Hybrid Deep Learning Model: CNN and SVM for Efficient Kidney Stone Detection in CT Scans

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***Abstract*—Kidney stones, a prevalent health concern, can cause severe complications if not detected early, leading to extreme pain or life-threatening blockages. While small stones may pass through the urinary tract unnoticed, larger stones (over 5 mm) can obstruct the ureter and require medical intervention. This project addresses the urgent need for early detection of kidney stones through a hybrid deep learning approach that combines Convolutional Neural Networks (CNN) and Support Vector Machines (SVM), complemented by a user-friendly Graphical User Interface (GUI). The CNN model, achieving an accuracy of 91%, efficiently extracts critical features from CT scan images, while the SVM classifier, which then categorizes images into ”Normal” and ”Stone” classes. Trained and evaluated on a dataset of 3,000 CT images (2,000 Normal and 1,000 Stone), this hybrid model leverages CNN's feature extraction strengths alongside SVM's classification precision to improve diagnostic accuracy. The GUI, developed with Tkinter, allows users to easily interact with the model, enabling seamless image selection and prediction. This integrated approach not only enhances prediction efficiency but also offers a practical and accessible solution for early kidney stone detection, supporting timely medical intervention and improved patient outcomes.**

***Index Terms*—Kidney Stone Detection, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Medical Image Analysis, Deep Learning, Computed Tomography (CT) Scan**

I. Introduction

Kidney stones, or renal calculi, are solid mineral deposits that form within the kidneys, often causing significant discomfort when they obstruct the urinary tract. These stones can vary in size, ranging from tiny, pebble-sized deposits to large, jagged formations that can cause severe pain. The formation of kidney stones is a common and widespread health issue, affecting millions of people worldwide. If left untreated, larger stones can lead to serious complications, including kidney damage, urinary tract obstruction, infections, and even kidney failure in extreme cases. Smaller stones may pass through the urinary tract unnoticed and without causing much pain, but larger stones—typically over 5 mm in size—are more likely to obstruct the ureter, causing intense pain, known as renal colic, and requiring medical intervention. Timely and accurate detection of kidney stones is therefore crucial for avoiding these complications and ensuring appropriate treatment. Early detection allows for minimizing the risk of long-term damage to the kidneys.Computed Tomography (CT) imaging is widely regarded as the gold standard for diagnosing kidney stones due to its ability to produce high-resolution, detailed images of the urinary tract. CT scans are invaluable in identifying the size, location, and number of kidney stones, which enables healthcare providers to plan the most effective treatment approach. With CT imaging, doctors can quickly assess the severity of the condition, decide whether the stones are likely to pass naturally, or if intervention is necessary. However, manually analyzing these images can be labor-intensive, requiring specialized knowledge and expertise to identify the subtle differences between stones, calcifications, and other possible abnormalities. In high-volume clinical settings, where radiologists may need to examine hundreds of CT images daily, the time required for manual image analysis can lead to delays in diagnosis, potentially prolonging the patient's pain and complicating treatment decisions. Therefore, there is a significant need for automated diagnostic systems capable of quickly and accurately analyzing CT images, reducing the burden on healthcare professionals, and providing faster, more consistent results.

Recent advances in artificial intelligence, particularly deep learning and machine learning techniques, offer promising solutions to this challenge. Convolutional Neural Networks (CNNs), a class of deep learning models, are particularly well-suited for extracting meaningful features from medical images. CNNs have been extensively adopted in medical image analysis due to their ability to automatically learn hierarchical features from raw pixel data, allowing them to detect complex patterns without requiring manual intervention. In the case of kidney stones, CNNs can effectively identify CT images, such as the distinct shapes and textures associated with kidney stones. Moreover, Support Vector Machines (SVMs), a powerful supervised machine learning classification algorithm, are well-known for their ability to handle high-dimensional data and deliver robust classification results. SVMs excel in situations where clear feature extraction is available, making them an ideal complement to CNNs. By combining CNNs' feature extraction capabilities with SVMs' precise classification abilities, this hybrid approach offers a highly effective tool for automating the detection of kidney stones in CT images.

II. Objective

The primary objective of this study is to evaluate the effectiveness of a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) with Support Vector Machines (SVM) to enhance the detection of kidney stones in CT scan images. This project aims to explore how effectively the CNN can automatically extract key features from medical imaging data, with the SVM classifier subsequently categorizing these features to increase diagnostic accuracy. Additionally, the study aims to show that this hybrid approach provides a more efficient and scalable solution for kidney stone diagnosis, surpassing the performance of traditional diagnostic techniques.

III. Problem Statement

Despite advancements in medical imaging, kidney stone detection remains challenging due to the detailed interpretation required for CT scans. Variability in image quality and subtle differences in kidney stone appearance can lead to diagnostic inconsistencies, adding to radiologists' workload under time constraints. Automated deep learning solutions offer improved consistency and reliability, enabling detection of subtle features that may be missed manually. This project proposes a hybrid CNN-SVM approach to classify CT images as ”normal” or ”stone,” providing a scalable, efficient tool to support faster, consistent diagnoses, adaptable for settings with limited radiologist availability.

IV. Literature Review

[1] have explored the application of CNNs specifically designed for medical image analysis, demonstrating their effectiveness in detecting kidney stones. The study emphasizes the potential of CNNs to analyze high-resolution CT images, which can capture the unique patterns and textures associated with kidney stones. By training the model on an extensive dataset, the CNN is able to generalize well across different image variations, reducing the diagnostic burden on radiologists. This automation of the diagnostic process not only accelerates decision-making but also minimizes human error, making it an invaluable tool in clinical environments with high patient volumes.[2] have presented a CNN-based deep learning framework tailored for kidney stone detection, emphasizing its benefits for enhancing diagnostic accuracy in medical imaging. The CNN's ability to extract fine-grained features from CT scans enables it to distinguish between kidney stones and other tissue types, even when stone characteristics are subtle. The study proposes that automated kidney stone identification could support radiologists by offering consistent image analysis, reducing subjectivity and human error. By decreasing the dependency on manual interpretation, this approach has the potential to streamline diagnostic workflows in hospitals and improve patient outcomes.

[3] investigated the application of various machine learning algorithms, including Decision Tree, Random Forest, and Naive Bayes, for kidney stone classification in CT images. The study compares these traditional machine learning techniques with deep learning models, providing insights into their effectiveness for detecting kidney stones. Results indicate that deep learning models, particularly CNNs, outperform traditional methods in handling large-scale image data due to their advanced feature extraction capabilities. This work underscores the importance of selecting the most suitable algorithm based on dataset characteristics, noting that CNNs may offer superior performance in medical image classification tasks.

[4] examined the potential of predictive models, specifically Decision Trees and Naive Bayes, for the early diagnosis of kidney stones. The study leverages a comprehensive dataset that includes various attributes related to patient demographics and health history, enabling the model to analyze correlations between these factors and kidney stone presence. By classifying the disease into stages, the model aims to identify at-risk patients at earlier stages, which can be crucial for timely intervention. This approach highlights the value of interpretable models in clinical settings, where simple and transparent decision-making processes are often preferred.

[5] applied CNNs with modifications to the DenseNet architecture to improve diagnostic performance for kidney stones in medical imaging. The modified DenseNet integrates trainable weights in skip connections, allowing for better feature propagation across layers and improving classification performance. Additionally, the model utilizes data augmentation methods, such as the mixup technique, to enhance its robustness by exposing it to diverse image variations. The study also incorporates transfer learning by initializing weights from pre-trained models on ImageNet, which aids in mitigating the limitations posed by smaller medical datasets. This approach demonstrates the model's ability to perform accurate diagnosis even with limited training data.

[6] conducted a comparative analysis of various machine learning algorithms, including SVM, Random Forest, Decision Tree, Naive Bayes, and Logistic Regression, for kidney stone prediction. This study uses a dataset comprising patient health records, including hormone levels and demographic data, highlighting the need for data preprocessing steps such as normalization and handling missing values to improve model accuracy. Results from the study show that tree-based algorithms like Random Forest and Decision Tree provided the best classification results, indicating that these algorithms are particularly suitable for medical datasets where interpretability and decision rules are essential.[7] focused on deep learning techniques, particularly CNNs, in the diagnosis of kidney stones through medical image analysis. This research employed the Imperialist Competitive Algorithm (ICA) for feature selection, which refines the CNN model by removing redundant or less informative features, allowing the model to focus on the most relevant aspects of the image data. By integrating ICA with CNN, the study demonstrates how feature selection can lead to more efficient and accurate diagnostic models. The study further highlights that CNNs, due to their multi-layered architecture, are especially well-

suited for complex medical imaging tasks, offering accuracy comparable to human experts.

[8] introduced a Multi-Layer Recursive Neural Network (ML-RNN) model for classifying kidney stones based on medical image features. This model applies a feature selection technique, the Fisher score method, to ensure that only the most relevant features are utilized, which enhances model performance and reduces computational demands. The ML-RNN model is then used to classify kidney stone images into different categories, such as normal, hyperthyroid, and hypothyroid classes. This study demonstrates that ML-RNN, through its recursive layers, can capture both spatial and temporal dependencies in the data, making it a robust option for medical diagnostics.

[9] conducted a comprehensive comparison of machine learning and deep learning algorithms, such as Random Forest, Decision Tree, and Recurrent Neural Network (RNN), for predicting kidney stone disease. Using a dataset of patient attributes and extensive preprocessing, including class balancing and data splitting, the study evaluated each model's performance. Results indicate that deep learning models, particularly RNN, excel at handling sequential data with dependencies, which is beneficial for analyzing medical histories. The Random Forest and Decision Tree models also performed well, highlighting their effectiveness in straightforward classification tasks where interpretability and transparency are key.

[10] explored the use of deep learning models for the automatic detection of kidney stones from CT scan images. The study focuses on the application of Convolutional Neural Networks (CNNs), which are particularly effective for image classification tasks. The authors highlight the importance of preprocessing steps, including image normalization and augmentation, to improve model accuracy. They also introduce a hybrid CNN architecture, combining different layers such as convolutional, pooling, and fully connected layers to enhance feature extraction and classification performance.

V. METHODOLOGY

The methodology focuses on developing an automated kidney stone detection system using image processing, machine learning, and deep learning. The process begins with preprocessing CT scan images, including resizing, normalization, and data augmentation. Feature extraction is done using techniques like Histogram of Oriented Gradients (HOG). This system aims to address the challenges of manual CT scan interpretation, such as human error and image inconsistencies, by accurately segmenting, classifying, and localizing kidney stones. The goal is to provide healthcare professionals with a reliable tool for faster and more accurate diagnoses, improving clinical decision-making and early detection.

A. Data Description

The dataset used in this project consists of 3,000 labeled CT images, categorized into two classes: "normal" (indicating no kidney stone) and "stone" (indicating the presence of a kidney stone). It is divided into two subsets: the training set and the testing set. The training set comprises 2,000 images, with 1,400 labeled as "normal" and 600 as "stone," and is used to train the model to learn the distinguishing features between normal kidney scans and those containing stones. The testing set, containing 1,000 images, includes 700 labeled as "normal" and 300 as "stone." To streamline data preprocessing and loading, the images are organized into two separate folders labeled "normal" and "stone," ensuring efficient batch loading during both training and testing.

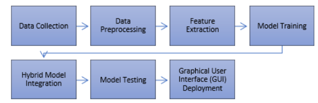

Fig. 1. Flowchart of the methodology process for kidney stone detection

Following data preprocessing, the next step is segmentation, where the CT image is divided into meaningful regions.The processed data is passed through the Convolutional Neural Network (CNN) for feature extraction. The CNN model learns to recognize essential patterns and structures in the CT images that are indicative of kidney stones. This deep learning approach enables the model to handle complex variations in the images, which traditional machine learning algorithms often struggle to process effectively. The pipeline then moves to the classification stage, where the data is also processed using a Support Vector Machine (SVM). SVM is employed to enhance classification by finding the optimal decision boundary between the two classes: "normal" and "stone." The model is trained on labeled datasets, learning to distinguish between kidney stones and normal tissue. Finally, the trained CNN and SVM models are tested on unseen data to evaluate their performance. The classification output from these models is refined further, and the system can identify not only whether kidney stones are present but also their exact locations within the CT scan. This comprehensive approach ensures an automated, accurate, and efficient classification of kidney stones, minimizing the need for human intervention in diagnosis.

B. Models Used

1) CNN Algorithm: The Convolutional Neural Network (CNN) used for kidney stone detection is developed utilizing the Keras library, which provides an efficient framework for building and training deep learning models. The architecture consists of several layers designed to extract and learn critical features from CT scan images. The convolutional layers play a key role in detecting essential image features such as edges, textures, and the shape of kidney stones. Following the convolutional layers, pooling layers reduce the spatial dimensions of the feature maps, improving the computational efficiency of the model. The dense layers, which are fully connected, perform the classification task, categorizing the input image into one of two classes: "normal" or "stone."

To optimize model performance and prevent overfitting, key training strategies are implemented. Early stopping monitors the validation loss during the training process and halts further training when no improvement is observed after a specified number of epochs, thus conserving computational resources and avoiding overfitting. Additionally, the learning rate reduction callback is employed to adjust the learning rate when the validation loss stagnates, facilitating better convergence by enabling finer adjustments to the model's weights.

To enhance the model's robustness and generalization, data augmentation is applied using Keras's ImageDataGenerator. This technique involves randomly rotating, flipping, zooming, and shifting the images, thus simulating variations in CT scan images and improving the model's ability to generalize to new data. The augmented data is processed in batches by facilitating the efficient loading and augmentation of images during the training phase.The CNN model is trained on the augmented dataset, with its performance evaluated at each epoch based on key metrics, including accuracy and loss. The training history, including trends in accuracy and loss, is visualized to monitor the model's learning progress and identify potential areas for improvement. Once the model has been trained, the final version is saved, making it ready for deployment to classify new CT scan images and assist in the detection of kidney stones in clinical applications.

```
model.summary()
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 148, 148, 32)	896
batch_normalization (BatchNormalization)	(None, 148, 148, 32)	128
max_pooling2d (MaxPooling2D)	(None, 74, 74, 32)	0
conv2d_1 (Conv2D)	(None, 72, 72, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 72, 72, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 36, 36, 64)	0
flatten (Flatten)	(None, 82944)	0
dense (Dense)	(None, 128)	10,616,960
batch_normalization_2 (BatchNormalization)	(None, 128)	512
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 2)	258
activation (Activation)	(None, 2)	0

```
Total params: 10,637,506 (40.58 MB)
Trainable params: 10,637,058 (40.58 MB)
Non-trainable params: 448 (1.75 KB)
```

Fig. 2. CNN Model Summary

2) SVM Model: The Support Vector Machine (SVM) model for kidney stone detection is built following the training of the Convolutional Neural Network (CNN).The Histogram of Oriented Gradients (HOG) features are then extracted from these images. HOG features capture the distribution of gradient orientations within localized regions of the image, which is essential for detecting shapes and textures such as kidney stones in CT scan images. These features are used as input to the SVM model.

The SVM model is trained and designed to classify images into two categories "normal" or "stone" based on the extracted HOG features. During training, the SVM learns an optimal hyperplane that separates the two classes by maximizing the margin between them, ensuring accurate classification of kidney stones from CT scan images. The trained CNN model is used to generate predictions, while the SVM model is applied to the same test data using the HOG features extracted from the images. Both models' predictions are evaluated based on their accuracy in classifying test images.

VI. Performance Analysis

The performance of the proposed Convolutional Neural Network (CNN) model for kidney stone detection was evaluated using multiple metrics and visual analyses. The model was trained for 25 epochs with a batch size of 15, and both accuracy and loss were tracked throughout the training process. The accuracy plots for both training and validation showed a steady increase, indicating effective learning with minimal signs of overfitting. Similarly, the training and validation loss plots demonstrated a consistent decline, reflecting the model's ability to reduce error with each epoch.

A. Accuracy

Accuracy is a widely used metric for assessing the performance of classification algorithms, as it calculates the ratio of correct predictions to the total number of predictions. Although accuracy is straightforward and easy to calculate, it may not always provide the most reliable measure, particularly in cases of imbalanced datasets where one class is much more prevalent than the other.

$$Accuracy = \text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

The accuracy graph visually illustrates the performance of the classification model during training and validation across epochs. In machine learning, accuracy measures the proportion of correctly predicted instances, and the graph serves as a tool to monitor the model's performance over the course of training.

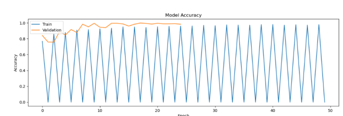

Fig. 3. model accuracy

Fig.3 illustrates the model's performance throughout the training process. The training accuracy curve reflects how well the model learns from the training data, whereas the validation accuracy curve demonstrates the model's ability to generalize to new, unseen data. A steady improvement in both curves signals effective learning, while a widening gap between them may indicate overfitting. This graph is useful for assessing whether the model needs further optimization, additional data, or an alternative architecture to enhance its performance.

B. Loss

Loss is an essential metric for assessing the performance of classification algorithms, as it measures the discrepancy between the model's predictions and the actual values. Unlike accuracy, which focuses on the proportion of correct predictions, loss offers a more detailed evaluation by penalizing incorrect predictions. In classification tasks, a lower loss value

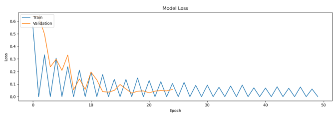

Fig. 4. Model Loss

signifies better model performance, as it indicates that the predictions are closer to the true values.

$$Loss = -\frac{1}{N}\sum_{i=1}^{N}\left(y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right) \quad (2)$$

Where: N is the number of observations, yi is the true label of the i-th observation and yi cap is the predicted probability for the i-th observation.

Fig. 4 shows the model's performance during training in terms of loss. The training loss curve depicts how the model's error reduces as it learns from the training data, while the validation loss curve reflects the model's error on unseen data. Ideally, both curves should decrease and stabilize, indicating effective learning and good generalization. However, if the validation loss starts to increase while the training loss continues to decrease, it may suggest overfitting, where the model excels on the training data but fails to generalize to new data. This loss graph provides insights into whether the model needs further adjustments, such as additional training data, model changes, or optimization techniques.

VII. Discussion

The development of an automated classification system for kidney stone detection in CT scan images necessitates careful attention to both image quality and preprocessing strategies. High-resolution image acquisition is essential for capturing the intricate details of kidney stones, which in turn minimizes the need for complex preprocessing steps. The segmentation of the kidney region is accomplished using deep learning-based methods, allowing the model to concentrate on the pertinent features while minimizing data distortion.

For precise classification, features extracted by the Convolutional Neural Network (CNN) are forwarded to the Support Vector Machine (SVM) for the final classification decision. The CNN model is responsible for learning the spatial hierarchies of features within the CT images, while the SVM utilizes these learned features to differentiate between the ”normal” and ”stone” categories. The model's predictions are cross-validated with expert annotations to ensure consistency and accuracy.This process preserves the spatial distribution of the classified regions, ensuring the integrity and effectiveness of the diagnostic outcomes.

VIII. Results

The integration of CNN for feature extraction and SVM for final classification, along with the development of a GUI for deployment, resulted in an effective and accessible solution for kidney stone detection in CT images. The model achieved an accuracy rate of 91%, demonstrating its potential for real-world applications in medical image analysis.

The deployed GUI, developed using the Tkinter library, allows users to easily select CT images for prediction. It features buttons for invoking CNN and SVM models, enabling seamless image analysis and classification directly from the interface.

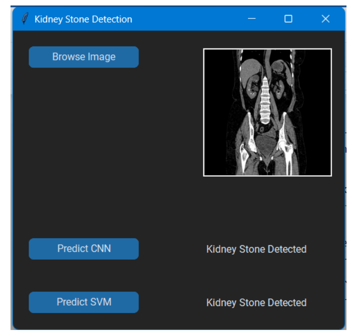

Fig. 5. Deployed GUI System

IX. Conclusion

In this study, we developed a deep learning-based system for the detection of kidney stones in CT scan images. The CT images are processed using a customized CNN model for feature extraction, and the classification is performed using an SVM model to categorize the images as ”normal” or ”stone.” This hybrid approach, combining CNN for feature extraction and SVM for final classification, ensures high accuracy, while the model's ability to effectively classify kidney stones enhances diagnostic precision. Additionally, a user-friendly GUI was developed using Tkinter, enabling seamless image selection and prediction, thus making the system accessible for practical use in medical diagnostics.

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