Ultrasound Image Classification for Kidney Stone Detection Using CNN-SVM Hybrid Model

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ABSTRACT
Kidney stones are a common urological problem that, if not identified and treated promptly, can result in excruciating pain and complications. This paper suggests a novel method based on classification algorithms for kidney stone detection. There are several important steps in the approach. An ultrasonic image dataset must be first collected and preprocessed with adaptive thresholding, Gaussian filter, and unsharp masking before trying to enhance the picture and remove noise. The dataset is then shortly separated into train and test sets. Data augmentation techniques are used on the training set to improve its diversity. The individual CNN architecture, which is designed for the feature extraction process from utile images. It consists of multiple convolution layers, max-pooling layers, ReLU (rectified linear unit) layers etc. and the model is trained on a train set using Adam optimizer. The ultrasound dataset is processed to extract Grey-Level Cooccurrence Matrix (GLCM) features and these are concatenated with the CNN extracted features. We concatenate the extracted features and employ a Support Vector Machine (SVM) classifier to learn. Testing: In the testing phase, accuracy as well as sensitivity and specificity is computed for the learned classifier on the test dataset. This paper provides a robust method for the detection of kidney stones based on classification algorithms. The method it proposes can help in swifter detection of stone formation in kidneys than its changes and detection for enhanced patient outcomes.
Obtained results via the proposed method reached 93.22%, with a sensitivity of 92,5% and specificity of 93.59%.
Keywords: kidney stone, ultrasound, classification, Convolutional Neural Network, Support Vector Machine, Grey-Level Co-occurrence Matrix.

1. INTRODUCTION

Also referred to as kidney stones, renal calculi are referred to as hard deposits that form within the kidney. They comprise of a variety of salts and minerals that have the ability to crystallize and stick together, including uric acid, calcium and oxalate. Urolithiasis or kidney stones are one of the most painful conditions that a human being can have and can cause a tremendous amount of pain. The management of kidney stones differs according to the size and position of the stones but in most cases offers analgesics, hydration, and in some cases surgery or other routes for stone removal[1].

Because kidney stones are a major health concern in many people worldwide, they should be treated immediately. Their diagnosis is therefore important in medical imaging [2]. Traditional methods of detecting kidney stones on ultrasound images use a lot of manual interpretation, which can be laborious and subjective. Convolutional Neural Nets, or CNNs, have recently shown much promise for automated medical image recognition and interpretation. CNNs are perfect for tasks such as kidney stone detection because they can automatically detect features from images[3].

Applying filters such as sharp masking and Gaussian filters on ultrasound image datasets to improve the performance of our model yields real ultrasound datasets By increasing the clarity and quality of images, such filters weaken the ability of CNN and GLCM to extract important features.

In this paper, we present a new method that combines Support Vector Machines (SVMs) for classification with CNN and GLCM for feature extraction. CNN is used to extract relevant features from ultrasound images, capturing the details necessary to accurately identify kidney stones[4]. Then, The GLCM features are combined with the CNN features to generate feature vectors for the training and testing sets. Using these features, SVM is trained to distinguish between images with and without kidney stones.

Our goal is to create a reliable and accurate kidney stone detection system using image enhancement methods, integration of CNN and GLCM for feature extraction, and SVM for classification. This system can increase the accuracy and efficiency of kidney stone detection, helping patients, as detailed in the block diagram in Figure 1.

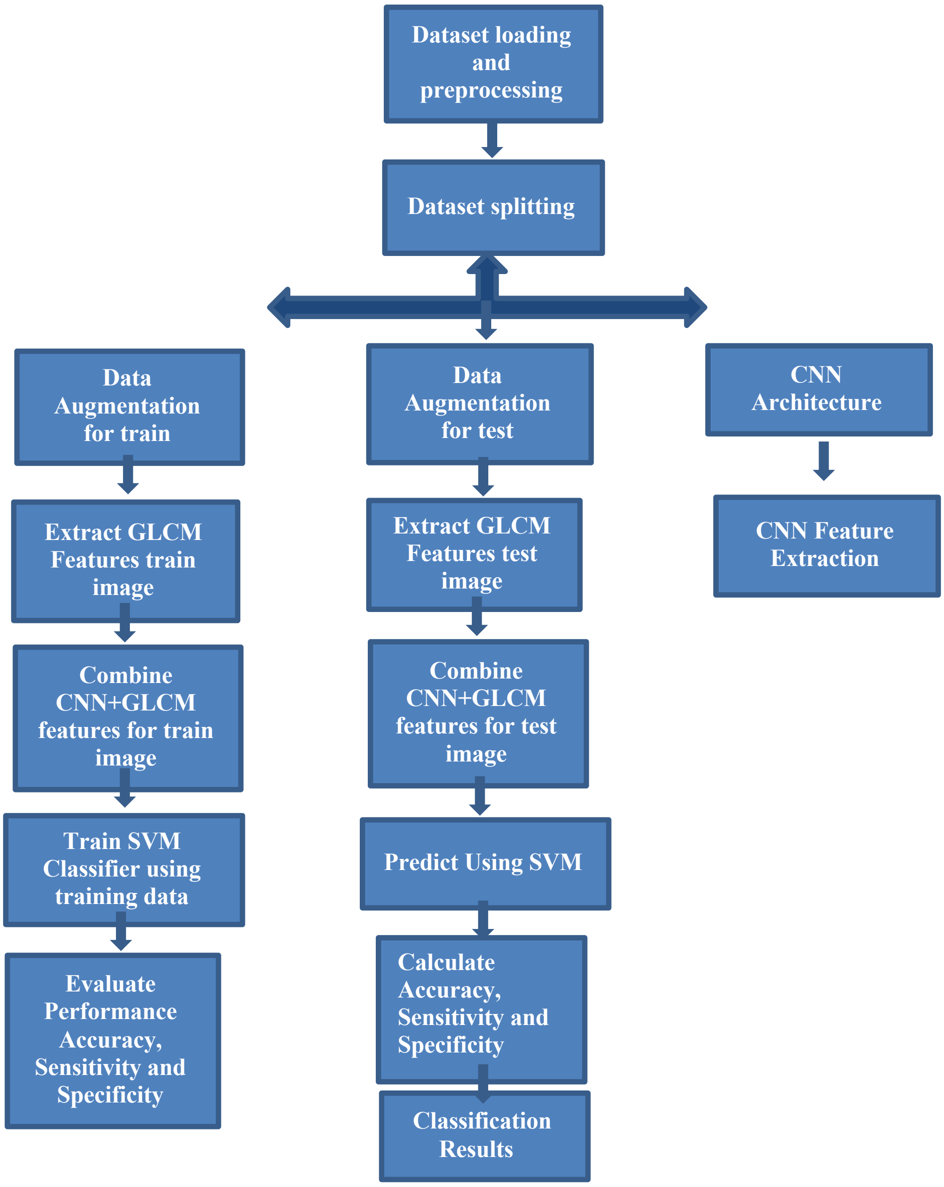

Figure 1: classification block diagram.

1.1 Related work

Kumar et al. (2012) compared neural network algorithms for kidney stone diagnosis, finding that a multilayer perceptron with backpropagation achieved the highest accuracy[5]. Verma et al. (2017) addressed challenges in low-resolution ultrasound images, achieving high accuracy with KNN and SVM in detecting kidney stones[6]. Chak et al. (2019) aimed to automatically detect kidney stones using digital signal processing, achieving high accuracy by combining ANN with SVM classification[7]. M. Akshaya et al. (2020) proposed a Back Propagation Network (BPN) with Principal Component Analysis (PCA) for feature extraction, achieving superior accuracy in detecting kidney stones in Magnetic Resonance (MR) images, even with noise[8]. K. Yildirim et al. (2021) developed a deep-learning model for coronal Computed Tomography (CT) images, achieving 96.82% accuracy in detecting kidney stones without image segmentation, highlighting the need for diverse datasets[9]. I. Aksakalli et al. (2021) evaluated machine learning methods for kidney stone detection, finding Decision Trees (DT) to be the most effective with an 85.3% success rate, emphasizing accurate detection for diagnosing kidney diseases[10]. K. Chaitanya Nagu et al. (2021) employed the Gray Level Co-occurrence Matrix (GLCM) and Fuzzy C-Mean (FCM) for early detection in CT images, achieving a 98.8% accuracy rate using Back Propagation Network (BPN)[11]. These studies collectively highlight the advancements in using Artificial Intelligence (AI) and machine learning for kidney stone detection, offering efficient and accurate diagnosis methods.

1.2 Description of dataset

The renal ultrasound imaging data sets are the source of the dataset that we utilized to interpret our suggested method. Our renal ultrasound image model's objective is to assess how well various feature selection and machine learning approaches function. In this study, we utilize a real ultrasound dataset consisting of images captured from patients with suspected kidney stones. The dataset is characterized by its diversity, containing images with varying stone sizes, shapes, and locations within the kidney. This diversity is essential for training robust models capable of accurately detecting kidney stones in different scenarios. The majority of the provided dataset is standard for the area of ultrasound image study[12].

At the Doctor's Clinic, Specialty Diagnostic Radiology, Ali Asim, Iraq, Nineveh, data is collected from a single healthy participant 300 images of cases with normal kidneys and others with kidney stones, as stated by the provided data has been separated into two categories: kidney without stone and kidney with stone. To determine the overall machine learning algorithm's accuracy for classification, all of the supplied ultrasound imaging data of the kidney is divided into three main sections: the Training set, Test set, and Validation data.

2. METHODOLOGY

To explore and apply the proposed method, we utilized a real ultrasound dataset and MATLAB environment for implementation.

2.1 Data preprocessing

Although ultrasound imaging is a widely used and valuable diagnostic tool, it has some limitations compared to other imaging modalities such as minimally invasive and non-minimally illuminated ultrasound imaging resolution may be small compared to other imaging modalities such as magnetic resonance imaging (MRI)) or computed tomography (CT) scans Become comprehensive, Ultrasound imaging is also a safe technique because it so not emit ionizing radiation[13], making it especially useful for those with nephrolithiasis Data were obtained which were preprocessed for enhancement by repeating images using Lanczos interpolation (3rd order), it is known that Lanczos interpolation preserves information and is good for image size conversion, The appropriate Delivering results is known this is important to ensure that the rest of the process is successfully completed[14].

2.2 Removing background and small objects

Converts the image to grayscale, adaptive thresholding using Otsu's Method applies adaptive thresholding to create a binary image, adaptive thresholding dynamically determines thresholds for local regions based on the local histogram, this adaptability makes Otsu's method more robust in handling variations in lighting and contrast within an image than the standard thresholding[15]. Fills holes in the binary image, removes small objects from the binary image, preprocesses the original image using the mask applies the binary mask to the original image, adjusts the contrast and brightness of the preprocessed image, and after adjustments converts the adjusted RGB image to grayscale, applies Gaussian filtering to the final grayscale image for smoothing, and applies un-sharp masking to the final grayscale image for sharpening, as shown in Figure 2.

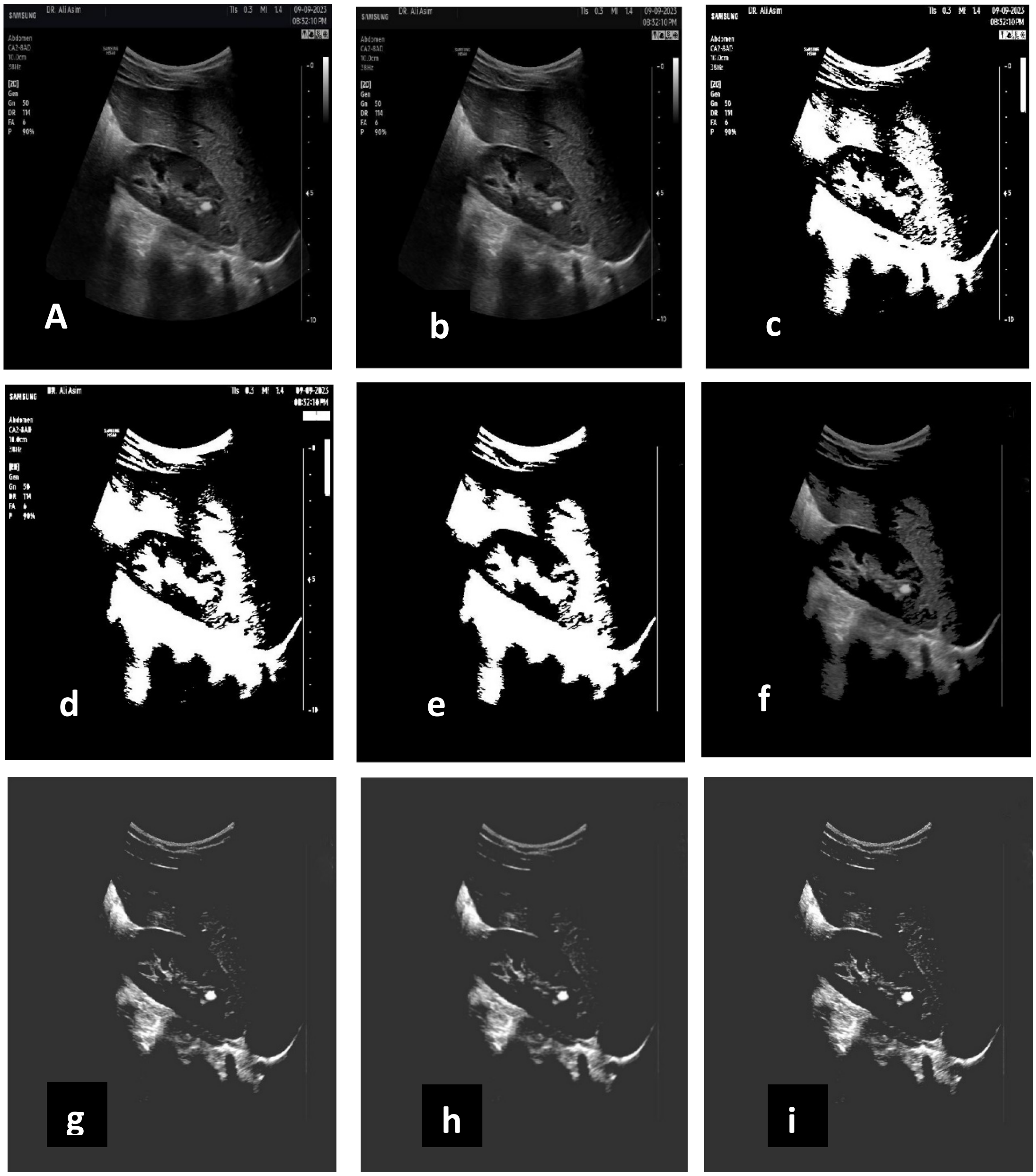

Figure 2:(a) original image (b) grayscale image (c) binary image (d) filled image (e) cleaned image (f) preprocessed image (g) adjusted image (h) smoothed image (i) sharpened image.

2.3 Split dataset

The dataset is split into training and testing sets using the `splitEachLabel` function. This function randomly splits the images while ensuring that each label has the specified proportion in both sets, with 70% of the data used for training, this value was adopted because, after several experiments of separating values between 60% and 80% for training and the rest for testing, I found that the best result for training was with a value of 70% for training and the rest for testing. This type of split is commonly used to train machine learning models and evaluate their performance on unseen data[16].

2.4 Data augmentation

It is a technique used to artificially increase the size of a dataset by creating modified versions of images in the original dataset. This can help improve the performance and robustness of machine learning models, especially when the original dataset is limited in size[17]. The data augmentation settings increase the effective size of the dataset by applying random transformations to the images, this helps in improving the generalization of the model and reducing overfitting by providing the network with more diverse examples to learn from.

The original dataset contains 300 images, and the data augmentation settings specified will introduce variability into each image, effectively increasing the dataset size, Random X Reflection and Random Y Reflection each image can be flipped horizontally and/or vertically, effectively doubling the dataset size (600 images), Random Rotation each image can be rotated by a random angle within the specified range (-10 to 10 degrees), increasing the dataset size further, Random X Scale and Random Y Scale each image can be scaled along the horizontal and/or vertical axis by a random factor within the specified range (0.8 to 1.2), this can increase the dataset size even more.

2.5 CNN Model Definition

CNN is designed to handle data that is organized into grids, such as audio or image files. CNNs perform very well in problems involving image recognition and classification. They are made up of many layers that are trained to identify different aspects of the input data, starting from simple features like edges and shapes in early layers, to more complex features in deeper layers[18]. The network then uses these learned features to make predictions about the input data, such as identifying objects in images, because CNN architecture provided outstanding classification, it was chosen to construct the kidney stone detection system[19]. The CNN architecture is suitable for feature extraction from ultrasound images. Here's a breakdown of the CNN layers and their functions:

Image Input Layer: Accepts input images of size 227x227x3.

Convolutional Layers: Three sets of convolutional layers followed by ReLU activation functions, these layers help extract various features from the input images.

Max Pooling Layers: Three max-pooling layers with a stride of 2, these layers reduce the spatial dimensions of the feature maps, helping to retain the most important features.

Fully Connected Layers: Two fully connected layers with 1024 and `numClasses` neurons, respectively, followed by ReLU activation, these layers further extract features and prepare the features for classification.

Softmax and Classification Layer: The softmax layer converts the final layer activations into class probabilities, and the classification layer specifies the output classes for the network, the block diagram of CNN is shown in Figure 3.

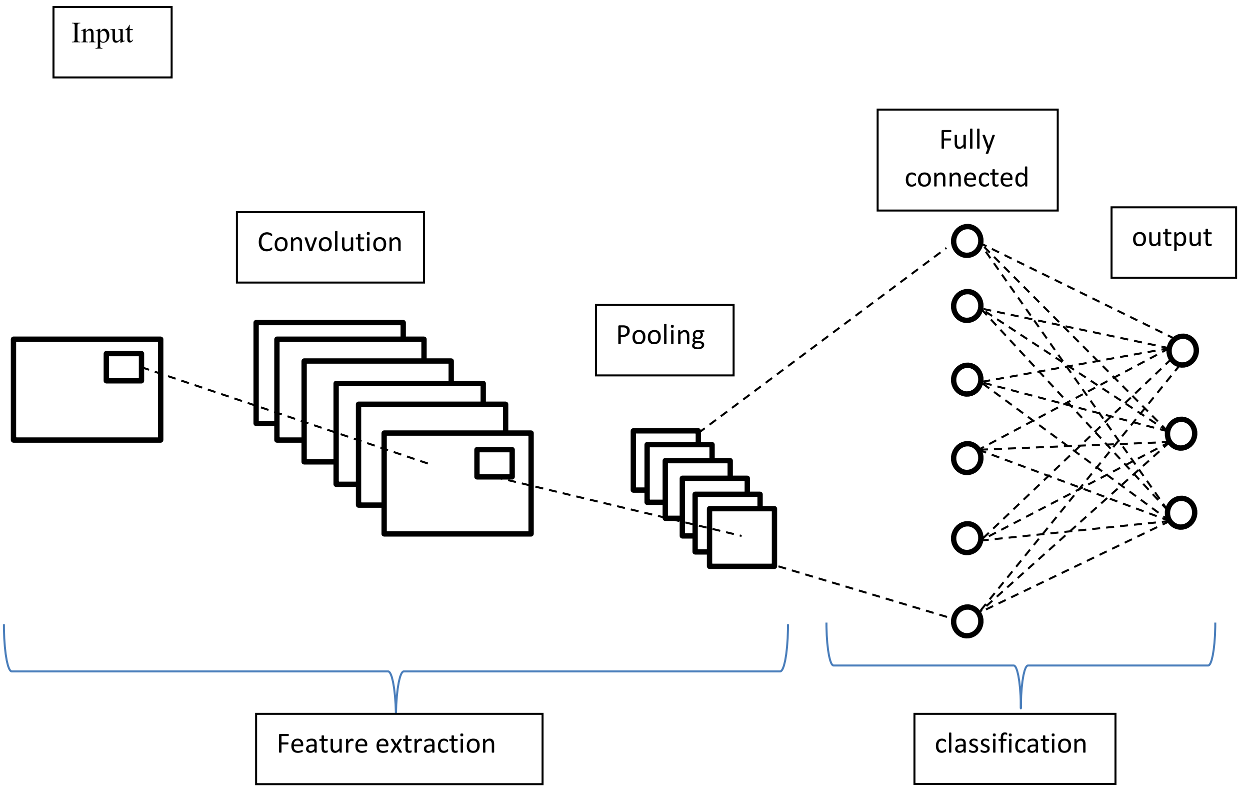

Figure 3: diagram of a basic convolutional neural network (CNN) architecture.

2.6 Training the CNN

Training the CNN involves using the `trainNetwork` function to train the network on the augmented training dataset, the `layers` variable defines a custom CNN architecture suitable for feature extraction from ultrasound images. It consists of several convolutional layers with relu activation functions, max-pooling layers for downsampling, and fully connected layers for classification. Dropout layers are also included to reduce overfitting[20].

The `options` variable specifies the training options, including the use of the Adam optimizer (Adam), Adam optimizer is commonly used in machine learning for various tasks[21], mini-batch size of 32, maximum epochs of 100 epochs, the initial learning rate of 1e-4, validation data, and other parameters, these options control how the network is trained and how the training progress is monitored.

2.7 GLCM Feature Extraction

Identifying meaningful texts or forces is a methodology in itself, it involves identifying and extracting specific shapes or forces from the image These forces work ships as systematically skilled algorithms of helps to understand their path and make basic predictions based on omissions[22].

GLCM is an image processing method to describe the texture of an image. The spatial arrangement of the intensity levels in an image is called its texture, and can provide important information about the surface properties of objects in an image A GLCM consists of a rectangular matrix where each (i, j) denotes the frequency of two pixels in the image at a certain offset and a given direction The direction containing f indicates where the two point, while the offset sets their relative position[23].

Ultrasound images are processed to obtain GLCM features as a type of texture analysis, for each of the four offset directions, four features (Contrast, Homogeneity, Energy, and Correlation) are computed, yielding a total of 16 features per image[24].To ensure the matrix has the right size and structure, it is customary to start with zeros before the GLCM features are computed and placed in it. This step avoids any unexpected behavior or mistakes that can arise from improperly initializing the matrix before populating it with the computed features[25]. These characteristics record texture information at a lower level. Conversely, the CNN features extract more complex semantic information from the images. Kidney stone detection ultrasound image datasets are used to train the CNN model. For both the training and testing datasets, features are taken from the learned CNN model after training. The activations function is used to achieve this; it takes features from a given layer (fc_1) and outputs them as rows because the (fc_1) layer often contains features that are more abstract and high-level compared to earlier layers and the (fc_1) layer typically has a large number of units, which means the features extracted from this layer have a high dimensionality[26], by combining these GLCM and CNN features, the model can potentially improve its ability to classify kidney images accurately.

2.8 Support Vector Machine (SVM) Classifier

Support Vector Machines (SVMs) are a type of supervised learning model used for classification and regression tasks, many benefits come with it, including a strong theoretical base, global optimization, the solution's sparsity, nonlinearity, and generalization[27].By establishing a decision boundary between two classes, it hopes to make it possible to predict labels based on one or more feature vectors. The orientation of this decision boundary, often referred to as the hyperplane, is designed to place it as far away as feasible from the nearest data points from each class, support vectors are these nearest points[28].

Given the following labelled training dataset:

(X_1, Y_1),……, (X_n, Y_n), $X_i \in R^d$ and $Y_i \in$ (-1,+1) where Y_i are the class labels (positive or negative) of training compound i, and xi is its feature vector representation. Then, $wx^T +$ b=0 can be used to define the ideal hyperplane. where x is the input feature vector, b is the bias, and w is the weight vector. For every component in the training set, the w and b would meet the following inequalities:

If Y_i= 1, then wx_i^T + b ≥ +1.

If Y_i= −1, then wx_i^T+ b ≤ −1.

Finding w and b so that the hyperplane divides the data and maximizes the margin is the goal of training an SVM model. 1 / || w || 2. Vectors $X_i$are designated as support vectors if $|Y_i|$ $(wx_i^T+$ b) = 1. Figure 4 explains this operation.

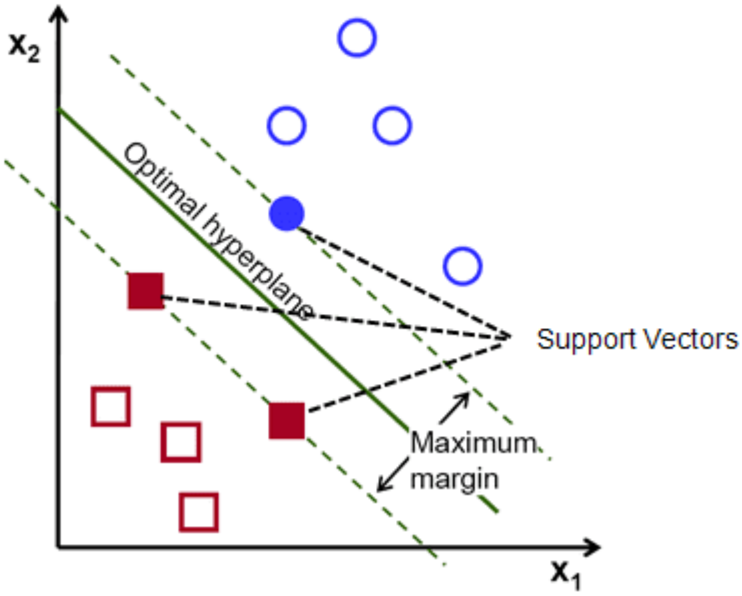

Figure 4: SVM model two classes (red against blue) where classified.

After extracting the GLCM features, they are combined with the CNN features to form a more comprehensive feature set for each image. This combined feature set is then used as input to the SVM classifier, enhancing its ability to distinguish between different classes of kidney images. The selected elements from the training dataset (`XTrain`) and the corresponding labels (`train.Labels`) are used as input to the `fitcsvm` function.`XTrain` is the matrix on which each row depends there for a type of the image , and `train`. Labels` contains the corresponding labels (e.g., normal or abnormal) for each image in the training data set. In addition, GLCM (Gray-Level Co-occurrence Matrix) features are computed for each image and combined with CNN features to create accurate features [29]. These GLCM features capture texture information in images, generating SVM classification the ability to discriminate between classes is greater kidney models SVM model (`SVMModel). `) Implementation of combined features After being trained to recognize patterns among the features that distinguish between images in different classes, the trained SVM models can then be based on the parameters learned from the training data to distribute new images. Training of the SVM classifier is necessary to identify discriminatory features in the dataset that can distinguish between kidney images. The SVM learns decision thresholds in the feature space separating classes, enabling it to classify new unseen images more efficiently. Training progress is shown in Figure 5.

2.9 Evaluate the SVM classifier

The test dataset can be used to test the trained SVM model to assess its performance on unseen data, the accuracy of SVM classification is performed from real labels (`test.Labels`) using predicted labels (`YPred`). compare it to it. achieved 93.22% accuracy, 92.5% sensitivity, . The specificity was 93.59%, indicative of kidney stones. A powerful approach to classify medical images is to train an SVM classifier with features retrieved from CNN and GLCM. It takes advantage of the capabilities of GLCM to encode texture information and the capabilities of CNN to extract complex features from images. Then to improve the performance of the classifier, SVM combines both types of features to produce an efficient classifier in highdimensional features[30].

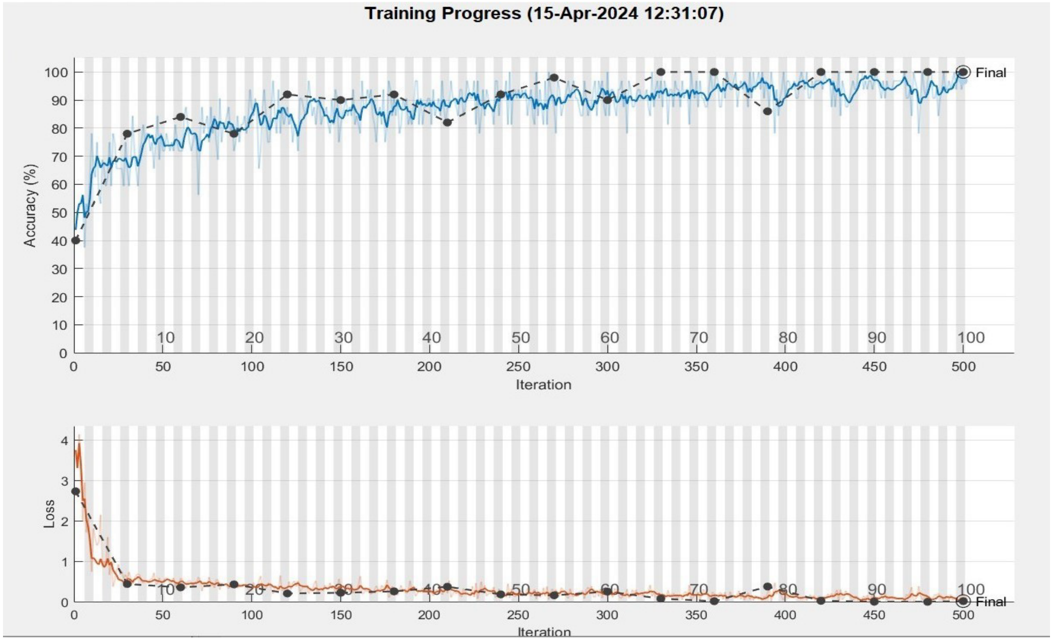

Figure 5: training progress of 100 epochs and 500 iterations for kidney stone detection.

3. RESULT AND DISCUSSION

A specially designed convolutional neural network (CNN) architecture has been developed to extract features from ultrasound images. The CNN contains multiple convolutional layers, max-pooling layers, rectified linear unit (ReLU) activation functions, and the training set is trained with an Adam optimizer in addition to gray-level co-occurrence matrix (GLCM) features extracted from ultrasound images , are added to the features extracted by CNN and then the Support Vector Machine (SVM) classifier is trained with this combination of features. The performance of the trained classifier is evaluated on a test set, and metrics such as accuracy, sensitivity, and specificity are calculated. This method provides a reliable and accurate method for the diagnosis of kidney stones by a classification system. The proposed method achieves an accuracy of 93.22%, with a sensitivity of 92.5% and a specificity of 93.59%, which can improve patient outcomes by improving kidney stone detection and treatment.

4. CONCLUSIONS

This paper proposes a novel method that combines CNN and GLCM for feature extraction and SVM for classification to provide accurate and efficient detection of kidney stones CNN is used to capture complex information from ultrasound images in, which is necessary for the accurate diagnosis of kidney stones. These features are then combined with texture features extracted by GLCM. The resulting feature vector is used to train an SVM classifier to distinguish images with and without kidney stones. This combined approach takes advantage of the strengths of CNN and GLCM in capturing relevant features from images. Our approach which includes image enhancement, CNN feature extraction, and SVM classification methods exhibits great potential to detect real conceptual gems, thus providing a new, more accurate method, etu effective, and not a personality replacement for traditional manual alternatives.

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