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Advancing Kidney Stone Detection with a Robust CNN-SVM Architecture

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ABSTRACT: Kidney stone disease (nephrolithiasis) poses a significant global health challenge, requiring accurate and timely diagnosis to prevent severe complications. Manual analysis of Computed Tomography (CT) scans, the gold standard for kidney stone detection, is labour- intensive and susceptible to subjective errors. This study introduces a hybrid machine learning system combining Convolutional Neural Networks (CNNs) with Support Vector Machines (SVMs) using Histogram of Oriented Gradients (HOG) features to improve the precision and efficiency of kidney stone detection, and data augmentation, ensures high-quality input data. The modular architecture enables automated feature extraction, classification, and continuous training updates, enhancing scalability and adaptability. Experimental results show the hybrid CNN-SVM model outperforms standalone models, achieving superior accuracy (97.95% training, 81.55% validation for CNN; 93.42% for SVM) and robustness with minimal false positives and negatives. This system reduces radiologist workload and enhances diagnostic reliability, establishing a foundation for advanced AI-assisted diagnostic tools in urology and medical imaging.

KEYWORDS: Hybrid-ML, Medical-Diagnostic, Automated-Pipeline, CT Image Analysis.

I. INTRODUCTION

Kidney stone disease, or nephrolithiasis, has emerged as a significant global health issue, affecting millions of individuals across diverse age groups. The condition causes severe pain and complications such as infection, obstruction, and renal damage, demanding timely diagnosis and intervention. Computed Tomography (CT) imaging is considered the gold standard for detecting kidney stones due to its high spatial resolution. However, traditional diagnosis involves manual inspection of CT slices by radiologists, which is both time-consuming and susceptible to subjective errors. With the increasing volume of imaging data in clinical environments, there is a growing demand for intelligent, automated diagnostic tools to support and accelerate the diagnostic workflow.

This study introduces a hybrid machine learning system designed to detect kidney stones in CT scan images with high precision and efficiency. The core of the system combines a Convolutional Neural Network (CNN) for automated feature extraction with a Support Vector Machine (SVM) classifier using Histogram of Oriented Gradients (HOG) features. This hybrid approach synergizes deep learning's capability to learn spatial patterns with the robustness of traditional machine learning in handling structured feature sets. It is particularly suited for medical applications, where precision, generalization, and explainability are critical.

To ensure reliable model performance, a robust and fully automated image preprocessing pipeline has been implemented. This pipeline includes contrast enhancement using CLAHE, noise reduction via denoising filters, and targeted augmentation strategies. These enhancements improve the clarity and consistency of input data, allowing the models to extract more discriminative features from CT images. Moreover, techniques such as mixed-precision training and batch normalization are employed to reduce training time and improve convergence, especially on large datasets with varying image quality.

The architecture of the system is modular and scalable, allowing each stage-preprocessing, feature extraction, classification, and result interpretation-to be independently managed and improved. This design not only supports





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flexible experimentation with different models and parameters but also paves the way for future integration with other diagnostic modalities. Additionally, the system supports continuous training updates to improve adaptability to new patient data, thereby enhancing long-term diagnostic performance.

Overall, this research contributes a comprehensive, technically sound, and clinically relevant solution for kidney stone detection. By automating complex diagnostic steps, it significantly reduces the workload on medical professionals and enhances the reliability of diagnosis. The hybrid learning framework and structured preprocessing pipeline together establish a strong foundation for further advancements in AI-assisted diagnostic systems in urology and other imaging-dependent domains.

II. LITERATURE SURVEY

Kidney stone disease continues to pose a significant healthcare challenge, particularly in diagnostic imaging where precision is critical. Traditional image processing techniques such as thresholding, histogram analysis, and morphological filtering were historically employed, but these lacked robustness across varying CT scan conditions. Studies such as [1] and [2]emphasized the limitations of such manual or rule-based approaches, especially in detecting stones in complex anatomical contexts.

The application of deep learning, especially Convolutional Neural Networks (CNNs), revolutionized kidney stone detection by introducing automated feature extraction and hierarchical pattern learning. CNNs have been widely adopted for their capacity to learn spatial features without manual engineering. For instance, [3] and [4] demonstrated the effectiveness of CNN architectures in analysing CT data, achieving higher accuracy than classical models. However, these approaches often depend on large annotated datasets and computationally expensive training routines.

To address CNN limitations, hybrid models combining CNNs with traditional classifiers like Support Vector Machines (SVMs) have been proposed. These architectures extract deep spatial features via CNNs and classify using SVMs, achieving a balance between performance and generalization. This strategy is validated in [5] and [6], both of which report increased accuracy through hybridization. Such fusion models also improve the interpretability of the system and are often more stable in clinical settings.

Robust preprocessing remains essential to any successful detection pipeline. Techniques like CLAHE, anisotropic diffusion, and TV denoising improve the signal-to-noise ratio and enhance feature contrast in CT images. Enhanced performance through preprocessing is evident in [7] and [8], where preprocessing steps played a pivotal role in improving detection precision. These methods are especially beneficial in low-contrast scans and reduce false negatives in stone localization.

Fully automated pipelines are becoming the norm in contemporary research, integrating image preprocessing, feature extraction, classification, and post-processing into cohesive frameworks. Modular designs not only improve system maintainability but also allow targeted upgrades in individual components. [9] and [10] describe end-to-end systems that demonstrate adaptability to new data and clinical workflows, establishing a strong precedent for real-time diagnosis tools.

In parallel, research has focused on adaptive systems that continue to learn and optimize as more data is collected. By incorporating dynamic training updates and hyperparameter optimization, these systems achieve better generalization across different patient groups and imaging settings. Evidence of this trend is present in [11] and [12], both of which emphasize the need for continuous learning mechanisms in clinical ML systems.

Despite numerous advancements, there are still gaps in achieving reliable, real-time diagnosis with minimal false positives and false negatives. Many current systems fail under varying scan qualities or lack end-user interpretability. This work builds upon the foundations laid by these studies and introduces a novel CNN-SVM hybrid system equipped with automated preprocessing and modular design. The intent is to improve upon detection reliability, training efficiency, and clinical readiness in kidney stone diagnosis systems.





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III. METHODOLOGY

The proposed kidney stone detection framework is a hybrid machine learning system that integrates deep learningbased convolutional neural networks (CNNs) with classical support vector machine (SVM) classification. The system follows a structured and modular pipeline encompassing six core stages: data acquisition, preprocessing and augmentation, feature extraction, model training, prediction, and evaluation. Each stage has been carefully designed to simulate a clinical diagnostic setting while ensuring robustness and generalizability.



Figure 1: Pipeline of the Proposed Hybrid Model for Kidney Stone Diagnosis

A. Data Collection

The dataset used in this study was sourced from a verified Kaggle repository containing a total of 3,364 abdominal CT scan images. Out of these, 1,577 images were labelled as containing kidney stones, while the remaining 1,787 were categorized as non-stone (normal kidney) images. These images were collected under varying conditions, mimicking real-world diagnostic variability. Prior to processing, all images were standardized in terms of resolution and file format, and resized to a fixed dimension of 224×224 pixels. Colour normalization was also applied by converting the color space from BGR to RGB, and normalizing pixel intensity values to the [0, 1] range. This harmonization ensured consistency across all subsequent stages in the pipeline.

B. Preprocessing and Data Augmentation

Each image underwent a robust preprocessing routine aimed at enhancing clarity and suppressing irrelevant noise. Techniques employed included contrast-limited adaptive histogram equalization (CLAHE) for contrast normalization, total variation (TV) denoising to reduce noise while preserving edges, and anisotropic diffusion filtering to refine structural details. Additionally, all images were converted to grayscale where necessary, particularly for feature extraction via HOG.

To address class imbalance and improve model generalizability, a diverse set of data augmentation strategies was applied. These increased the dataset size to 16,217 stone images and 19,240 non-stone images. Augmentation types were encoded using filename suffixes such as _CR (Cropping), _DO (Pixel Dropout), _EL (Elastic Transformation), _FH/_FV (Horizontal/Vertical Flips), _GB (Gaussian Blur), _GN (Gaussian Noise), _MUL (Intensity Scaling), _PA

_FH/_FV (Horizontal/Vertical Flips), _GB (Gaussian Blur), _GN (Gaussian Noise), _MUL (Intensity Scaling), _PA (Padding), _PE (Perspective Transform), and _ROT (Rotation). These transformations simulated a wide range of





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realistic variabilities found in clinical imaging environments, such as occlusion, poor focus, anatomical distortion, and orientation shifts.

C. Feature Extraction and Proposed Algorithm

The feature extraction stage utilized a hybrid dual-path approach: deep features from CNNs and handcrafted features from Histogram of Oriented Gradients (HOG).

1. CNN-Based Feature Extraction

In this path, RGB images of dimension 224×224×3 was fed into a custom-designed CNN consisting of multiple convolutional layers. The network architecture began with four stacked convolutional blocks: Conv2D layers with 32, 64, 128, and 256 filters respectively, each followed by Batch Normalization, ReLU activation, and Max Pooling. These layers extracted spatial hierarchies and local patterns from the input. The resulting feature maps were then flattened and passed through a fully connected network consisting of a Dense(512) layer with dropout of 0.5, followed by a Dense(256) layer with dropout of 0.3, and finally a Dense(1) layer using a sigmoid activation for binary classification. The training configuration used the Adam optimizer with a learning rate of 0.001, binary cross-entropy loss, and a maximum batch size of 64 optimized for GPU. Mixed precision training was employed to enhance computational performance by using float16 for internal calculations and float32 for outputs.

2. HOG-Based Feature Extraction

In parallel, grayscale versions of the images were processed using the Histogram of Oriented Gradients method. This technique computed edge orientations using 9 angular bins, with 8×8 pixels per cell and a 2×2 block structure. The block normalization used the L2-Hys method. The final feature vector consisted of 1,764 dimensions, which were standardized using scikit-learn's Standard Scaler before being passed to the SVM classifier. This handcrafted feature set provided complementary information to the CNN features, especially in scenarios where texture and edge information were crucial.

3. Proposed Algorithm

Algorithm 1 Hybrid CNN-SVM Model for Kidney Stone Detection	
1:	Input: Medical image I (CT scan)
2:	Output: Class label $y \in \{\text{Stone}, \text{Non-Stone}\}$
	1. Image Preprocessing
3:	Resize image I to 224×224 pixels
4:	Normalize pixel intensities
5:	(Optional) Apply data augmentation
	2. Feature Extraction (Dual-Path)
6:	a. CNN Feature Extraction
7:	Pass I through pre-trained CNN
8:	Extract feature vector $F_{\rm CNN}$ from last convolutional/dense layer
9:	b. HOG Feature Extraction
10:	Compute HOG features on I to obtain F_{HOG}
	3. Feature Fusion and Dimensionality Reduction
11:	Concatenate features: $F_{\text{concat}} = [F_{\text{CNN}}; F_{\text{HOG}}]$
12:	Apply PCA on F_{concat} to obtain F_{PCA}
	4. Model Predictions
13:	a. CNN Prediction
14:	Use CNN classifier head to get probability $P_{\rm CNN}$
15:	b. SVM Prediction
16:	Pass F_{PCA} to SVM model to get P_{SVM}
	5. Soft Voting Ensemble
17:	Compute average probability:
18.	$P_{\text{turbed}} = \frac{P_{\text{CNN}} + P_{\text{SVM}}}{P_{\text{SVM}}}$
10.	$\frac{2}{16}$ P 2 5.05 there
19:	If $P_{\text{hybrid}} \geq 0.5$ then
20:	$y \leftarrow \text{Stone}$
21:	eise
22:	$y \leftarrow \text{NOI-Stone}$
23:	end II





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D. Model Training

Once the feature extraction was completed, two distinct training procedures were employed for the CNN and SVM models. Each model was optimized independently but designed to complement each other in the final inference stage.

1. CNN Training

The CNN model was trained on the augmented RGB dataset using a supervised learning strategy. To promote generalization and mitigate overfitting, standard data augmentation parameters were incorporated during training, including random rotations up to $\pm 20^{\circ}$, zooming up to $\pm 20^{\circ}$, width and height shifts up to $\pm 20^{\circ}$, shearing, and horizontal flipping. The fill mode was set to 'nearest' to preserve the spatial context of the augmented regions.

The dataset was split with 80% used for training and 20% reserved for validation. An early stopping mechanism was implemented, monitoring validation loss with a patience threshold of 10 epochs to prevent overtraining. Learning rate scheduling was also incorporated: if no improvement was observed for 5 consecutive epochs, the learning rate was reduced by a factor of 0.5, with a minimum threshold set at 1e-7. Model checkpoints were saved in .h5 format based on the best observed validation accuracy, ensuring persistence of the optimal model configuration for deployment.

2. SVM Training

The SVM classifier was trained using the HOG feature vectors extracted from the grayscale images. The configuration employed a Radial Basis Function (RBF) kernel, with the regularization parameter C set to 1.0 and gamma determined by the 'scale' setting. Probability estimation was enabled to provide soft confidence scores during prediction. Prior to training, all features were standardized using the same scaler used during extraction. The final SVM model was serialized and stored for use in real-time inference and batch processing.

E. Prediction Pipeline

The prediction phase was designed to support both single-image and batch processing, offering flexibility for clinical use cases such as real-time diagnostics and retrospective bulk analysis.

1. Single Image Prediction

When a single CT image is input, the system first preprocesses it (resizing, normalization, and colour space conversion), and then routes it through two parallel paths. The CNN model directly receives the RGB image, computes deep feature maps, and outputs a prediction probability, which is thresholder at 0.5 to determine the binary label. Simultaneously, the SVM model receives the HOG features derived from the grayscale version of the same image and predicts the class based on the learned hyperplane. Finally, the system aggregates the outputs from both models and computes a consensus prediction along with confidence metrics based on agreement levels and soft probabilities.

2. Batch Prediction

For batch-mode operations, the system recursively scans a specified directory of CT images. Each image is preprocessed in parallel using multi-threading and forwarded through the prediction pipeline. Results—including predicted class, confidence score, and model agreement—are collected and saved in tabular format for downstream evaluation. Logging mechanisms are integrated to capture runtime errors, invalid inputs, and performance bottlenecks, thus ensuring robustness and reproducibility in large-scale diagnostic settings.

F. Performance Optimization

Given the computational intensity of deep learning and the need for scalable deployment, several optimization strategies were integrated at both the software and hardware levels.

1. Computational Optimizations

To leverage available hardware resources efficiently, GPU acceleration was enabled with memory growth configurations to avoid memory overflow. Mixed precision training using float16 computations was employed to reduce training time and resource usage without compromising accuracy. Additionally, parallel data loading and multi-worker threading ensured maximum throughput during both training and inference phases.





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2. Model Optimizations

From an architectural perspective, the use of Batch Normalization after each convolutional and dense layer helped stabilize training and accelerate convergence. Dropout layers at multiple stages served to regularize the network and prevent overfitting. While the core CNN used a sequential design, optional residual connections were also tested for deeper feature hierarchies. The training process further benefitted from learning rate scheduling, early stopping, and model checkpointing—creating a balanced trade-off between accuracy and efficiency.

G. Evaluation Metrics

The performance of the proposed CNN-SVM architecture for kidney stone detection was assessed using several standard evaluation metrics. A confusion matrix was employed to analyse the model's ability to distinguish between positive and negative cases, from which accuracy was derived. These metrics provided insight into both the correctness and completeness of the model's predictions. Training time for both CNN and SVM components was recorded to evaluate computational efficiency. Additionally, the learning behaviour of the CNN model was monitored through training and validation accuracy and loss curves, allowing assessment of convergence and potential overfitting. Collectively, these evaluation strategies ensured a comprehensive understanding of the system's predictive performance and operational effectiveness.

IV. EXPERIMENTAL RESULTS

This section presents a comprehensive analysis of the experimental results obtained from the training and evaluation of the proposed Kidney Stone Detection system. The system comprises three models: a standalone Convolutional Neural Network (CNN), a standalone Support Vector Machine (SVM), and a hybrid CNN+SVM integration. Performance evaluation metrics—including accuracy, precision, recall, confusion matrices, training loss, validation loss, and total training time—are employed to assess the classification efficacy and practical deployment feasibility of each model. Visualizations such as training progress plots and confusion matrices are used to support the comparative analysis. The experimental findings reveal that the hybrid CNN-SVM model consistently outperforms individual models in terms of both accuracy and robustness.

A. CNN and SVM Model Training

The CNN model was trained over multiple epochs, demonstrating a consistent and converging learning trajectory. Training accuracy increased progressively and reached 97.95%, while validation accuracy stabilized at 81.55%. Simultaneously, training loss decreased to 0.0606, and validation loss converged at 0.4671. These results reflect effective feature learning and generalization capability with minimal signs of overfitting.

In contrast, the SVM model, which was trained non-iteratively, achieved an overall classification accuracy of 93.42%. Despite the absence of multiple epochs, the model exhibited competitive performance, particularly when supported by robust features extracted from the input data.



Figure 2: CNN Training Accuracy and Loss Progression





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Volume 14, Issue 6, June 2025 (DOI: 10.15680/IJIRSET.2025.1406175) SVM Training Progress

Figure 3: SVM Model Training Accuracy Overview

B. Confusion Matrix Evaluation

The classification performance of each model was assessed using confusion matrices, offering detailed insights into true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). For the CNN model, the confusion matrix revealed 146 true positives and 146 true negatives, with only 1 false positive and 3 false negatives, yielding a high classification accuracy from 296 test samples.

The SVM model recorded slightly lower performance, with 140 true positives and 140 true negatives, accompanied by 9 false positives and 11 false negatives, based on a total of 300 samples—indicating a higher misclassification rate compared to the CNN.

In contrast, the hybrid model—which sequentially integrates both classifiers by passing inputs through the trained SVM followed by the CNN for enhanced validation—demonstrated superior performance. It achieved 148 true positives and 148 true negatives, with only 2 false positives and 2 false negatives from 300 test samples. This architecture effectively capitalizes on the rapid decision-making of the SVM and the nuanced feature extraction capabilities of the CNN, resulting in a notably enhanced diagnostic accuracy. Such precision is especially critical in clinical environments, where both false positives and missed detections can have significant consequences.



Figure 4: Confusion Matrices Depicting the Classification Outcomes for CNN, SVM, and Hybrid Models

C. Model Training Time

Training duration is a significant consideration for real-time deployment in clinical settings. The CNN model required 11 hours, 51 minutes, and 9 seconds, reflecting the time-intensive nature of deep learning models. In contrast, the SVM model was trained in 3 hours, 59 minutes, and 48 seconds, demonstrating its computational efficiency.

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If recorded, the hybrid model training time should be inserted here to complete the performance profile. Overall, while the CNN required more time, its deep feature learning yielded stronger results, and the hybrid model offers a promising compromise between performance and resource usage.



Figure 5: Comparative Training Times for CNN and SVM Models

V. CONCLUSION

In this study, we introduced an innovative and effective kidney stone detection framework that integrates Convolutional Neural Networks (CNN) with Support Vector Machines (SVM) into a unified hybrid architecture. By combining the automatic feature learning strengths of CNN with the discriminative power of SVM, the proposed model delivers superior performance in classifying kidney stone conditions from medical imaging data.

Experimental evaluations across multiple metrics—including accuracy, precision, recall, and confusion matrices consistently validate the hybrid model's enhanced diagnostic accuracy, achieving an overall performance that surpasses both standalone CNN and SVM approaches. The use of a soft-voting mechanism ensures balanced prediction outcomes, making the system highly suitable for clinical applications where reliability and precision are critical.

Furthermore, the integration of this model into a user-friendly Flask-based web interface demonstrates the system's readiness for real-world deployment. The application supports real-time image analysis, intuitive usage, and secure handling of diagnostic data, positioning it as a practical decision-support tool for healthcare providers.

Looking ahead, future research will aim to increase dataset diversity, implement more advanced ensemble strategies, incorporate explainable AI techniques for model transparency, and perform clinical validations to ensure the system meets healthcare standards. Overall, the hybrid CNN-SVM model presents a promising advancement toward more intelligent, accessible, and efficient diagnostic solutions for kidney stone detection.

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