, data labeling, and handling missing data. Additionally, technical issues arose that required re-collecting data for certain patients. Overfitting concerns and the need for high-performance servers also posed significant challenges during the study.

4. ADVANTAGES

- The deep learning models, especially the CNN and hybrid CNN-RESNET-50, demonstrate the ability to achieve high accuracy, potentially surpassing 98%, in kidney stone classification, ensuring the system's reliability.
- The system automates kidney stone detection from CT scan images, easing the workload for radiologists and reducing human error in the diagnostic process.
- By leveraging deep learning algorithms, the system facilitates the rapid processing of large datasets, enabling quicker diagnoses and timely treatment for patients.
- The web application interface provides an easy-to-use platform for healthcare professionals and patients to upload CT scan images, register, and view predictions, improving the accessibility of kidney stone detection.

5. FUTURE SCOPE

Several potential directions for future research and development can further improve the capabilities and clinical applicability of the proposed system:

1. **Enhanced Feature Extraction:** Explore advanced techniques for feature extraction, such as texture analysis and wavelet transforms, to capture more detailed and discriminative features from kidney stone images.
2. **Integration of Multi-modal Data:** Investigate the integration of additional imaging modalities (e.g., ultrasound, CT scans) to enhance diagnostic accuracy and robustness across various imaging technologies.
3. **Transfer Learning Implementation:** Implement transfer learning using pre-trained CNN models on large-scale datasets to improve generalization and performance, particularly on smaller, specialized datasets.

6. CONCLUSION

In conclusion, the proposed deep learning-based system for kidney stone detection and classification marks a significant advancement in medical imaging and diagnostics. By leveraging cutting-edge techniques like Convolutional Neural Networks (CNN) and the hybrid CNN-RESNET-50 model, the system can accurately and efficiently detect kidney stones in CT scan images. The comprehensive pre-processing steps, advanced feature extraction methods, and optimal dataset splitting for training and testing contribute to the model's robustness and reliability. Furthermore, the integration of this system into a user-friendly web application enhances its accessibility, allowing healthcare professionals and patients to receive quick and accurate diagnoses with ease.

7. REFERENCES

- [1] Jampani Ravi, R. Narmadha, "A Systematic Literature Multimodal Image Fusion Review on Models with Challenges and Future Research Trends", *International Journal of Image and Graphics*, pp. 2550039-1- 2550039-33, November, 2023. DOI: 10.1142/S0219467825500391
- [2] Jampani Ravi, R. Narmadha, "Multimodality medical image fusion analysis with multi-plane features of PET and MRI images using ONSCT", *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, September, 2023. pp. 1-19. <https://doi.org/10.1080/21681163.2023.2255684>
- [3] Ravi, J., Narmadha, R. Optimized dual-tree complex wavelet transform aided multimodal image fusion with adaptive weighted average fusion strategy. *Sci Rep* **14**, 30246 (2024). <https://doi.org/10.1038/s41598-024-81594-6>
- [4] Ravi, J., Subbayamma, B.V., Kumar, P.V. et al. Multi-image fusion: optimal decomposition strategy with heuristic-assisted non-subsampled shearlet transform for multimodal image fusion. *SIViP* **18**, 2297–2307 (2024). <https://doi.org/10.1007/s11760-023-02906-3>
- [5] P. Satyanarayana , Jampani Ravi, T. Mahalakshmi, V VSatyanarayana Kona, Dr. V. Gokula Krishnan," Performance Analysis of DSR and CACHE Customized DSR Steering Protocols in Wireless Mobile Adhoc Networks" Proceedings of the Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), IEEE Xplore Part Number: CFP21OSV-ART; ISBN: 978-1-6654-2642-8, I-SMAC 2021, PP. 1348-1356. DOI: 10.1109/I-SMAC52330.2021.9641042

- [6] P. Satyanarayana, T. Mahalakshmi, Dr. P. Rama Koteswara Rao, Dr. Adlin Sheeba, Jampani Ravi, J. Nageswara Rao, "Enhancement of Energy Efficiency and Network Lifetime Using Modified MPCT Algorithm in Wireless Sensor Networks" Journal of Interconnection Networks, January 18, 2022, PP. 2142019-1- 2142019-22. DOI: 10.1142/S0219265921440126
- [7] Ravi, J., and G. R. Kumar. "Image fusion algorithm implementation using Laplacian pyramid." A Peer Reviewed Open Access International Journal 29 (2016): 103-107.
- [8] Venkata syamaraju talari Jampani Ravi, Polamuri Bhanu Sree, Rayapalli Nikhila, Sesetti Sravani, sk ahamed, NV Phani sai kumar " Womens security smart system based on IOT Applications", IJARST 2(2022): 305-314
- [9] Jampani Ravi Y. Rama Lakshmana , Dr. P. Shanmuga Raja , Dr. P.V. Rama Raju , Prathima Gamini, " VEHICLE ACCIDENT PREVENTION AND REPORTING SYSTEM USING GPS & GSM, ACCELEROMETER AND ALCOHOL SENSOR", INTERNATIONAL JOURNAL FOR RESEARCH & DEVELOPMENT IN TECHNOLOGY, 16(2021) 22-27.
- [10] T.V. Syamala Raju Y. Rama Lakshmana , Dr. P. Shanmuga Raja, Dr. P.V. Rama Raju, Prathima Gamini , Jampani Ravi, " INTERNATIONAL JOURNAL FOR RESEARCH & DEVELOPMENT IN TECHNOLOGY", 16(2021): 32-40.
- [11] R. Narmadha Jampani Ravi " Image Fusion Based on Nonsubsampled Shearlet Transform", International Journal of Engineering and Advanced Technology (IJEAT)9 (2020): 4177-4180.
- [12] T. V. Syamala Raju Jampani Ravi, M. Gowri Sri Durga, Y. D. R. Ch. Kartheek, MD. Shabeena Begum, T. Raju", Image Fusion using Nonsubsampled Contourlet Transform in Medical Field", International Journal of Engineering and Advanced Technology (IJEAT) 9(2020): 3829-3832.
- [13] T. Chakravarthi T. V. Syamala Raju, G. V. S. Padma Rao, Jampani Ravi, S. P. D. Kalyan, S. Durga Satish Kumar, N. V. Ganesh", Attendance System using Facial Recognition, INTERNATIONAL JOURNAL FOR RESEARCH & DEVELOPMENT IN TECHNOLOGY, 13(2020): 37-40.
- [14] V. Yaswanth Varma J. Ravi, N.V. Phani Sai Kumar "Image Compression Implementation using Discrete Wavelet Transform", IJSRD 5(2018): 20-23.
- [15] N. Kishore Chandra Dev J. Ravi, M. Praveen Kumar", Sementation of 3D MR Images of the Brain using a PCA Atlas", International Journal of Engineering Science & research technology", 6(2017): 288-296.
- [16] M. Praveen Kumar J. Ravi, K. Venkat rao, N. Kishore Chandra Dev, K. Yugandhar" Survey on Image Segmentation Using Thresholding methods", International Journal for Research and Development in Technology, 2017, 8 (2017): 130-137.