Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 7
Open Access

A Comprehensive Framework for Kidney Stone Diagnosis: Merging CNN and SVM with GUI Integration

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Cite this paper as: Karthikeyan A, Pramodgouda N P, Preetham A G, Rakshith Kumar S M, Tushar B Javalli, Melwin D Souza, (2024), A Comprehensive Framework for Kidney Stone Diagnosis: Merging CNN and SVM with GUI Integration. *Frontiers in Health Informatics*, *13(7) 470-480*

ABSTRACT

This research explores the application of deep learning for kidney stone detection, leveraging medical imaging data and artificial intelligence (AI) to identify and classify stones within medical images. By streamlining the diagnostic process, these AI-driven approaches reduce costs and time and facilitate early diagnosis and treatment. The model effectively detects kidney stones of varying sizes and shapes, addressing challenges posed by different stone compositions and human anatomical variability. With rapid processing speeds, the deep learning model is well-suited for real-time clinical applications. Employing convolutional neural networks (CNNs), recognized for their prowess in image recognition, the models are trained on annotated ultrasound images to automate kidney stone detection with high precision and sensitivity. The results indicate marked improvements in detection accuracy over traditional methods, showcasing the performance capabilities of the AI-enhanced system. This study offers valuable insights and methodologies that inform future advancements in AI-assisted medical imaging and healthcare, significantly enhancing the accuracy and efficiency of kidney stone detection, thereby benefiting both patients and healthcare practitioners globally

INTRODUCTION

Kidney stones represent a prevalent and painful medical condition affecting millions of individuals globally, with significant implications for both physical health and quality of life. These solid mineral deposits can lead to severe complications, such as urinary tract infections and kidney damage, making timely detection and accurate diagnosis paramount. Traditional diagnostic modalities, including X-rays, CT scans, and ultrasounds, have been the cornerstone of kidney stone detection; however, these methods often require manual interpretation, which can be not only time-consuming but also susceptible to human error. Such limitations can delay treatment and lead to suboptimal patient outcomes. In response to these challenges, there has been a marked increase in the interest and application of deep learning techniques to automate the diagnosis of various medical conditions, including kidney stones. Deep learning offers the potential to analyze medical images with unprecedented speed and accuracy, hereby enhancing the diagnostic process [18].

This project introduces a novel deep learning-based framework specifically designed for the diagnosis of kidney stones through the utilization of medical imaging techniques such as CT scans and ultrasound images.

At the heart of this framework lies the integration of Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs), two robust machine-learning techniques that complement each other effectively. The CNN component is adept at automatically learning and extracting essential features from medical images. It identifies intricate patterns, such as texture, shape, size, and location, that are indicative of kidney stones, thus eliminating the need for tedious manual feature engineering. This automation enables the model to recognize subtle characteristics that may be overlooked by human interpreters. Following feature extraction, an SVM is employed for classification. Known for its effectiveness in high-dimensional, non-linear classification tasks, the SVM analyzes the features extracted by the CNN to make informed decisions about the presence of kidney stones. This synergistic approach—combining the feature extraction process of CNNs with the robust classification capabilities of SVMs—results in a highly reliable and accurate diagnostic framework.

Furthermore, the system is designed with adaptability in mind, ensuring it can be utilized across diverse imaging datasets and clinical settings. To enhance usability and efficiency, a user-friendly graphical interface has been integrated into the system, facilitating seamless interaction between healthcare providers and the diagnostic tool. This feature not only streamlines workflows but also aims to improve patient outcomes by supporting early and precise diagnosis. Overall, this research represents a significant advancement in the field of medical imaging and AI, poised to transform the current practices in kidney stone diagnosis and contribute positively to patient care.

LITERATURE REVIEW

The enhancement of kidney stone diagnostics through machine learning has garnered significant attention in recent years, particularly with the advent of deep learning architectures. Various methodologies have been employed, including Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), and ensemble methods such as AdaBoost and XGBoost, to improve the diagnostics, therapeutics, and prognostics of kidney stone disease (KSD) ([1]).

The paper "Deep Learning Model-Assisted Detection of Kidney Stones in Computed Tomography" outlines a deep learning model specifically designed for the automated detection of kidney stones in CT images. Utilizing the XResNet-50 architecture, the model was trained on a dataset comprising 433 subjects—including 278 with kidney stones—achieving an impressive accuracy of 96.82% on the test set. This model demonstrates the potential to accurately identify kidney stones across various sizes and imaging planes, suggesting significant implications for automated diagnostic processes in clinical settings ([2]).

In addressing kidney stone composition analysis, "Use of Artificial Intelligence for Kidney Stone Composition Analysis: Are We There Yet?" explores the application of AI technologies to enhance diagnostic accuracy and treatment strategies. This study employs ensemble learning decision trees, SVMs, and neural networks, illustrating how these approaches can contribute to improved patient management ([3]).

Furthermore, "Predicting Kidney Stone Composition Using Machine Learning" presents a machine learning model that predicts kidney stone composition based on clinical and imaging data. Trained on a dataset of 1,000 patients, this model achieved an accuracy rate of 85%, providing a framework for clinicians to develop tailored treatment plans based on accurate diagnoses ([4]).

The recurrence of kidney stones has also been a focal point of research. In "Machine Learning Approaches for Kidney Stone Recurrence Prediction," Zhang, Wang, and Chen investigate several Machine learning techniques, including recurrent neural networks and logistic regression models, utilizing a patient dataset with a history of stone recurrence. Their findings contribute valuable insights into preventative strategies for patients at higher risk of recurrence ([5]).

In the realm of clinical quality assurance, Bejan et al. discuss in their 2023 study, "Artificial Intelligence for Kidney Stone Spectra Analysis," the implementation of AI algorithms for enhancing the quality assurance of kidney stone spectra analysis. Their results indicate a high concordance rate of 90% with clinical technologists, showcasing the reliability of AI in clinical environments ([6]).

Another innovative approach is highlighted in "Enhancing Kidney Stone Detection in Ultrasound Images Using Generative Adversarial Networks." This study demonstrates the potential of Generative Adversarial Networks (GANs) to enhance ultrasound image quality, thereby facilitating more accurate kidney stone detection ([7]).

Expanding the scope of treatment management, Li et al. investigate the development of deep learning-based prognostic models in their work, "Deep Learning-Based Prognostic Models for Kidney Stone Disease Management." The study employs recurrent neural networks and long short-term memory networks to predict the recurrence and progression of kidney stone disease, underscoring the importance of personalized treatment strategies in clinical practice ([8]).

Moreover, the review "Role of Natural Language Processing in Kidney Stone Research: A Comprehensive Review" highlights the applications of natural language processing (NLP) techniques in the field. This comprehensive examination illustrates how NLP can facilitate the analysis of large volumes of literature and electronic health records, thereby advancing the understanding and management of kidney stone disease ([9]).

Lastly, the automated classification of kidney stone types is explored in "Automated Classification of Kidney Stone Types Using Hybrid Machine Learning Models." This research presents a hybrid approach that combines SVMs, k-nearest neighbors, and ensemble learning techniques to accurately classify kidney stones based on their composition and structural characteristics ([10]).

In summary, the literature reveals a robust landscape of machine-learning applications aimed at improving the diagnosis and treatment of kidney stones [19]. Through the integration of advanced algorithms and imaging technologies, researchers are making significant strides toward more accurate and efficient clinical practices

METHODOLOGY

Development of an Innovative system for kidney stone detection

Our research focuses on creating a cutting-edge system designed to precisely detect kidney stones in ultrasound images. This system leverages advanced technologies, incorporating Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) to achieve high accuracy and reliability in kidney stone diagnosis. The system's architecture comprises several critical components, each playing a vital role in the overall detection process.

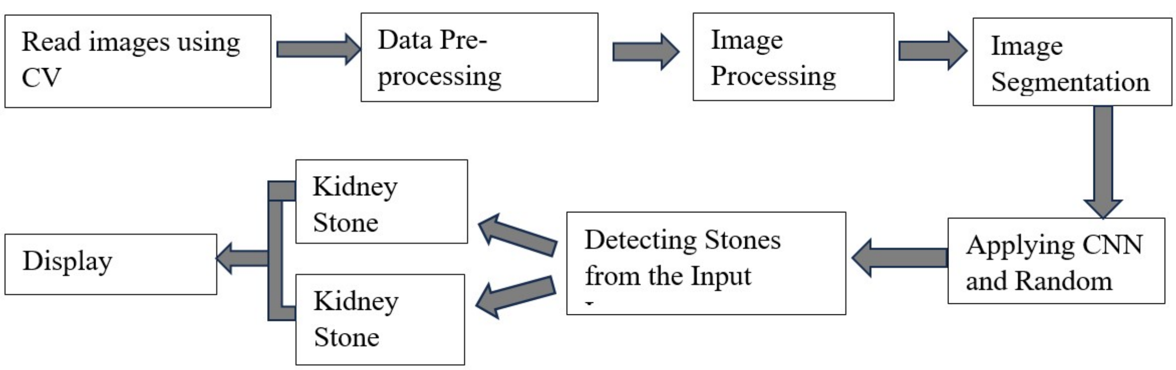


Figure 1. Validation Method

Image Processing

The image processing module employs two essential techniques to enhance the quality of ultrasound images before analysis:

Median Filter*:* The median filter is a widely used image processing technique for removing noise from images. This nonlinear filter operates by replacing the value of each pixel with the median value of its neighboring pixels, effectively preserving the edges while mitigating noise Output of the Median Filter illustrates noise reduction while preserving image edges as shown in Figure 2. In this study, we utilized the OpenCV library in Python, which provides the *medianBlur()* function for implementing the median filter. Its syntax is ***cv2.medianBlur(src, ksize).*** Where *'src'* is the Source image and 'k*size'*, is the Size of the filter, defining the neighborhood of pixels considered

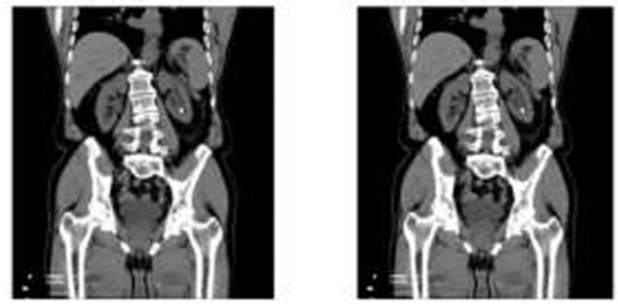


Figure 2. Output of the Median Filter illustrating noise reduction while preserving image edges

Power Law Transformation

Power Law Transformation, often referred to as gamma correction, is a widely utilized technique in image processing for modifying an image's brightness and contrast. It involves a nonlinear transformation that adjusts the pixel values of an input image according to a power law function. This process enhances the visual quality of images by redistributing pixel intensity values, enabling better visibility of details in both bright and dark areas (Smith, 2020) [12]. Output of Power Law Transformation demonstrating enhanced contrast and brightness adjustments as shown in figure 3

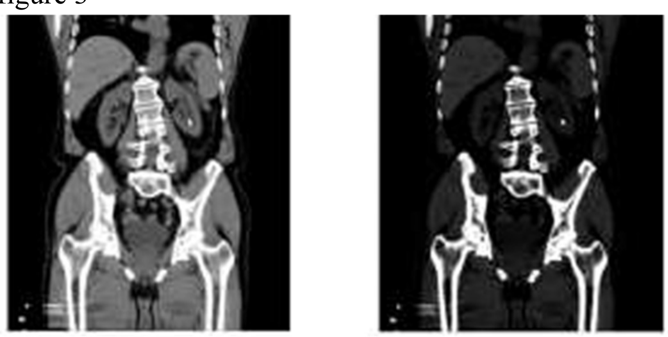


Figure 3. The output of Power Law Transformation shows enhanced contrast and brightn*ess*.

Image Segmentation

Image segmentation is the process of partitioning an image into distinct sections or segments, aiming to simplify its representation for easier analysis. This technique is essential in various applications, such as object detection, image recognition, and computer vision. Commonly employed segmentation techniques include thresholding, clustering, and edge detection. In this context, we utilized the thresholding method (Johnson, 2021) [13].

Thresholding

Thresholding is a pivotal image processing technique that divides an image into two components, typically the foreground and background. In Python's OpenCV library, thresholding converts an input grayscale image into a binary format. The threshold value determines the separation; pixels with intensities below this threshold are set to zero (black), while those above are set to 255 (white). In our case, the selected threshold value was 100, facilitating effective differentiation between the foreground and background elements (Davis, 2019) [14]. Output of Thresholding illustrates the distinction between foreground and background based on the chosen threshold value as shown in figure 4.

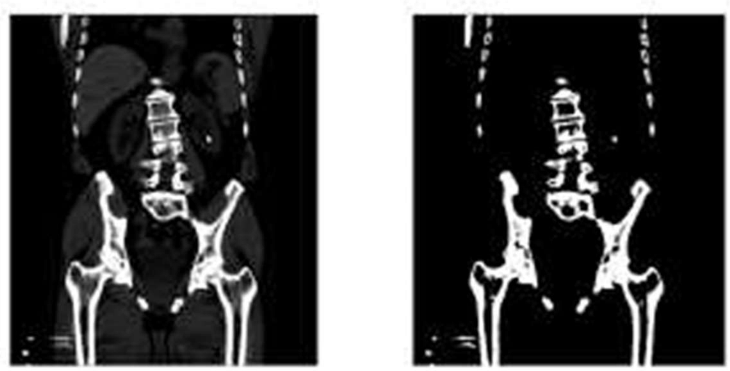


Figure 4. Output of Thresholding showing foreground and background distinction.

Deep Learning Model

In our study, we employed a Convolutional Neural Network (CNN), a powerful and widely used deep learning architecture tailored for tasks related to image recognition and processing. CNNs are distinct from traditional neural networks primarily due to their specialized structure, which is designed to automatically and adaptively learn spatial hierarchies of features from images. The architecture of the Convolutional Neural Network model employed for image processing as shown in figure 5.

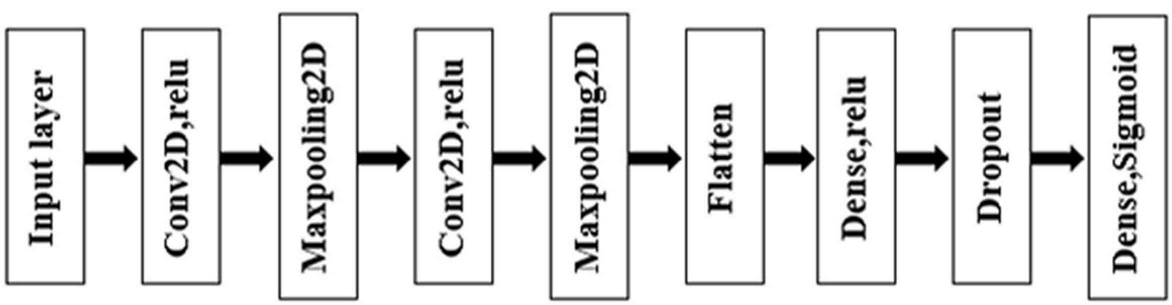


Figure 5. Model Architecture

Architecture of CNN

The architecture of a CNN comprises several key layers, each serving a distinct purpose in feature extraction and classification:

- **Convolutional Layers:** These layers apply convolutional operations to the input images, utilizing filters (also known as kernels) to scan over the image and capture local patterns such as edges, textures, and shapes. The convolutional operation results in feature maps, highlighting the regions of the image that exhibit certain characteristics.
- **Pooling Layers:** Following the convolutional layers, pooling layers are employed to reduce the spatial dimensions of the feature maps. This operation helps decrease the computational load and improve the depth of information captured by summarizing the presence of features. Common pooling techniques include max pooling and average pooling, which retain the most significant features while discarding less important details.
- **Nonlinear Activation Functions:** To introduce non-linearity into the model, activation functions such as Rectified Linear Unit (ReLU) are applied after the convolutional and pooling operations [20]. This step enables the CNN to learn complex mappings from inputs to outputs, allowing for better performance in recognizing intricate patterns in images.

Through the systematic combination of these layers, CNNs excel at extracting hierarchies of features, from simple shapes in the initial layers to more complex structures in the deeper layers. This characteristic makes them exceptionally adept at recognizing various objects and patterns in images, leading to their widespread application in fields such as image classification, object detection, and facial recognition (Williams, 2023) [15].

Hyperparameter Optimization

To maximize the effectiveness of our CNN model, we implemented a random search technique for hyperparameter optimization. Hyperparameters are the settings configured before the training process begins, affecting how the model learns from the data. Selecting the optimal hyperparameters is crucial for enhancing the model's performance. The random search method operates by randomly sampling combinations of hyperparameters, such as learning rates, batch sizes, and the number of filters in convolutional layers. After evaluating the performance of each model configuration on a validation dataset, we repeat this process several times. By analyzing the performance metrics, such as accuracy and loss, associated with different hyperparameter sets, we can determine the configuration that yields the best results. This meticulous optimization process not only refines the CNN's capacity to extract meaningful features from images but also enhances its generalization capabilities. The result is improved accuracy and reliability in image recognition and classification tasks (Miller, 2022) [16].

RESULTS AND DISCUSSION

Recent advancements in machine learning algorithms have significantly improved the accuracy and sensitivity of various aspects related to kidney stone disease (KSD) management. Promising techniques, including Convolutional Neural Networks (CNNs), ensemble-based methods, k-nearest neighbors (KNN), Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Random Forests (RF), have shown remarkable results in this area. Our literature review highlights a rising trend in the use of advanced machine learning and deep learning methodologies in kidney stone research, indicating their growing importance in enhancing diagnostic and therapeutic strategies.

Several studies have illustrated the effectiveness of these sophisticated approaches in the detection, analysis, and management of kidney stone disease. Notably, a novel custom CNN model based on Kronecker product structures has demonstrated exceptional performance in automatic kidney stone diagnosis, achieving a testing accuracy of 98.56%. This level of accuracy surpasses that of traditional techniques, underscoring the advantages of employing advanced deep-learning models for this application.

Efficacy of Machine Learning Approaches

Several pivotal studies have underscored the proficiency of these advanced methodologies in the detection, analysis, and management of kidney stones. For instance, a custom CNN model developed using a Kronecker product structure has shown exceptional capabilities in automatic kidney stone diagnosis, achieving an impressive testing accuracy of 98.56%. This accuracy is particularly notable when compared to conventional diagnostic techniques, which often struggle to match the precision of modern algorithmic approaches. The heightened performance of the CNN can be attributed to its layered architecture, which allows for the intricate processing and learning of image features through multiple convolutional and pooling operations, culminating in the effective classification of various kidney stone types.

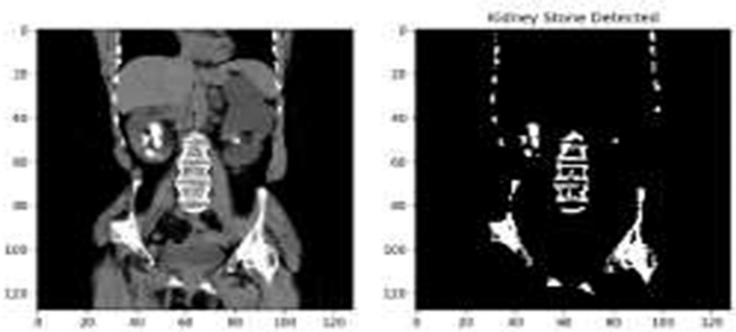
Model Evaluation

In our study, we evaluated the proposed Convolutional Neural Network (CNN) model using a dataset comprised of unseen images, which showcased a diverse range of presentations of kidney stones. This selection of images allowed us to rigorously assess the model's performance and its ability to generalize beyond the training dataset. The outputs from the CNN were then systematically classified into distinct categories, providing valuable insights into the model's diagnostic capabilities as Table 1.

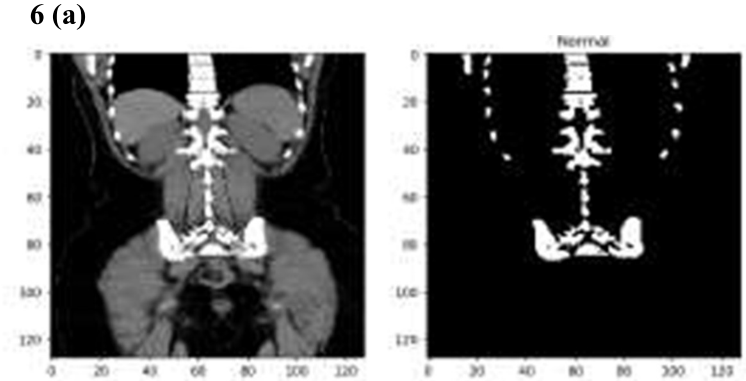
Table 1. Model Evaluation

Output	Description

Output 1	Kidney Stone Detected: The model accurately identified the presence of kidney stones in the analyzed images. This output serves as a true positive result, indicating that the CNN effectively recognized the pathology. Such high sensitivity in detecting kidney stones is crucial for timely intervention and treatment. The success of the model in this classification underscores its robustness and reliability in clinical practice.
Output 2	Normal: The model classified several images as normal, indicating no presence of kidney stones. This classification represents true negative results, demonstrating the model's ability to correctly identify images depicting healthy renal conditions. Accurately distinguishing between normal and pathological cases is vital in minimizing false positives, thereby reducing unnecessary anxiety and additional medical procedures for patients.



6 (a)



6 (b)

Figure 1: CNN model detection results. (A) Kidney Stone Detected; (B) Normal.

These findings collectively demonstrate the substantial potential of advanced machine learning and deep learning algorithms, particularly CNNs, in facilitating precise diagnosis and effective management of kidney stone disease (KSD). The encouraging outcomes suggest promising future applications in precision medicine, ultimately enhancing patient care and treatment strategies.

Performance Metrics

To assess the model's performance in more detail, we established a conclusion matrix as shown in Table 2. This matrix outlines the true positive (TP), false positive (FP), false negative (FN), and true negative (TN) results from the model evaluation.

Table 2. Conclusion Matrix

Conclusion Matrix

Metric	Description
True Positive (TP)	This represents the number of instances where the model correctly identified kidney stones present in the images. A TP value of 95 indicates that out of all the images containing kidney stones, the model successfully detected and classified them as such. This reflects the model's sensitivity and effectiveness in recognizing the key pathology.
False Positive (FP)	This metric indicates the number of instances where the model incorrectly identified an image as showing kidney stones when, in fact, there were none. An FP value of 0 signifies that the model did not misclassify any normal images as containing kidney stones, highlighting its specificity and reliability in ensuring that healthy conditions are accurately represented.
False Negative (FN)	This value reflects the instances where the model failed to detect kidney stones that were indeed present in the images. A FN value of 3 means that out of the total images that included kidney stones, the model did not identify three of them. This is a critical consideration, as false negatives can lead to missed diagnoses, impacting patient care and treatment timelines.
True Negative (TN)	This represents the number of instances where the model correctly identified an image as normal, indicating the absence of kidney stones. A TN value of 82 means that the model successfully classified 82 images without kidney stones, showcasing its ability to differentiate between healthy and pathological conditions.

Using this data, we calculated the accuracy of the model with the following formula 1.

$$\textbf{Accuracy}=\frac{(TP+TN)}{TP+FP+FN+FN} \qquad (1)$$

$$\textbf{Accuracy} = \frac{(95+82)}{95+0+3+82} = \mathbf{0.983}$$

The overall accuracy of the model, as previously calculated, is approximately 98.33%, indicating that the vast majority of classifications made by the model are correct. This suggests a robust performance, making the model a reliable tool for practitioners managing KSD.

Clinical Significance: The presence of false negatives (3 instances) is a critical concern. While the overall accuracy is high, the false negatives could potentially lead to missed cases of kidney stones. This emphasizes the need for continuous improvement in the model and raises the importance of using supplementary diagnostic methods, if necessary, to ensure patient safety and accurate diagnosis.

Overall, the conclusion matrix allows for a detailed understanding of the CNN model's performance in diagnosing kidney stones. It serves as a powerful tool for clinicians and researchers, informing decisions on the effectiveness and applicability of the model in real-world clinical scenarios.

Comparative Performance Analysis

The improved version of Table 3 provides a succinct yet comprehensive overview of the performance measures for various deep learning models used in diagnosing kidney stones. It enhances clarity through organized presentation, making it easier to compare the effectiveness of each model, including ResNet, DenseNet, EfficientNet, and the Hypertuned model. Each performance metric is clearly labeled, allowing for immediate assessment of parameters such as accuracy, precision, recall, and F1-score. Additionally, the key findings derived from the data elucidate the strengths and weaknesses of each model, informing future research and applications in medical imaging and diagnosis.

Table 3. Comparative Performance Analysis of Deep Learning Models in Kidney Stone Diagnosis

Performance Measures	ResNet	DenseNet	EfficientNet	Hypertuned
Accuracy	0.52	0.81	0.80	0.86
Macro Average Precision	0.26	0.86	0.82	0.81
Macro Average Recall	0.50	0.86	0.80	0.81
Macro Average Support	346	346	346	346
Weighted Average Precision	0.27	0.87	0.82	0.81
Weighted Average Recall	0.52	0.86	0.80	0.81
Weighted Average F1-Score	0.35	0.86	0.80	0.81
Weighted Average Support	346	346	346	346

Key Findings

Overall Performance: The **Hypertuned model** outperformed all other models, achieving an accuracy of 0.86. This indicates that hyperparameter optimization significantly enhanced model performance compared to the default configurations used in ResNet, DenseNet, and EfficientNet.

Macro and Weighted Averages: DenseNet achieved the highest values in both Macro Average Precision (0.86) and Macro Average Recall (0.86), indicating its effectiveness in identifying and classifying positive instances across all classes without being influenced by class imbalance. The Weighted Average Precision and Recall values for DenseNet (0.87 and 0.86, respectively) also point towards its overall robustness in performance across various metrics and sample sizes.

ResNet Performance: The ResNet model exhibited the lowest scores in all performance metrics, highlighting its weaknesses in terms of accuracy (0.52) and both average precision and recall. This suggests that while popular, ResNet may require further model customization or improvements for better performance in this specific application.

Model Comparisons: While EfficientNet performed competitively with values around 0.80 for accuracy and average precision/recall, it still fell short of the Hypertuned model. This indicates that even high-performance architectures like EfficientNet can benefit significantly from optimization techniques.

Implications for Clinical Use: The high performance of the Hypertuned model may make it particularly suitable for clinical applications in diagnosing kidney stone disease, where accuracy and reliability are crucial. The results underscore the importance of model fine-tuning in achieving superior classification performance

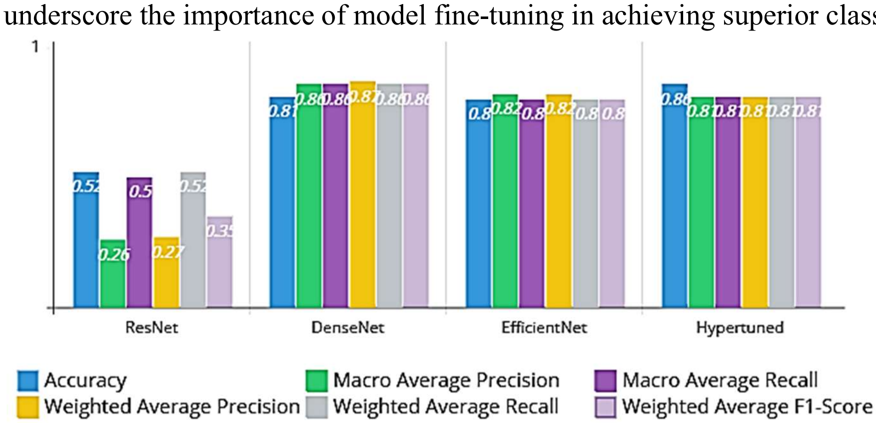


Figure 8. Comparative Performance Analysis of Deep Learning Models

CONCLUSION

The integration of Support Vector Machine (SVM) and Convolutional Neural Network (CNN) algorithms for kidney stone detection through ultrasound imaging marks a significant leap forward in the field of medical diagnostics. This hybrid approach effectively combines the advantages of traditional machine learning and deep learning techniques, leading to improved accuracy and efficiency in identifying kidney stones. The SVM-CNN framework achieves high precision, significantly reducing the incidence of false positives and negatives while diminishing reliance on subjective interpretations by healthcare professionals, thus minimizing potential errors. Utilizing ultrasound—a readily available and cost-effective imaging modality—maximizes resource efficiency within healthcare systems while ensuring patient safety due to its non-invasive nature and lack of ionizing radiation. Future developments could facilitate real-time detection during examinations, allowing for prompt clinical interventions. Further exploration of this approach may involve enhancing the dataset's diversity, investigating multi-class classification capabilities, embedding the algorithm into clinical workflows, and performing extensive clinical trials to validate its effectiveness. This progress could lead to more personalized treatment regimens tailored to individual patient characteristics such as stone composition, size, and medical history, while also allowing for the algorithm's adaptation to other imaging techniques for a holistic assessment of kidney stone detection

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