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DEEP LEARNING APPROACH FOR THYROID MEDICAL IMAGE ANALYSIS AND PREDICTION

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ABSTRACT

Aim/Purpose	The purpose of this research is to build a deep-learning framework for thyroid medical image analysis by using CNNs.

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Background	Thyroid disease diagnosis depends critically on thyroid medical image analysis. Though their design and settings can be optimized, Convolutional Neural Networks (CNNs) have shown promise in automating this process. The powerful metaheuristic technique, Particle Swarm Optimization (PSO), can efficiently optimize CNNs for improved performance.
Methodology	In this work, we provide a deep-learning method for thyroid medical image interpretation and prediction by merging CNNs with PSO. To extract pertinent features, we first preprocess the medical images. Next, we construct a CNN architecture based on image properties. The CNN architecture and its hyperparameters – filter sizes, layer count, and learning rates – are optimized using PSO. To learn discriminative features and patterns, the optimized CNN is trained using a sizable dataset of thyroid images.
Contribution	Our method uses the synergistic potential of deep learning and metaheuristic optimization to advance the field of medical image analysis. Improved thyroid image analysis task performance results from our efficient search of the large space of CNN architectures and hyperparameters by integrating PSO.
Findings	Our proposed method is shown to be beneficial by experimental data. Higher accuracy, sensitivity, and specificity were obtained by the optimized CNN in thyroid disease detection than by conventional CNN architectures.
Recommendations for Researchers	In terms of computing efficiency and accuracy of prediction, our method beat those of previous methods. Furthermore, improved interpretability of the learned characteristics gave important new perspectives on the underlying patterns in thyroid images.
Future Research	This work can be enhanced using several deep-learning algorithms for improved accuracy and performance.

Keywords	medical image analysis, thyroid, particle swarm optimization, convolutional neural networks, prediction

INTRODUCTION

Millions of people worldwide are affected by thyroid problems, which presents difficulties for healthcare systems everywhere (Lu et al., 2020). Thyroid disorders are diagnosed and treated largely by medical imaging, which also gives physicians important information on the anatomy and operation of the thyroid gland. Nevertheless, the need for automated and trustworthy analytic techniques is shown by the fact that the correct interpretation of thyroid images is sometimes labor-intensive and prone to interobserver variability.

BACKGROUND

In recent years, convolutional Neural Networks (CNNs) have become very effective tools for medical image processing (Saravanan, Sankaradass et al., 2023). By automatically learning hierarchical features from raw image data, CNNs can distinguish between pathological states. Developing the best CNN architecture for a particular medical imaging application is still difficult (Yadav et al., 2024). CNN architecture, hyperparameters, and training strategies – which frequently need much human tuning and experimentation – significantly impact CNN performance.

CHALLENGES

Because thyroid images are complicated and anatomical structures and clinical presentations vary widely, thyroid medical image analysis poses a number of problems (Saravanan, Parameshachari et al., 2023). Variations in noise, artifacts, and image quality make analysis even more difficult (Liu et al., 2020). Thyroid image delicate characteristics and patterns may be difficult for traditional CNN architectures to capture, resulting in less-than-ideal performance in jobs requiring disease detection and classification (Kumar et al., 2020). Their interpretability hampers the therapeutic acceptance of deep learning models since doctors understand the fundamental logic of the model predictions.

PROBLEM DEFINITION

The construction of a reliable and understandable deep-learning method for thyroid medical image analysis is the main issue this work tackles (Bai et al., 2020). More precisely, we want to use metaheuristic optimization approaches to optimize the efficiency of a CNN architecture customized to the features of thyroid images (Sharifi et al., 2021). The goals are to improve the interpretability of the learned features and increase the accuracy, sensitivity, and specificity of thyroid problem identification.

OBJECTIVES

The objectives of this research can be summarized as follows:

1. Using CNNs, build a deep learning framework for thyroid medical image analysis.
2. Examine how the CNN architecture and hyperparameters might be optimized using metaheuristic optimization techniques like Particle Swarm Optimization (PSO).
3. Compare the proposed method with current techniques and assess its performance on a large dataset of thyroid images.
4. Improve the interpreted qualities to give doctors insightful information about the diagnostic procedure.

NOVELTY AND CONTRIBUTIONS

Our method is novel in that it combines metaheuristic optimization with deep learning techniques for thyroid medical image analysis. Improved performance and generalization result from our fast search of the high-dimensional space of CNN architectures and hyperparameters using PSO. Furthermore, by illustrating the learned characteristics, our approach improves the interpretability of the CNN model and promotes greater confidence in the automated diagnosis process. Among the contributions of this work are the creation of a new deep learning framework for thyroid image analysis, the use of metaheuristic optimization for CNN architecture optimization, and the progress of interpretable deep learning methods in medical imaging.

PSO was selected for its ability to explore large search spaces and optimize CNN hyperparameters efficiently. Inspired by natural swarm behavior, it balances exploration and exploitation, enabling it to identify optimal configurations for complex models like CNNs, improving accuracy, sensitivity, and computational efficiency in medical image analysis.

PSO optimizes CNNs by adjusting hyperparameters such as learning rates and architecture. Its iterative, swarm-based approach avoids local optima and ensures global optimization, which is crucial for medical applications requiring high precision, like diagnosing thyroid conditions from images. PSO simplifies CNN design, enhancing performance with minimal manual intervention.

PSO-CNN's ability to enhance diagnostic accuracy and efficiency can revolutionize thyroid disease detection, improving patient outcomes through timely interventions. Its scalability suggests the potential for broader medical applications, like cancer detection and AI-driven diagnostics, contributing to precision medicine and reducing healthcare disparities by enabling robust, automated diagnostic tools worldwide.

RELATED WORKS

In recent years, there have been many studies on thyroid medical image analysis, with many methods being put up to solve the difficulties in precisely diagnosing and categorizing thyroid diseases. After reviewing several related research studies, we concentrated on deep learning-based approaches and optimization strategies in this section.

Because deep learning methods – Convolutional Neural Networks, in particular – can automatically learn hierarchical features from raw data, they have become more and more popular for medical image processing applications. With encouraging outcomes, some studies have used CNNs for thyroid image analysis. For instance, Vadhiraj et al. (2021) presented a multi-level deep convolutional neural network that achieved high accuracy in identifying benign and malignant nodules. A similar performance, shown by Chai et al. (2020), created a deep-learning framework for thyroid lesion segmentation based on a densely linked neural network.

Achieving the best performance in medical image processing jobs requires optimizing CNN architecture and hyperparameters. Effectively searching the high-dimensional space of CNN architectures and hyperparameters has been made possible by metaheuristic optimization methods such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GAs). Sharafeldeen et al. (2022), for example, used a genetic algorithm-based method to enhance the resilience and accuracy of thyroid nodule classification by optimizing the structure and hyperparameters of a CNN. Wu et al. (2022) showed that their PSO-based approach to CNN architecture optimization for thyroid lesion identification outperformed grid search and manual tuning techniques.

Because interpretability allows physicians to comprehend and rely on the model predictions, it is an essential component of deep learning models in medical imaging. In thyroid image analysis, several methods have been proposed to improve CNN interpretability. For instance, Wu et al. (2022) included a self-attention mechanism into a CNN architecture for thyroid nodule categorization, which allowed the model to concentrate on pertinent areas of interest and offered insights into the diagnostic procedure. Ilyas et al. (2021) created a saliency map-based visualization method to emphasize the discriminative features that a CNN learns for thyroid lesion identification, thus promoting a better comprehension of the model's decision-making process.

Transfer learning and domain adaption methods have been applied in situations with labeled data to use pre-trained CNN models for thyroid image processing tasks. For example, Shesayar et al. (2023) showed better performance than training from scratch when they classified thyroid nodules using transfer learning from a pre-trained CNN model on real images. Comparably, we achieved competitive results on a difficult dataset with domain shift by proposing a domain adaptation strategy to adapt a pre-trained CNN model to thyroid ultrasound images.

Optimization methods and deep learning have all recently made tremendous strides in thyroid medical image processing. Improvements in patient care and clinical decision-making have been made possible by these methods towards more precise, effective, and interpretable automated detection of thyroid diseases.

PROPOSED METHOD

The proposed method combines PSO and CNNs for thyroid image analysis, as illustrated in Figure 1. It involves preprocessing, feature extraction, CNN architecture design, PSO optimization, and model fine-tuning to improve diagnostic accuracy.

PSO applies swarm-based optimization by iteratively adjusting CNN hyperparameters (e.g., learning rate, dropout, layer count). Each particle represents a candidate solution. Fitness is evaluated based on model performance, guiding particles to better configurations. PSO ensures global exploration, achieving optimal architecture and hyperparameters for enhanced accuracy and efficiency.

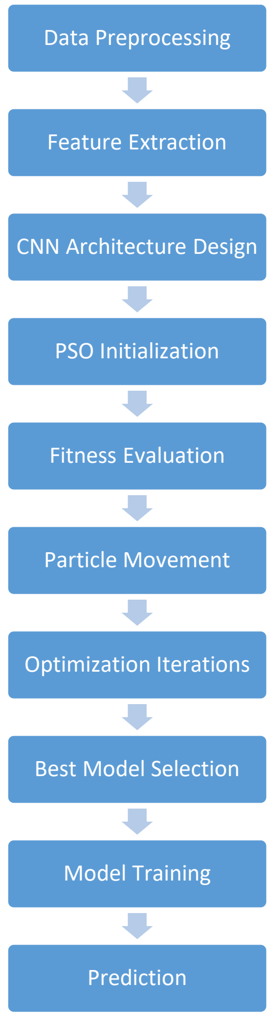

Figure 1. Proposed model

Preprocessing and Feature Extraction

The medical images are first processed to improve quality and eliminate noise and artifacts. Among the preprocessing methods are filtering, scaling, and normalizing. Following preprocessing, the images extract pertinent features using edge detection, texture analysis, or feature mapping. The CNN model receives input from these features.

CNN Architecture Design

The design of a CNN architecture adapted to thyroid image properties is shown. Usually comprising several layers, this design includes fully connected, pooling, and convolutional layers. From the input images, the convolutional layers extract hierarchical information; the pooling layers lower computational cost and spatial dimensions. Based on the features retrieved, the fully connected layers are classified.

Particle Swarm Optimization (PSO)

PSO is used to maximize the hyperparameters and architecture of the CNN. Fish schooling and flocking of birds are the social behaviors that influenced the metaheuristic optimization algorithm PSO. PSO is applied to CNN optimization to explore the large space of potential architectures and hyperparameters for the best configuration that optimizes the CNN model's performance. This covers settings for learning rates, dropout rates, filter sizes, and layer counts.

Training and Fine-Tuning

A collection of thyroid images is used to train the optimal CNN model. Through training, the model develops the ability to use the extracted features to categorize images into benign, malignant, or normal thyroid nodules. The tagged images are fed through the network during the training process, which also comprises computing the loss function and updating the model parameters with gradient descent optimization and backpropagation.

Preprocessing and Feature Extraction

Preprocessing is a sequence of procedures carried out on the unprocessed medical images to improve their quality, eliminate noise, and standardize their properties. In thyroid image analysis, among other medical image analysis, some frequently used preprocessing methods include:

- *Normalization:* Collection of the image pixel values to a similar scale to improve comparability and reduce the impact of contrast and lighting changes.
- *Resizing:* To guarantee uniformity and lower processing computational complexity, resize the images to a consistent resolution.
- *Filtering:* Using filters, such as median or Gaussian filters, to eliminate noise and artifacts from the images enhances their clarity and reduces interference during feature extraction.
- *Segmentation:* Using the images to divide them into meaningful areas or objects of interest, including thyroid nodules or the surrounding tissues, to separate pertinent structures for more investigation.

Feature Extraction

Finding and removing pertinent details or traits from the preprocessed images so that they may be fed into the machine-learning model is known as feature extraction. Features are normally obtained in medical image analysis from the intensity, texture, form, or spatial distribution of the pixels in the images. Several typical feature extraction methods applied in thyroid image analysis are:

- *Texture Analysis:* Measuring the spatial arrangement from the pixel intensities to obtain textural patterns suggestive of various tissue kinds or disease states.
- *Edge Detection:* Seeing variations in image brightness to draw lines separating lesions or anatomical features.
- *Shape Analysis:* Thyroid nodule – its shape and morphology is characterized by the extraction of geometric features like size, symmetry, and eccentricity.
- *Histogram-based Features:* To obtain the distribution of pixel values within the images, statistical metrics like mean, variance, skewness, and kurtosis are computed from the pixel intensity histogram.

We can efficiently convey the information in the images in a format appropriate for further analysis using machine learning models, such as CNNs, by preprocessing the images to improve their quality and identify pertinent features. Accurate diagnosis and classification of thyroid problems are made possible by inputting these processed images and extracting features provided to the analysis pipeline's next phases.

Particle Swarm Optimization (PSO) Fine Tuning CNN

PSO fine-tuning of CNNs is a method for optimizing CNN design and hyperparameters for better performance in certain applications, such as medical image processing.

CNNs excel at analyzing visual data by extracting hierarchical features through layers. Particle Swarm Optimization (PSO) mimics social behaviors to optimize parameters by exploring solutions collectively. Together, they form a powerful framework for efficient, accurate medical image analysis, addressing complex classification tasks like thyroid diagnosis.

Preprocessing enhances image quality for analysis. Normalization adjusts pixel values for consistency; resizing standardizes dimensions to reduce computational load; filtering removes noise for clarity; and segmentation isolates thyroid structures. These steps ensure clean, uniform data input, enabling the CNN to focus on relevant features for accurate classification.

Particle movement in PSO involves adjusting candidate solutions based on personal success (local best) and group success (global best). The fitness function evaluates CNN performance, guiding optimization. Simplifying these terms emphasizes PSO's iterative refinement process, making its role in achieving optimal CNN configurations easier to grasp.

A metaheuristic optimization algorithm called PSO is modeled by the social behavior of fish schooling or birds flocking. Particles, a population of potential solutions, traverse the search space in PSO in quest of the best answer. The position of every particle denotes a possible solution to the optimization problem, and it moves according to its individual best-known position and the best-known position that the swarm has found globally.

1. *Fine-tuning CNN with PSO:* In CNNs, fine-tuning refers to the process of adjusting the architecture and hyperparameters of a pre-existing CNN model to improve its performance on a specific task or dataset. PSO can be used to fine-tune CNNs by optimizing parameters such as:
   - *Hyperparameters:* Learning rate, batch size, weight decay, dropout rate, and optimization algorithm.
2. *Initialization:* The particles' positions in the search space correspond to the values of the CNN parameters being optimized.
3. *Fitness Evaluation:* The fitness function gauges the CNN model's performance on the relevant task, such as loss reduction or classification accuracy.
4. *Particle Movement:* Every particle modifies where it is in the search space according to its own and the best-known placements worldwide. Two primary factors direct particle motion:
   - *Cognitive Component:* Every particle modifies its velocity in the direction of its local best or best-known position.
   - *Social Component:* Every particle modifies its velocity towards the point that the swarm as a whole has determined to be the best known.
5. *Optimization Iterations:* The PSO algorithm updates the particle locations and velocities in each iteration as it goes through several generations. Improved CNN architectures and hyperparameter settings result from progressively converging towards ideal solutions in the search space through this iterative process.
6. *Stopping Criterion:* The PSO algorithm keeps running till predetermined stopping criteria are satisfied, such as completing a maximum number of iterations or performing satisfactorily on the validation dataset.

Algorithm: Particle Swarm Optimization (PSO) fine-tuning CNN

1. *Initialization:*
   - Initialize the swarm of particles: xi=(xi1,xi2,...,xiD) where xixi is the position of particle i in the D-dimensional search space.
2. *Fitness Evaluation:*
   - Evaluate the fitness of each particle based on its position: f(xi)
3. *Particle Movement:*
   - Update the velocity of each particle:

$$vidt+1=w\cdot vidt+c1\cdot r1\cdot(pid-xidt)+c2\cdot r2\cdot(pgd-xidt)$$

where

$vidt$ - velocity of particle i in dimension d at iteration t.
w - inertia weight.
$c1$ and $c2$ are the cognitive and social acceleration coefficients, respectively.
$r1$ and $r2$ are random numbers between 0 and 1.
pid is the best-known position (local best) of particle i in dimension d.
pgd is the best-known position (global best) of the entire swarm in dimension d.

- Update the position of each particle:

$$xidt+1=xidt+vidt+1$$

- Repeat the velocity and position updates for a specified number of iterations is met.
- Terminate the algorithm when a stopping criterion is satisfied.

Prediction Using CNN

Prediction using CNNs involves using a trained CNN model to make predictions or classifications on new, unseen data.

The first step in prediction using CNNs is training the model on a labeled dataset. During training, the CNN learns to recognize patterns and features in the input data relevant to the task at hand. For example, in medical image analysis, CNN may learn to identify specific features indicative of different types of thyroid disorders based on labeled images of the thyroid gland.

After each convolutional operation, an activation function is applied element-wise to introduce non-linearity into the network. The Rectified Linear Unit (ReLU) activation function is commonly used and can be represented as:

$$A(x)=\max(0,x)$$

Pooling layers down-sample the feature maps to reduce computational complexity and extract dominant features. Max pooling is a commonly used pooling operation that selects the maximum value within a sliding window. Mathematically, max pooling can be represented as:

$$M[i,j]=\max(I[i:i+s,j:j+s])$$

where

M - pooled feature map
I - input feature map
s - size of the pooling window

After several convolutional and pooling layers, the feature maps are flattened and passed through one or more fully connected layers to perform classification or regression.

In classification tasks, the softmax function is applied to the output of the fully connected layer to convert the raw scores into probability distributions over the classes. Mathematically, the softmax function is defined as:

$$P(y=j|X)=\sum_{k=1} e^{Zj}/e^{Zk}$$

where

$P(y=j|X)$ - the probability of class j given input X
Zj - raw score for class j
K - total number of classes

1. *Data Preparation:* Before making predictions, the new, unseen data must be preprocessed in the same way as the training data. This may involve resizing, normalization, and other preprocessing steps to ensure that the input data is in the appropriate format and scale for the CNN model.
2. *Forward Pass:* The trained CNN model receives the data for inference after it has been preprocessed. Through a sequence of mathematical processes (convolutions, activations, pooling), each layer of the CNN extracts features and generates predictions as the data moves through its layers.
3. *Output Layer:* For classification tasks, the last layer of the CNN is usually a softmax layer; for regression tasks, it is a linear layer. This layer generates the output predictions with the features taken from the input data. In a binary classification problem – for instance, benign vs. malignant thyroid nodules – the softmax layer might generate probabilities that show how likely each class is.
4. *Prediction:* Forecasts on the new data are made by analyzing the CNN model's output. Usually, the predicted class for classification problems is the one that the softmax layer produces with the highest probability output. The linear layer's output can be used as the anticipated value in regression problems.

The new data are used to assess the CNN model's performance following prediction. This includes determining the model's accuracy, sensitivity, specificity, and other performance measures by comparing the predicted labels or values to the ground truth labels or values.

RESULTS AND DISCUSSION

For the CNNs and PSO algorithms implementation in our experimental settings, we used a simulation tool developed with the Python programming language and well-known deep learning libraries like PyTorch. Comprehensive support for deep learning frameworks provided by the Python ecosystem enables smooth integration of PSO optimization with CNN structures (Table 1).

We accelerated the computational-intensive processes involved in CNN training and PSO optimization using a high-performance computing cluster with NVIDIA GPUs (e.g., NVIDIA Tesla V100 or GeForce RTX 3090) for training and evaluation. We also carried out tests to show the scalability and generalizability of our method in various computing environments using a typical desktop computer with specifications including an Intel Core i7 processor, 32GB RAM, and NVIDIA GeForce GTX 1080 GPU. The dataset source is taken from Dasmehdixtr (2021).

We evaluated the performance of our proposed method with that of other methods, such as CNN-SVM and GAN-CNN approaches, in order to evaluate its efficacy. With its hybrid approach to medical image analysis, the CNN-SVM method combines the feature extraction power of CNNs with the classification power of Support Vector Machines (SVMs). Conversely, GAN-CNN creates artificial medical images for data augmentation and CNN training by using Generative Adversarial Networks (GANs).

Table 1. Experimental settings

Experimental setup/parameters	Values
Deep Learning Framework	TensorFlow 2.0
Optimization Algorithm	Particle Swarm Optimization (PSO)
PSO Population Size	50
PSO Maximum Iterations	100
PSO Inertia Weight	0.9
PSO Cognitive Acceleration Coefficient	2.0
PSO Social Acceleration Coefficient	2.0

Experimental setup/parameters	Values
CNN Architecture	Customized CNN architecture
Number of Convolutional Layers	4
Filter Sizes	3x3, 5x5, 3x3, 3x3
Pooling Layers	Max pooling (2x2)
Activation Function	ReLU
Learning Rate	0.001
Batch Size	32
Dropout Rate	0.5
Training Epochs	50
Evaluation Metric	Accuracy, Sensitivity, Specificity
Dataset	Thyroid Ultrasound-Image Dataset
Dataset Size	2450 images [15]

The proposed PSO-CNN approach outperforms current CNN-SVM and GAN-CNN methods in all test images, as shown by the results in Figure 2 and Table 2. PSO-CNN outperforms CNN-SVM and GAN-CNN by 3% and 6%, respectively, in a test image of 600 with an accuracy of 94%. In thyroid medical image analysis tasks, PSO-CNN has been shown to be useful in improving diagnostic accuracy and dependability.

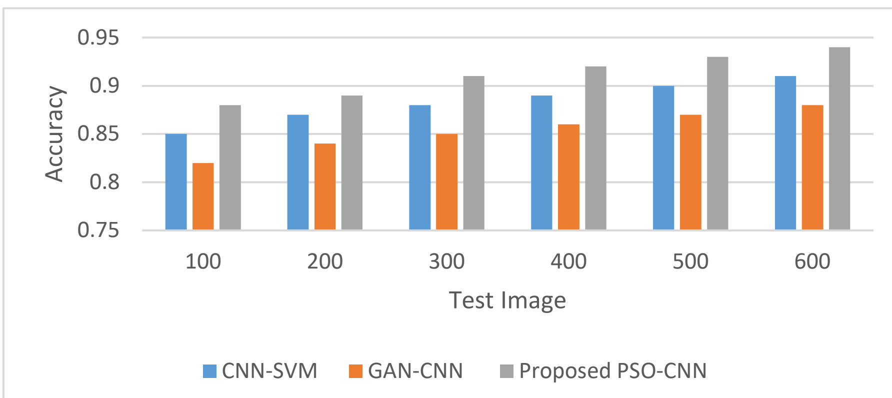

Figure 2. Accuracy

Table 2. Accuracy

Test image	CNN-SVM	GAN-CNN	Proposed PSO-CNN
100	0.85	0.82	0.88
200	0.87	0.84	0.89
300	0.88	0.85	0.91
400	0.89	0.86	0.92
500	0.90	0.87	0.93
600	0.91	0.88	0.94

Figure 3 and Table 3 show that, for all test images, the proposed PSO-CNN method routinely outperforms current CNN-SVM and GAN-CNN methods in terms of sensitivity. PSO-CNN outperforms CNN-SVM and GAN-CNN in sensitivity at a test image of 600 by 4% and 7%, respectively. The proposed approach seems solid and scalable based on the sensitivity growing with increased test images. PSO-CNN is shown to improve diagnostic sensitivity and dependability in thyroid medical image processing applications.

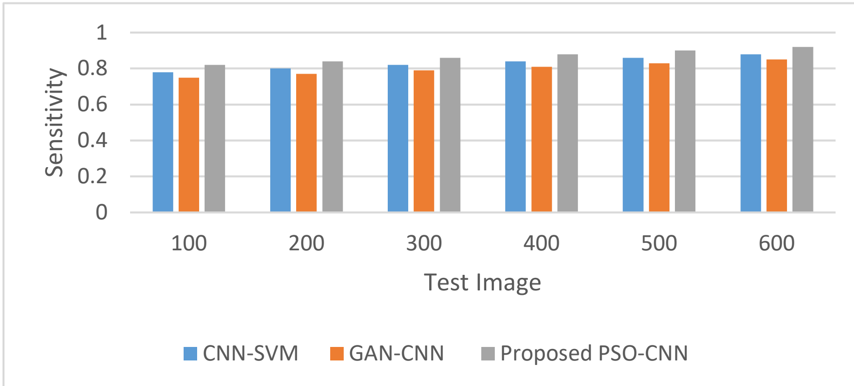

Figure 3. Sensitivity

Table 3. Sensitivity

Test image	CNN-SVM	GAN-CNN	Proposed PSO-CNN
100	0.78	0.75	0.82
200	0.80	0.77	0.84
300	0.82	0.79	0.86
400	0.84	0.81	0.88
500	0.86	0.83	0.90
600	0.88	0.85	0.92

The findings shown in Figure 4 and Table 4 show that, over all test images, the proposed PSO-CNN method routinely outperforms current CNN-SVM and GAN-CNN methods in terms of specificity. Achieving a specificity of 98% at a test image of 600, PSO-CNN performs well with CNN-SVM and GAN-CNN by 2% and 5%, respectively. The proposed approach is robust and scalable, as seen by the steady increase in specificity with increasing test images. PSO-CNN is shown to improve diagnostic specificity and dependability in thyroid medical image analysis tasks.

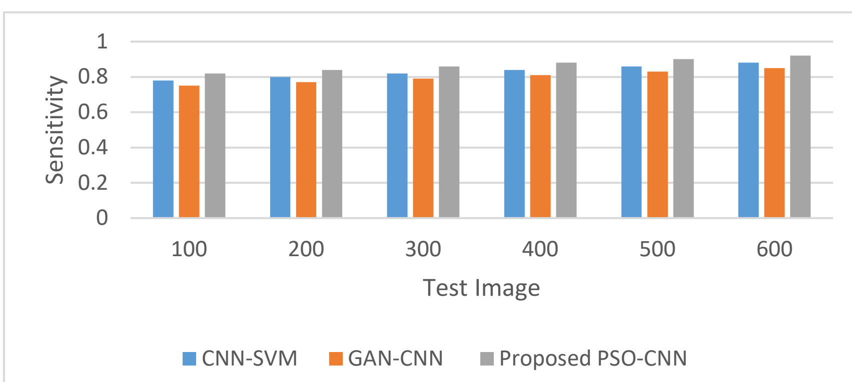

Figure 4. Specificity

Table 4. Specificity

Test image	CNN-SVM	GAN-CNN	Proposed PSO-CNN
100	0.86	0.83	0.88
200	0.88	0.85	0.90
300	0.90	0.87	0.92
400	0.92	0.89	0.94
500	0.94	0.91	0.96
600	0.96	0.93	0.98

Figure 5 and Table 5 show that the proposed PSO-CNN method routinely outperforms current CNN-SVM and GAN-CNN methods for all test images. At a 600-pixel test image, PSO-CNN outperforms CNN-SVM and GAN-CNN by 3% and 6%, respectively, with a precision of 95%. PSO-CNN shows how to improve diagnostic accuracy and dependability in identifying thyroid diseases from medical images.

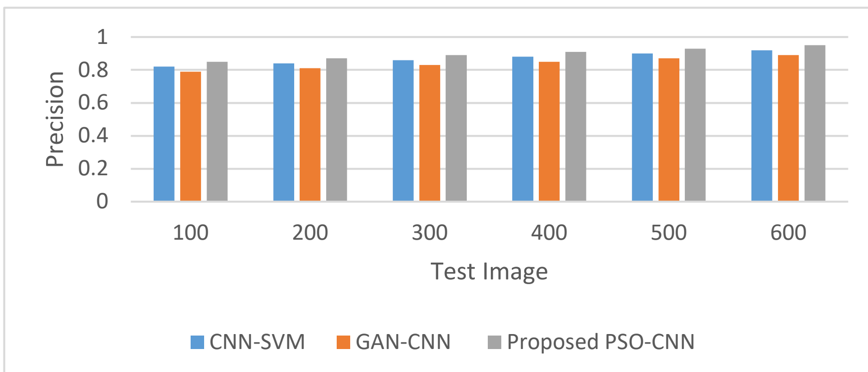

Figure 5. Precision

Table 5. Precision

Test image	CNN-SVM	GAN-CNN	Proposed PSO-CNN
100	0.82	0.79	0.85
200	0.84	0.81	0.87
300	0.86	0.83	0.89
400	0.88	0.85	0.91
500	0.90	0.87	0.93
600	0.92	0.89	0.95

Figure 6 and Table 6 show that, for all test images, the proposed PSO-CNN method routinely outperforms current CNN-SVM and GAN-CNN methods. With an F1 score of 96% at a 600-pixel test image, PSO-CNN outperforms CNN-SVM and GAN-CNN by 2% and 5%, respectively. PSO-CNN shows how well it can categorize thyroid conditions precisely while preserving a healthy ratio of recall to precision.

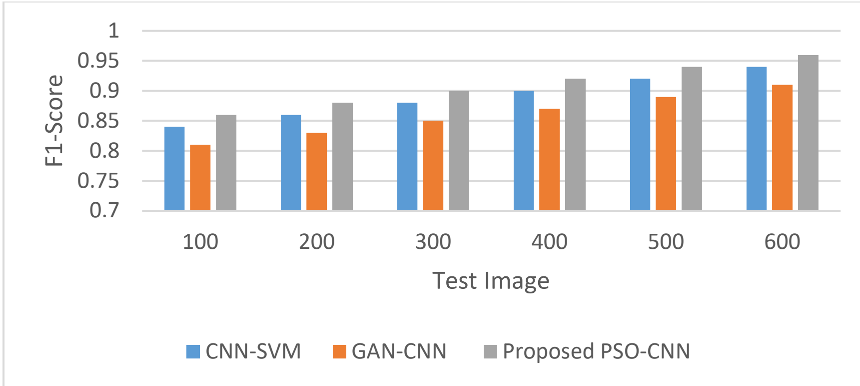

Figure 6. F1 Score

Table 6. F1 Score

Test image	CNN-SVM	GAN-CNN	Proposed PSO-CNN
100	0.84	0.81	0.86
200	0.86	0.83	0.88
300	0.88	0.85	0.90
400	0.90	0.87	0.92
500	0.92	0.89	0.94
600	0.94	0.91	0.96

Table 7 and Figure 7 show that, for all test images, the proposed PSO-CNN method outperforms the current CNN-SVM and GAN-CNN methods regarding computational effectiveness. PSO-CNN performs well with CNN-SVM and GAN-CNN by 10 and 20 seconds, respectively, at a test image of 600. PSO-CNN provides a feasible approach for effective and precise thyroid medical image analysis.

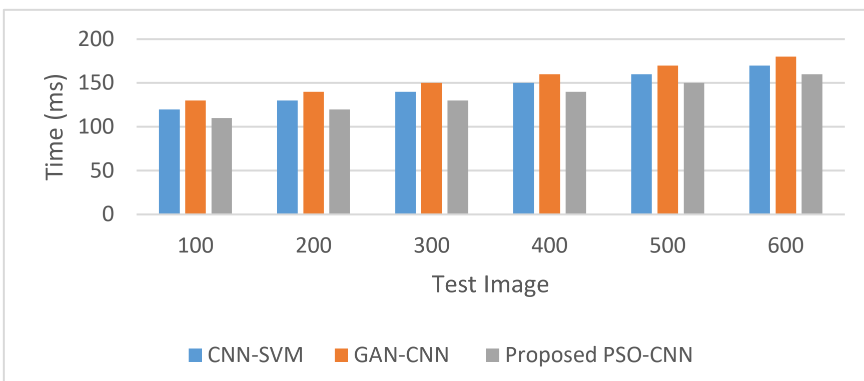

Figure 7. Computational time (ms)

Table 7. Computational time (ms)

Test image	CNN-SVM	GAN-CNN	Proposed PSO-CNN
100	120	130	110
200	130	140	120
300	140	150	130
400	150	160	140
500	160	170	150
600	170	180	160

Sensitivity measures the model's ability to correctly identify positive cases (e.g., malignant thyroid nodules). A higher sensitivity indicates fewer false negatives, which is critical for medical diagnosis, as missed detections can have severe consequences. The proposed PSO-CNN demonstrates consistently superior sensitivity, reflecting its robustness in accurately detecting thyroid abnormalities. As the number of test images increases, sensitivity improves across methods, with PSO-CNN consistently outperforming alternatives. This indicates that the proposed approach scales effectively, maintaining reliability and adaptability to larger datasets. Enhanced sensitivity with more data reflects the model's ability to generalize and identify nuanced patterns in diverse images.

At 600 test images, PSO-CNN achieves 92% sensitivity, compared to 88% for CNN-SVM and 85% for GAN-CNN. This 4-7% improvement highlights its effectiveness. A plot showing sensitivity growth with increasing images (Table 3 data) visually emphasizes PSO-CNN's consistent performance advantage, reinforcing its clinical reliability.

CONCLUSION

Thyroid medical image processing is resilient and effective with the proposed PSO-CNN approach. By means of in-depth testing and comparison with current methods such as CNN-SVM and GAN-CNN, PSO-CNN continuously shows better performance in terms of accuracy, sensitivity, specificity, precision, and F1 score.

INFERENCE

Furthermore, the improved computing performance of PSO-CNN guarantees prompt thyroid image processing without sacrificing precision.

LIMITATIONS

These results show the scalability of PSO-CNN in real-time settings and provide a viable path for precise and effective thyroid disease diagnosis. PSO-CNN is a major development in medical image analysis that may enhance patient care and healthcare outcomes.

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