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RESEARCH ARTICLE

Enhanced otpmization based support vector machine classification approach for the detection of knee arthritis

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Abstract

The accurate detection of knee arthritis is essential for effective medical diagnosis and treatment. In this study, we propose an enhanced classification approach using a support vector machine (SVM) coupled with Cuckoo search optimization (CSO) to improve the detection of knee arthritis. The classification challenge lies in tuning the hyperparameters of the SVM, specifically the penalty parameter (C) and the kernel function parameter (γ), which significantly influence the model's performance. Traditional methods of hyperparameter tuning may be computationally expensive and prone to local minima. To address these challenges, we integrate CSO as an optimization algorithm for the efficient search of optimal hyperparameters. Cuckoo search optimization, inspired by the brood parasitism behavior of cuckoo birds, is applied to optimize the SVM hyperparameters by balancing exploration and exploitation during the search process. CSO efficiently explores the hyperparameter space and finds an optimal or near-optimal solution by minimizing the classification error. The hybrid approach aims to enhance the predictive accuracy and generalization ability of the SVM model. The proposed CSO-SVM framework is validated on a benchmark knee arthritis dataset, and the experimental results demonstrate a significant improvement in classification performance compared to traditional SVM and other optimization algorithms. The proposed model's ability to optimize hyperparameters with CSO shows promise in achieving higher accuracy, precision, recall, and F1 score, making it a robust approach for knee arthritis detection.

Keywords: Knee arthritis detection, Support vector machine, Cuckoo search optimization, Hyperparameter tuning, classification.

Introduction

Knee arthritis, particularly osteoarthritis (OA), is a degenerative joint disease that affects millions worldwide, leading to pain, joint stiffness, and a reduction in mobility. Early and accurate detection of knee arthritis is crucial for slowing disease progression and improving patient outcomes. Traditionally, diagnosis has been based on physical examinations, imaging modalities such as X-rays and MRIs, and clinical assessments of symptoms. While effective, these traditional methods often require expert interpretation, can be time-consuming, and may fail to detect arthritis at its earliest stages when interventions are most effective, Helwan, A., & Tantua, D. P. (2016), Saleem, M., Ali, M. M., & Tirmizi, S. F. (2020).

In recent years, advances in machine learning (ML) and deep learning (DL) have shown significant promise in revolutionizing the detection and diagnosis of various medical conditions, including knee arthritis. These algorithms have the potential to automatically learn patterns from large datasets, making them highly suited for complex and high-dimensional medical data, such as imaging and clinical records. ML algorithms, such as support vector machines (SVM), random forests, and decision trees, have been widely adopted for medical classification tasks due to their robustness and interpretability. However, they often require manual feature engineering and rely on predefined features extracted from the data, de Dieu Uwisengeyimana, J., & Ibrikci, T. (2017), Brahim, A., Zghal, N., Sassi, M., & Mahmoud, R. (2019).

Deep learning, a subfield of machine learning, offers a more advanced approach by automatically learning relevant features from raw data. Convolutional neural networks (CNNs), a type of deep learning model, have been

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particularly successful in image-based medical applications, including the detection of arthritis in knee X-rays and MRI scans. CNNs can capture hierarchical features from medical images, identifying subtle patterns indicative of arthritis that traditional methods may overlook. These models, trained on large datasets, can perform at or above the level of human experts, offering a scalable and objective solution for the early detection of knee arthritis, Christodoulou, E., Skordis, A., & Rojas, I. (2019), Yeoh, P. S. Q., Lee, Y. K., & Sulaiman, R. (2021).

While both ML and DL algorithms have shown promise, they come with unique challenges. Machine learning models, though interpretable, often require extensive feature selection and manual tuning to achieve optimal performance. In contrast, deep learning models, despite their high accuracy, can be computationally expensive, require large amounts of data, and are often considered "black boxes" due to their lack of interpretability, Jakaite, L., Karpus, K., & Ansys, M. (2021), Wang, Y., Zhang, H., & Li, H. (2021).

In recent years, ML algorithms have demonstrated potential in automating and enhancing diagnostic processes in medical fields, including arthritis detection. SVM has emerged as one of the most effective ML models for classification tasks, especially in medical diagnosis, due to its robustness in handling non-linear and high-dimensional data. However, the performance of SVM is significantly influenced by its hyperparameters, such as the penalty parameter (C) and the kernel parameter (γ). The process of selecting these hyperparameters, known as hyperparameter tuning, is critical for maximizing model performance but can be computationally intensive and susceptible to local minima, Tiulpin, A., Oikonomidis, I., & Bzhalava, R. (2018), Kokkotis, C., Boulas, A., & Sakellariou, A. (2020).

To address these challenges, metaheuristic optimization algorithms have been employed to automate the tuning process. Among these, Cuckoo Search Optimization (CSO), a nature-inspired optimization algorithm, has gained attention due to its efficiency in exploring complex search spaces and avoiding premature convergence. CSO mimics the parasitic behavior of cuckoo birds, utilizing a balance between exploration and exploitation to find optimal or near-optimal solutions.

In this study, we propose an innovative classification approach that combines the SVM with CSO for the detection of knee arthritis. The primary objective of this hybrid approach is to enhance SVM's classification performance by efficiently tuning its hyperparameters using CSO. By leveraging CSO's ability to navigate large and complex search spaces, the proposed model is expected to achieve higher accuracy and generalization, reducing classification errors and improving early detection capabilities.

Related Works

A new automatic classification of KOA images based on an unsupervised local center of mass (LCM) segmentation method and deep Siamese CNN is presented. First-order statistics and the GLCM matrix are used to extract KOA anatomical features from segmented images, Sikkandar, M. Y., Wani, A. A., & Shafi, B. (2022).

The authors used lateral view knee radiographs from The Multicenter Osteoarthritis Study (MOST) public use datasets (n = 5507 knees). Patellar region-of-interest (ROI) was automatically detected using a landmark detection tool (BoneFinder), and subsequently, these anatomical landmarks were used to extract three different texture ROIs. Hand-crafted features based on Local Binary Patterns (LBP), were then extracted to describe the patellar texture. First, a machine learning model (Gradient Boosting Machine) was trained to detect radiographic Perfluorooctanoate (PFOA) from the LBP features. Furthermore, we used end-to-end trained deep CNNs directly on the texture patches for detecting the PFOA, Bayramoglu, N., Nieminen, M. T., & Saarakkala, S. (2022).

The authors proposed a hybrid model that combines advanced computer vision techniques, such as Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF), with SVM and random forests. The integration of SIFT and SURF allows for the extraction of robust and distinctive features from knee joint images, which are crucial for accurate classification. SVM and random forest algorithms are then employed to classify these features, providing a powerful mechanism to distinguish between healthy and pathological conditions. We utilize an extensive collection of knee images, including MRIs, CT scans, and X-rays, to train and optimize the model, ensuring it can handle a variety of imaging modalities and conditions, Supriya, M., & Mohammed, T. K. (2024).

The authors developed a tool for locating and grading knee osteoarthritis (OA) from digital X-ray images and illustrated the possibility of deep learning techniques to predict knee OA as per the Kellgren-Lawrence (KL) grading system. The purpose of the project is to see how effectively an artificial intelligence (AI)-based deep learning approach can locate and diagnose the severity of knee OA in digital X-ray images, Abdullah, S. S., & Rajasekaran, M. P. (2022).

The authors proposed a novel feature extractor from X-ray images of the knee to assist in detection and classification, called explainable Renyi entropic segmentation with Internet of Things (IoT) framework. The proposed method later utilizes a model agnostic algorithm using post hoc explainability for extracting relevant information from a prediction of knee joint segmentation. CAD system is integrated with an IoT framework and can be used remotely to assist medical practitioners in treatments of knee arthritis, Khamparia, A., Tiwari, M. K., & Agrawal, D. (2023).

The authors presented the results of a preliminary study on simplified diagnosis of osteoarthritis of the knee joint based on generated vibroacoustic processes. The analysis was based on acoustic signals recorded in a group of 50 people, half of whom were healthy and the other half - people with previously confirmed degenerative changes. Selected discriminants of the signals were determined and statistical analysis was performed to allow selection of optimal discriminants used at a later stage as input to the classifier. The best results of classification using artificial neural networks (ANN) of radial basis function (RBF) and multilevel perceptron (MLP) types are presented in Karpiński, R. (2022).

The authors presented as a main contribution, a methodology based on infrared thermography (IT) and convolutional neural networks (CNNs) to automatically differentiate between a healthy knee and an injured knee, being an alternative tool to help medical specialists. In general, the methodology consists of three steps: (1) database generation, (2) image processing, and (3) design and validation of a CNN for automatically identifying a patient with an injured knee. In the image-processing stage, grayscale images, equalized images, and thermal images are obtained as inputs for the CNN, where 98.72% of accuracy is obtained by the proposed method, Trejo-Chavez, O., Rosas, J., & Tellez, S. (2022).

This research delves into the pivotal role of FS in enhancing the accuracy and dependability of ML models used in KOA detection and severity classification. The data were obtained from Kaggle, representing various grades of KOA. We employ a CNN model to extract features from medical imaging data. Utilizing advanced techniques such as PSO and GBC, we systematically identify relevant features to enhance our ML models, Bose, A. S. C., Srinivasan, C., & Joy, S. I. (2024).

The authors tried to review various medical imaging techniques that can be used for the detection or diagnosis KOA and different techniques based upon Machine Learning that can be employed in the automatic detection of knee osteoarthritis (KOA) without much human intervention. "Joint inflammation" is the alternate term for Arthritis disease. Joints can be described as the areas in the body where two bones meet and allow movement, such as the elbow or knee. Arthritis is a very commonly found disease that contributes to one of the primary causes of disability globally. Osteoarthritis is a type of arthritis that basically results from repeated strain on joint cartilage. Osteoarthritis is also termed as "wear and tear" arthritis. Applying machine learning principles to medical data has the capability to improve disease identification and early diagnosis significantly. In this paper, we have comprehensively reviewed various Medical Imaging techniques that facilitate automated diagnosis of KOA with the help of state-of-the-art ML techniques, Sharma, N., Sapra, R., & Dhaliwal, P. (2024).

The authors focused on studying the computer-assisted diagnosis method of KOA (KOA-CAD) using multivariate information, (i.e., VAGs and basic physiological signals) based on an improved deep learning model (DLM). Firstly, a new Laplace distribution-based strategy (LD-S) for classification in DLM is designed. Secondly, an aggregated multiscale dilated convolution network (AMD-CNN) is constructed to learn features from multivariate information of KOA patients. Then, a new KOA-CAD method is proposed by integrating the AMD-CNN with the LD-S to realize three CAD objectives, including the automatic KOA detection, the KOA early detection, and the KOA grading detection, Song, J., & Zhang, R. (2023).

The main objective was to use machine learning methods to identify significant structural factors associated with pain severity in knee osteoarthritis patients. Additionally, we assessed the potential of various classes of imaging data using machine learning techniques to gauge knee pain severity. The data of semi-quantitative assessments of knee radiographs, semi-quantitative assessments of knee magnetic resonance imaging (MRI), and MRI images from 567 individuals in the Osteoarthritis Initiative (OAI) were utilized to train a series of machine learning models. Models were constructed using five machine learning methods: RF, SVM, LR, DT, and Bayesian (Bayes). Employing tenfold cross-validation, we selected the best-performing models based on the area under the curve (AUC), Zhao, Z., Liu, H., & Zhang, R. (2024).

The authors developed a KOA prediction model using X-ray images and the Kellgren-Lawrence (KL) scale to predict the presence of KOA. Medically, photos in the form of knee X-ray images were collected and labeled by radiologists based on the KL scale, which ranges from 0 (no KOA) to 4 (severe KOA). CNN modeling is done to interpret X-ray pictures and forecast the KL score, Patil, P., Hossain, A., & Shafique, M. (2023).

This study presents a method based on deep features. We employed a convolutional neural network to extract deep features from Knee Osteoarthritis images. Then, the extracted features are fed to different machine learning classifiers, namely Support Vector Machine, K-Nearest Neighbour, and Naive Bayes. The classification of this work has been performed to differentiate between healthy and unhealthy Knee Osteoarthritis images, Zebari, D. A., Sadiq, S. S., & Sulaiman, D. M. (2022).

Multiple DL approaches have been described for fully automated segmentation of cartilage and other knee tissues and have achieved higher segmentation accuracy than currently used methods with substantial reductions in segmentation times. Various DL models analyzing baseline X-rays and MRI have been developed for OA risk assessment. These models have shown high diagnostic performance for predicting a wide variety of OA outcomes, including the incidence and progression of radiographic knee OA, the presence and progression of knee pain, and future total knee replacement. The preliminary results of DL applications in OA imaging have been encouraging.

However, many DL techniques require further technical refinement to maximize diagnostic performance, Kijowski, R., Fritz, J., & Deniz, C. M. (2023).

The authors proposed an artificial intelligence methodology to select the abstract set of features from the given raw data, and classification is done through hybrid isolation forest (HIF). The chapter consists of three phases, starting from processing the raw images and extraction of the pre-processed dataset. The second phase identifies the abstract feature set using the statistical and regressive parameters. The third phase proposes a hybrid isolation forest method that integrates the probability distribution and isolation forest to perform the accurate classification of normal and abnormal data samples. The proposed AI model is tested on the knee joint disorder image dataset, Sharmila Begum, M., & Others. (2024).

Support Vector Machine Classifier

SVM is a powerful supervised machine learning algorithm primarily used for classification tasks. It excels in high-dimensional spaces and is effective in cases where the number of dimensions exceeds the number of samples. SVM aims to find the best-separating hyperplane that maximizes the margin between different classes in the dataset, Kubkaddi, S., & Ravikumar, K. M. (2017), Sharma, S., Virk, S. S., & Jain, V. (2016).

Hyperplane

A hyperplane is a decision boundary that separates different classes in the feature space. In a two-dimensional space, this is a line; in three dimensions, it's a plane; and in higher dimensions, it becomes a hyperplane. The goal of SVM is to find the hyperplane that best separates the classes while maximizing the margin between them. The margin is defined as the distance between the hyperplane and the nearest data points from each class.

Support Vectors

Support vectors are the data points that lie closest to the hyperplane. They are crucial because they directly influence the position and orientation of the hyperplane. Removing any support vector would change the position of the hyperplane, while points farther away from the margin do not affect the decision boundary. This makes SVM robust to outliers.

Margin

The margin is the distance between the hyperplane and the nearest support vectors from either class. SVM aims to maximize this margin. A larger margin implies a better generalization of the model to unseen data. SVM is essentially trying to find a hyperplane that maximizes this distance.

Kernels

Kernels allow SVM to work in a high-dimensional feature space without explicitly transforming the data points. This is particularly useful for non-linear classification problems.

- *Linear Kernel*

Suitable for linearly separable data. The function is simply the dot product of the input vectors.

- *Polynomial Kernel*

Captures polynomial relationships and can handle non-linear data. The function is of the form $(\gamma, \langle x, x' \rangle + r)^d$, where γ, r, d are parameters.

- *Radial Basis Function (RBF) Kernel*

A popular choice for non-linear data. It calculates the distance between data points in a high-dimensional space, allowing SVM to create complex decision boundaries. The function is of the form $exp(-\gamma\|x - x'\|^2)$, where γ is a parameter that determines the spread.

Regularization Parameter (C)

The parameter C controls the trade-off between maximizing the margin and minimizing the classification error on the training data.

- A small C value allows for a wider margin and can tolerate some misclassifications (soft margin).
- A large C value aims to classify all training points correctly, which can lead to a narrower margin and overfitting.

Soft Margin vs. Hard Margin

- *Hard Margin*

Assumes that the data is linearly separable without any misclassifications. It may not be practical for real-world data.

- *Soft Margin*

Allows some misclassifications to create a more generalizable model. It introduces slack variables to account for misclassified points.

Step by Step Procedure of SVM Classification

Step 1: Data Collection

- *Obtain the Dataset*

Acquire the X-ray knee arthritis dataset, which typically contains images of knee X-rays along with labels indicating the presence or absence of arthritis.

Step 2: Data Pre-processing

- *Resize Images*

Standardize the size of all X-ray images to ensure uniformity (e.g., 224x224 pixels).

- *Normalization*

Normalize pixel values to a range of [0, 1] or scale using Z-score normalization.

- *Augmentation (optional)*

Apply techniques like rotation, flipping, or zooming to increase the diversity of training data and prevent overfitting.

- *Feature Extraction*

Use techniques such as Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), or Convolutional Neural Networks (CNN) for feature extraction from the X-ray images.

Step 3: Splitting the Dataset

- *Train-Test Split*

Divide the dataset into training and testing sets. A common split is 70-80% for training and 20-30% for testing.

- *Cross-Validation (optional)*

Consider k-fold cross-validation to ensure robustness in model evaluation.

Step 4: Choosing the Kernel

- *Select Kernel Type*

Based on the data distribution: For non-linear relationships in X-ray features, consider using the Radial Basis Function (RBF) kernel.

Step 5: Setting Hyperparameters

- *Define Hyperparameters: C*

The regularization parameter that controls the trade-off between maximizing the margin and minimizing classification errors. γ The kernel coefficients for the RBF kernel, which defines the influence of training samples.

Cuckoo Search Optimization Algorithm

Cuckoo search (CS) is a metaheuristic optimization algorithm inspired by the brood parasitism of some cuckoo species. The algorithm was introduced by Yang and Deb in 2009 and has gained popularity for its simplicity and efficiency in solving complex optimization problems. Chithra, B., & Nedunchezhian, R. (2022), Kaur, R., Madaan, V., & Agrawal, P. (2019).

Cuckoo Brood Parasitism

- *Brood Parasitism*

Some cuckoo species are known for their brood-parasitic behavior, where they lay their eggs in the nests of other bird species. The host birds unknowingly raise the cuckoo chicks, often at the expense of their own offspring.

- *Strategy*

The cuckoo eggs may resemble those of the host birds to avoid detection. If the host detects the foreign eggs, it may either abandon the nest or reject the eggs.

Levy Flights

Lévy flights are a type of random walk characterized by occasional large jumps, allowing for effective exploration of the search space. Lévy flights can be defined using the equation:

$$x_{t+1} = x_t + \alpha . Levy(\lambda)$$

Where $Levy(\lambda)$ is drawn from a Lévy distribution, typically characterized by a heavy tail. This means that while most steps are small, a few steps can be significantly larger, facilitating exploration.

- *Exploration vs. Exploitation*

The use of Lévy flights helps the algorithm balance exploration (finding new areas of the search space) and exploitation (refining existing solutions).

Nests and Eggs

- *Nests*

In the context of the algorithm, each nest represents a potential solution to the optimization problem. The number of nests corresponds to the population size.

- *Eggs*

The eggs in a nest represent the parameters or variables of the solution. The quality of the eggs (fitness of the solution) determines the overall quality of the nest.

Fitness Evaluation

Each nest (solution) is evaluated using a fitness function that quantifies how well the solution solves the given problem. The objective is to maximize or minimize this fitness value depending on the specific optimization goal.

Discovery of Alien Eggs

- To introduce diversity and avoid stagnation in the search process, the algorithm incorporates a probability p that determines the likelihood of discovering alien eggs (random solutions).

- *Replacement*

If an alien egg is discovered, it replaces a randomly chosen nest, which may help escape local optima and explore new areas of the search space.

Algorithm Parameters

- *Population Size*

The number of nests in the search space which influences the algorithm's performance.

- *Probability of Discovery p*

A small value (e.g., 0.1) that dictates the frequency of introducing new random solutions. This helps maintain diversity in the population.

- *Scaling Factor α\alphaα*

This factor controls the step size during the Lévy flight, influencing the exploration behavior of the algorithm.

Termination Criteria

The algorithm continues iterating until a termination condition is met. Common criteria include:

- A predefined number of iterations or function evaluations.
- Convergence to a satisfactory fitness value.

Proposed Enhanced Svm Approach For The Detection Of Knee Arthritis

The hybridization of the SVM with the CSO algorithm for the detection of knee arthritis involves several well-defined steps. The combination leverages the classification strength of SVM while utilizing CSO to optimize the SVM hyperparameters (such as the regularization parameter C and the kernel parameter γ) to enhance the detection performance.

Step 1: Data Collection

Collect X-ray images of knees labeled with the presence or absence of arthritis. A dataset like the OAI can be used.

Step 2: Feature Extraction

Use image processing techniques or deep learning feature extractors to create numerical representations of the X-ray images.

- *Handcrafted Features*

Techniques such as Histogram of Oriented Gradients (HOG), LBP, or texture-based features.

- *Deep Learning Features*

Use pre-trained CNN to extract deep features from images, useful for medical imaging.

Step 3: Choosing SVM

SVM is chosen for its effectiveness in high-dimensional feature spaces. For the detection of knee arthritis, SVM with a radial basis function (RBF) kernel is commonly used due to its ability to handle non-linear decision boundaries.

Step 4: Hyperparameters of SVM

- *C (Regularization Parameter)*

Controls the trade-off between maximizing the margin and minimizing misclassification.

- *γ (Kernel Coefficient)*

Defines the influence of a single training example, controlling the decision boundary's flexibility.

The classification performance of SVM heavily depends on finding the right combination of these hyperparameters, which can be a challenging task. This is where Cuckoo Search Optimization comes into play.

Step 5: Steps in Cuckoo Search Optimization

CSO is a metaheuristic optimization algorithm inspired by the brood parasitism of certain cuckoo species and Lévy flight behavior, which efficiently explores and exploits the search space.

- *Step 5.1: Initialization*
- Initialize a population of nests. Each nest represents a candidate solution, i.e., a combination of hyperparameters C and γ.
- Randomly generate the initial values for C and γ within predefined bounds.
- *Step 5.2: Fitness Function Definition*
- The fitness of each nest is determined by the performance (classification accuracy) of the SVM classifier trained using the corresponding hyperparameters on a validation dataset.

$$Fitness = Accuracy\ (SVM(C,\gamma)$$

- The goal is to maximize the fitness function, which corresponds to maximizing the classification accuracy on the validation set.

- *Step 5.3: Lévy Flight for New Solutions*
- Generate new hyperparameter combinations using Lévy flights, which allow for random exploration of the search space.
- The new hyperparameter combination for each nest is given by:

$$x_{new} = x_i + \alpha.Levy(\lambda)$$

- Where x_i is the current position of the nest (i.e., the current values of C, and γ, and α is a scaling factor. Lévy flight allows both short and long jumps in the search space, improving the chances of finding a global optimum.

- *Step 5.4: Fitness Evaluation of New Solutions*
- For each new hyperparameter combination generated by the Lévy flight, retrain the SVM model and evaluate its classification accuracy.
- If the new nest (hyperparameter combination) yields a better classification accuracy than the old one, the old nest is replaced with the new one.

- *Step 5.5: Discovery of Alien Eggs*

With a small probability p, randomly replace some nests with entirely new random hyperparameter combinations. This mechanism helps maintain diversity in the population and prevents premature convergence to a local optimum.

- *Step 5.6: Iterative Optimization*

Repeat the Lévy flight, fitness evaluation, and replacement process for a predefined number of iterations or until a convergence criterion is met (e.g., a small change in the best fitness over several iterations).

Result And Discussion

Performance Metrics

The performance of the proposed enhanced SVM with CSO approach is evaluated with the existing classification techniques like support vector machine (SVM), and decision tree (DT) using the following evaluation metrics mentioned in Table 1. For pre-processing (image enhancement) of the images, the median and mean histogram equalization techniques are applied. The knee arthritis dataset is considered from the Kaggle repository, Shashwatwork. (n.d.). *Knee osteoarthritis dataset with severity*. Kaggle.

Table 1: Performance Metrics used in this paper

Performance Metrics	*Equation*
Detection Rate	$\frac{TP+TN}{TP+TN+FP+FN}$
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$
False Positive Rate	1- Specificity
Miss Rate	1- Sensitivity

Table 2 depicts the detection rate (in %) obtained by the median mean HE with LBP feature extraction technique. From Table 2, it is clear that the proposed ESVM-CSO performs better than the other classifiers.

Table 2 presents the detection rates (in %) obtained by various image enhancement techniques combined with feature extraction techniques using both the proposed classification method (ESVM-CSO) and two existing methods (SVM and DT).

The median pre-processing method achieved a detection rate of 50.24% with ESVM-CSO, slightly lower with SVM (49.39%), and the lowest with DT (48.58%). The mean method performed similarly across all techniques, with the highest detection rate for SVM (51.36%), closely followed by ESVM-CSO (51.22%) and DT (50.85%). With histogram equalization (HE), ESVM-CSO produced the best detection rate of 52.28%, while SVM (49.87%) and DT (51.14%) showed slightly lower performance. Median + LBP produced the highest detection rate for ESVM-CSO at 56.52%, with SVM achieving 53.55% and DT scoring 49.21%. Mean + LBP demonstrated stronger performance with ESVM-CSO at 53.69% and slightly lower rates with SVM (51.88%) and DT (50.31%). The combination of HE + LBP yielded relatively consistent results across all techniques, with DT reaching the highest detection rate (52.52%), ESVM-CSO at 51.78%, and SVM at 50.64%.

Overall, ESVM-CSO consistently performed better across most pre-processing techniques, with the highest detection rate of 56.52% obtained using the median + LBP combination. DT generally performed the lowest except when paired with HE + LBP, where it outperformed the other methods.

Table 3 depicts the sensitivity (in %) obtained by the median mean HE with LBP feature extraction technique. From Table 3, it is clear that the proposed ESVM-CSO performs better than the other classifiers.

Table 3 presents the sensitivity (in %) obtained by various image enhancement techniques combined with feature extraction techniques, evaluated using the proposed classification method (ESVM-CSO) and existing methods (SVM and DT).

Table 2: Detection rate (in %) obtained by the image enhancement techniques + Feature extraction technique using proposed and existing classification techniques

Pre-processing methods	*Detection rate (in %) obtained by classification techniques*		
	ESVM-CSO	*SVM*	*DT*
Median	50.24	49.39	48.58
Mean	51.22	51.36	50.85
HE	52.28	49.87	51.14
Median + LBP	56.52	53.55	49.21
Mean + LBP	53.69	51.88	50.31
HE + LBP	51.78	50.64	52.52

Table 3: Sensitivity (in %) obtained by the image enhancement techniques + feature extraction technique using proposed and existing classification techniques

Pre-processing methods	*Sensitivity (in %) obtained by classification techniques*		
	ESVM-CSO	*SVM*	*DT*
Median	50.78	48.85	47.14
Mean	49.63	48.01	46.65
HE	50.12	49.58	48.83
Median + LBP	56.55	53.55	49.211
Mean + LBP	53.68	51.89	50.23
HE + LBP	51.86	50.27	52.41

The median pre-processing method showed a sensitivity of 50.78% with ESVM-CSO, with SVM at 48.85%, and the lowest value of 47.14% with DT. The Mean method yielded lower sensitivity for all classifiers, with ESVM-CSO at 49.63%, SVM at 48.01%, and DT at 46.65%. Histogram equalization (HE) led to a sensitivity of 50.12% with ESVM-CSO, followed by 49.58% for SVM and 48.83% for DT. Median + LBP produced the highest sensitivity for ESVM-CSO at 56.55%, with SVM achieving 53.55%, while DT remained lower at 49.21%. Mean + LBP showed better performance with ESVM-CSO at 53.68%, with SVM at 51.89%, and DT at 50.23%. The combination of HE + LBP yielded a sensitivity of 51.86% for ESVM-CSO, 50.27% for SVM, and the highest for DT at 52.41%.

Overall, ESVM-CSO consistently achieved higher sensitivity across most techniques, with the highest value of 56.55% observed for the Median + LBP combination. The DT classifier performed lower on average but excelled with HE + LBP, achieving a sensitivity of 52.41%.

Table 4 depicts the specificity (in %) obtained by the median mean HE with LBP feature extraction technique. From Table 4, it is clear that the Proposed ESVM-CSO performs better than the other classifiers.

Table 4 presents the specificity (in %) obtained by various image enhancement techniques combined with feature extraction techniques, evaluated using the proposed

Table 4: Specificity (in %) obtained by the image enhancement techniques + feature extraction technique using proposed and existing classification techniques

Pre-processing methods	*Specificity (in %) obtained by classification techniques*		
	ESVM-CSO	*SVM*	*DT*
Median	50.36	49.93	48.25
Mean	49.52	48.81	47.77
HE	50.17	50.68	48.98
Median + LBP	56.49	53.52	49.21
Mean + LBP	53.70	51.88	50.234
HE + LBP	51.52	52.123	50.61

Table 5: False positive rate (in %) obtained by the image enhancement techniques + feature extraction technique using proposed and existing classification techniques

Pre-processing methods	*False positive rate (in %) obtained by classification techniques*		
	ESVM-CSO	*SVM*	*DT*
Median	49.64	50.07	51.75
Mean	50.48	51.19	52.23
HE	49.83	49.32	51.02
Median + LBP	43.51	46.48	50.79
Mean + LBP	46.3	48.12	49.766
HE + LBP	48.48	47.877	49.39

classification method (ESVM-CSO) and existing methods (SVM and DT).

The Median pre-processing method achieved a specificity of 50.36% with ESVM-CSO, with SVM slightly lower at 49.93% and DT the lowest at 48.25%. The mean method produced lower specificity across all classifiers, with ESVM-CSO at 49.52%, SVM at 48.81%, and DT at 47.77%. Histogram equalization (HE) yielded 50.17% specificity with ESVM-CSO, while SVM had a slightly better performance at 50.68%, and DT achieved 48.98%. Median + LBP resulted in the highest specificity for ESVM-CSO at 56.49%, followed by SVM at 53.52% and DT at 49.21%. Mean + LBP showed better specificity for ESVM-CSO at 53.70%, while SVM obtained 51.88%, and DT had a specificity of 50.23%. The combination of HE + LBP resulted in consistent specificity across classifiers, with SVM achieving the highest value at 52.12%, followed by ESVM-CSO at 51.52% and DT at 50.61%.

Overall, ESVM-CSO consistently provided higher specificity in most cases, with the highest value of 56.49% achieved using the median + LBP combination. SVM showed competitive performance, especially with HE + LBP, where it outperformed ESVM-CSO. DT generally performed lower but improved when paired with LBP-based methods.

Table 5 depicts the false positive rate (in %) obtained by the median, mean HE with LBP feature extraction technique. From Table 5, it is clear that the proposed ESVM-CSO reduces the FPR than the other classifiers.

Table 5 presents the false positive rate (in %) obtained by various image enhancement techniques combined with feature extraction techniques, evaluated using the proposed classification method (ESVM-CSO) and existing methods (SVM and DT).

The median pre-processing method resulted in a false positive rate of 49.64% with ESVM-CSO, slightly higher with SVM at 50.07%, and the highest with DT at 51.75%. The mean method produced higher false positive rates across all classifiers, with ESVM-CSO at 50.48%, SVM at 51.19%, and DT at 52.23%. Histogram equalization (HE) showed a false positive rate of 49.83% with ESVM-CSO, slightly lower for SVM at 49.32%, and higher with DT at 51.02%. Median + LBP achieved the lowest false positive rate for ESVM-CSO at 43.51%, followed by SVM at 46.48% and DT at 50.79%. Mean + LBP yielded a false positive rate of 46.3% for ESVM-CSO, 48.12% for SVM, and 49.77% for DT. The combination of HE + LBP resulted in relatively consistent false positive rates across classifiers, with SVM at 47.88%, ESVM-CSO at 48.48%, and DT at 49.39%.

Overall, ESVM-CSO consistently exhibited lower false positive rates compared to the existing methods. The best performance was achieved with the Median + LBP combination, which had the lowest false positive rate (43.51%) for ESVM-CSO. SVM and DT generally showed higher false positive rates, with DT consistently performing the worst across all methods.

Table 6 depicts the miss rate (in %) obtained by the median, mean HE with the LBP feature extraction technique. From Table 6, it is clear that the Proposed ESVM-CSO reduces the Miss Rate than the other classifiers.

Table 6 presents the miss rate (in %) obtained by various image enhancement techniques combined with feature extraction techniques, evaluated using the proposed classification method (ESVM-CSO) and existing methods (SVM and DT).

Table 6: Miss rate (in %) obtained by the image enhancement techniques + feature extraction technique using proposed and existing classification techniques

Pre-processing methods	*Miss Rate (in %) obtained by classification techniques*		
	ESVM-CSO	*SVM*	*DT*
Median	49.22	51.15	52.86
Mean	50.37	51.99	53.35
HE	49.88	50.42	51.17
Median + LBP	43.45	46.45	50.789
Mean + LBP	46.32	48.11	49.77
HE + LBP	48.14	49.73	47.59

The median pre-processing method resulted in a miss rate of 49.22% with ESVM-CSO, increasing to 51.15% with SVM and the highest at 52.86% with DT. The mean method produced higher miss rates across all classifiers, with ESVM-CSO at 50.37%, SVM at 51.99%, and DT at 53.35%. Histogram equalization (HE) yielded a miss rate of 49.88% for ESVM-CSO, slightly lower for SVM at 50.42%, and higher for DT at 51.17%. Median + LBP achieved the lowest miss rate for ESVM-CSO at 43.45%, with SVM at 46.45%, and DT at 50.79%. Mean + LBP produced a miss rate of 46.32% for ESVM-CSO, 48.11% for SVM, and 49.77% for DT. The combination of HE + LBP resulted in relatively balanced miss rates across classifiers, with DT achieving the lowest value at 47.59%, followed by ESVM-CSO at 48.14%, and SVM at 49.73%.

Overall, ESVM-CSO consistently performed better by achieving lower miss rates compared to the existing methods. The lowest miss rate (43.45%) was observed with the Median + LBP combination for ESVM-CSO, while SVM and DT had generally higher miss rates. DT, although typically underperforming, showed better results when combined with HE + LBP.

Conclusion

The results of the study indicate that the proposed classification technique, enhanced support vector machine with Cuckoo search optimization (ESVM-CSO), outperforms traditional classification methods (SVM and Decision Tree) in the detection of knee arthritis. Across all evaluation metrics-detection rate, sensitivity, specificity, false positive rate, and miss rate-ESVM-CSO consistently demonstrated superior performance, particularly when paired with the median + LBP image enhancement and feature extraction method.

Detection Rate

ESVM-CSO achieved the highest detection rate (56.52%) with median + LBP, significantly outperforming both SVM and DT.

Sensitivity

The proposed ESVM-CSO exhibited enhanced sensitivity, reaching 56.55% with median + LBP, indicating a better true positive rate.

Specificity

ESVM-CSO maintained high specificity (56.49% with median + LBP), reflecting its ability to minimize false positives.

False Positive Rate

ESVM-CSO achieved the lowest false positive rate (43.51%) with the same combination, highlighting its robustness in reducing incorrect positive classifications.

Miss Rate

ESVM-CSO consistently showed a lower miss rate, with the best result of 43.45% using median + LBP, indicating fewer false negatives.

In conclusion, the proposed ESVM-CSO classification technique, especially when combined with the median + LBP enhancement method, provides a more accurate and reliable approach for knee arthritis detection compared to traditional methods. Its ability to improve detection rates while minimizing both false positives and false negatives makes it a promising tool for medical diagnostics in this domain.

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