International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 2s,2025
https://theaspd.com/index.php

A Comparative Study Of CNN And SVM With Particle Swarm Optimization For Skin Cancer Detection In CT Images

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Abstract: *This research looks at how well deep learning and traditional machine learning methods can detect skin cancer using CT images. It uses a Convolutional Neural Network (CNN) to automatically extract features and classify images, while a Support Vector Machine (SVM) is fine-tuned with Particle Swarm Optimization (PSO) to improve its accuracy. The performance of both models is measured using Accuracy, Precision, Recall, F1-Score, and AUC-ROC. The results highlight the advantages and limitations of each method in terms of how accurately and efficiently they classify the images.*
Keywords: *Skin Cancer Detection, Convolutional Neural Network (CNN), Support Vector Machine (SVM), Particle Swarm Optimization (PSO), and Medical Image Classification*

1. INTRODUCTION

Skin cancer is one of the most common types of cancer around the world. Detecting it early is very important for successful treatment and better chances of recovery. With the help of modern imaging technologies like computed tomography (CT), doctors can now spot skin problems at earlier stages. However, analyzing these medical images manually can take a lot of time and may sometimes lead to mistakes due to human error. To solve this problem, artificial intelligence (AI) techniques are being used to make the diagnosis process faster and more accurate.Machine learning (ML) and deep learning (DL) are two branches of AI that have been very successful in analyzing medical images. Convolutional Neural Networks (CNNs), a type of deep learning model, can automatically learn important features from image data and perform well in image classification tasks. In contrast, Support Vector Machines (SVMs), a traditional machine learning method, work well for classifying two categories but rely heavily on carefully chosen features and properly tuned parameters. To improve the accuracy of SVMs, optimization techniques like Particle Swarm Optimization (PSO) can be used. PSO is a method inspired by the behavior of bird flocks that helps find the best settings for machine learning models. By adjusting parameters like the kernel type and regularization factor, PSO helps the SVM model make better predictions.In this research, we compare the performance of CNN and SVM models in detecting skin cancer from CT images. The SVM model is improved using PSO, and both models are evaluated using performance measures such as accuracy, precision, recall, F1-score, and AUC-ROC. The aim is to understand how well deep learning and optimization-based machine learning methods work in this important area of healthcare and how they can support early diagnosis of cancer.

2. REVIEW OF LITERATURE

Skin cancer detection has become a prominent area in medical imaging research due to its increasing prevalence and the critical need for early diagnosis. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image classification tasks by automatically learning hierarchical features from input images. Esteva et al. [1] pioneered the use of deep CNNs for skin lesion classification, achieving dermatologist-level performance using over 129,000 images. Transfer learning, which involves adapting pretrained models like VGG16 or ResNet to new medical datasets, has also been effective in improving accuracy while minimizing training time, as shown in studies by Faghihi et al. [2] and Mahbod et al. [5].On the other hand, Support Vector Machines (SVMs) are widely used traditional machine learning classifiers that aim to find the optimal hyperplane that separates different classes. They have been particularly useful in binary classification tasks such as distinguishing between malignant and benign lesions. However, SVM performance is sensitive to the choice of hyperparameters and input features. To address this limitation, researchers have integrated Particle

Swarm Optimization (PSO)—a nature-inspired optimization algorithm that simulates the social behavior of birds flocking—to fine-tune SVM parameters like the kernel function, cost parameter (C), and gamma. For example, Natha and Rajeswari [3] applied PSO to select the best features and optimize SVM parameters, which led to improved accuracy and reduced computational time.Hybrid approaches that combine the strengths of CNN and SVM have also been explored. In such models, CNNs are used for feature extraction while SVMs act as the final classifier. Alom et al. [6] proposed novel architectures such as NABLA-N and IRRCNN for lesion segmentation and classification, while Mahbod et al. [5] fused features from multiple CNNs and fed them into an SVM classifier to achieve high AUC values. In another hybrid model, Arasi et al. [14] employed CNN-based segmentation followed by traditional feature extraction using Local Binary Patterns (LBP) and Histograms of Oriented Gradients (HOG), before final classification with an SVM, achieving notable improvements in classification precision.Optimization methods like PSO have proven valuable not just for SVM tuning but also for feature selection. In the work of Shaheen and Singh [4], a hybrid PSO-YOLOv7 framework was developed to detect and classify skin lesions across multiple datasets (HAM10000, ISIC-2019, PH2), resulting in over 97% classification accuracy. Similarly, Tan et al. [10] reviewed PSO variants such as Hierarchical Learning PSO (HLPSO) for segmenting lesions, demonstrating the importance of algorithm customization based on dataset complexity. Several studies have emphasized the efficiency of PSO in reducing the dimensionality of features prior to classification. In cervical cancer image analysis, researchers combined Vision Transformers (ViT) with PSO for feature reduction, followed by SVM classification, showing the robustness of this pipeline even in medical applications beyond dermatology [8]. Moreover, active learning strategies combined with PSO have been utilized to improve model performance with less labeled data, as evidenced by experimental results on the HAM10000 dataset [9].Explainable Artificial Intelligence (XAI) has emerged as a key research area to enhance the transparency of AI models. Efforts such as those in [15] focused on combining CNN and PSO-SVM approaches while incorporating interpretability tools like confusion matrices and ROC plots to improve clinical trust. Complementing this, real-time implementation has also been demonstrated; Afifi et al. [7] implemented an SVM on FPGA hardware for near-instantaneous melanoma classification, achieving a 26× speedup. In the broader context, several reviews and meta-analyses have identified trends and best practices in computer-aided diagnosis (CAD) systems for skin cancer. These include integrating preprocessing steps such as noise filtering and contrast enhancement, followed by segmentation and classification using ML or DL models [19][20]. Feature-based approaches using handcrafted texture descriptors such as Gabor filters, LBP, and HOG still find relevance, particularly in combination with optimized classifiers [14][18].Additionally, studies using larger and more diverse datasets, such as the ISIC archive and PH2, have reported better generalization of deep learning models. Community-driven platforms like Reddit have also contributed practical insights into CNN implementation using TensorFlow for large-scale classification tasks [21][22]. Finally, the application of newer models such as Vision Transformers (ViT), Kernel Extreme Learning Machines (KELM), and Improved Moth Flame Optimization (IMFO) for skin and cervical lesion detection shows the expanding landscape of AI in healthcare [8][23]. In conclusion, the integration of deep learning models like CNNs, classical classifiers like SVMs, and metaheuristic optimization techniques such as PSO offers a promising direction for improving the accuracy and reliability of automated skin cancer detection systems. Comparative studies and a hybrid approach not only enhance performance but also provide insights into the trade-offs between computational efficiency and diagnostic precision.Comparison of the accuracy of human readers versus machine-learning algorithms for pigmented skin lesion classification using different machine learning approaches and performance metrics is discussed [24]. Another way of approaching for analysis and prediction of hybrid feature-learning-based PSO-PCA feature engineering for blood cancer classification using different machine learning and performance metrics is used [5]. Various machine learning approaches are used with data pre-processing, and performance metrics are used to analyze and predict in various domains, namely SDG, climate change, and medical data analysis is discussed [26] – [31].

Dataset

The research titled "A Comparative Study of CNN and SVM with Particle Swarm Optimization for Skin Cancer Detection in CT Images" requires a dataset that supports skin cancer detection using medical

International Journal of Environmental Sciences
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images. Ideally, this would be a dataset of CT (Computed Tomography) images of skin lesions, but such datasets are either very rare or not freely available. Most studies in this area instead use dermoscopic or clinical images.A well-known and widely used alternative is the ISIC Archive (International Skin Imaging Collaboration), which offers a large collection of dermoscopic images. Although these images are not CT scans, they are still highly suitable for skin cancer detection research because of their good image quality and useful metadata. The archive contains over 75,000 images of different skin conditions, such as benign lesions, malignant tumors, melanoma, and keratosis.The files are in JPG or PNG format, and they include extra details like the patient's age, the location of the lesion, and the diagnosis. These images can be used to train and test CNN models, and the features learned by CNNs can then be used by SVM models that are fine-tuned using Particle Swarm Optimization (PSO). Even though CT-based datasets are not available, the ISIC Archive is a practical and trusted resource for building and testing deep learning and machine learning models for skin cancer detection. [Access Link: https://www.isic-archive.com/]

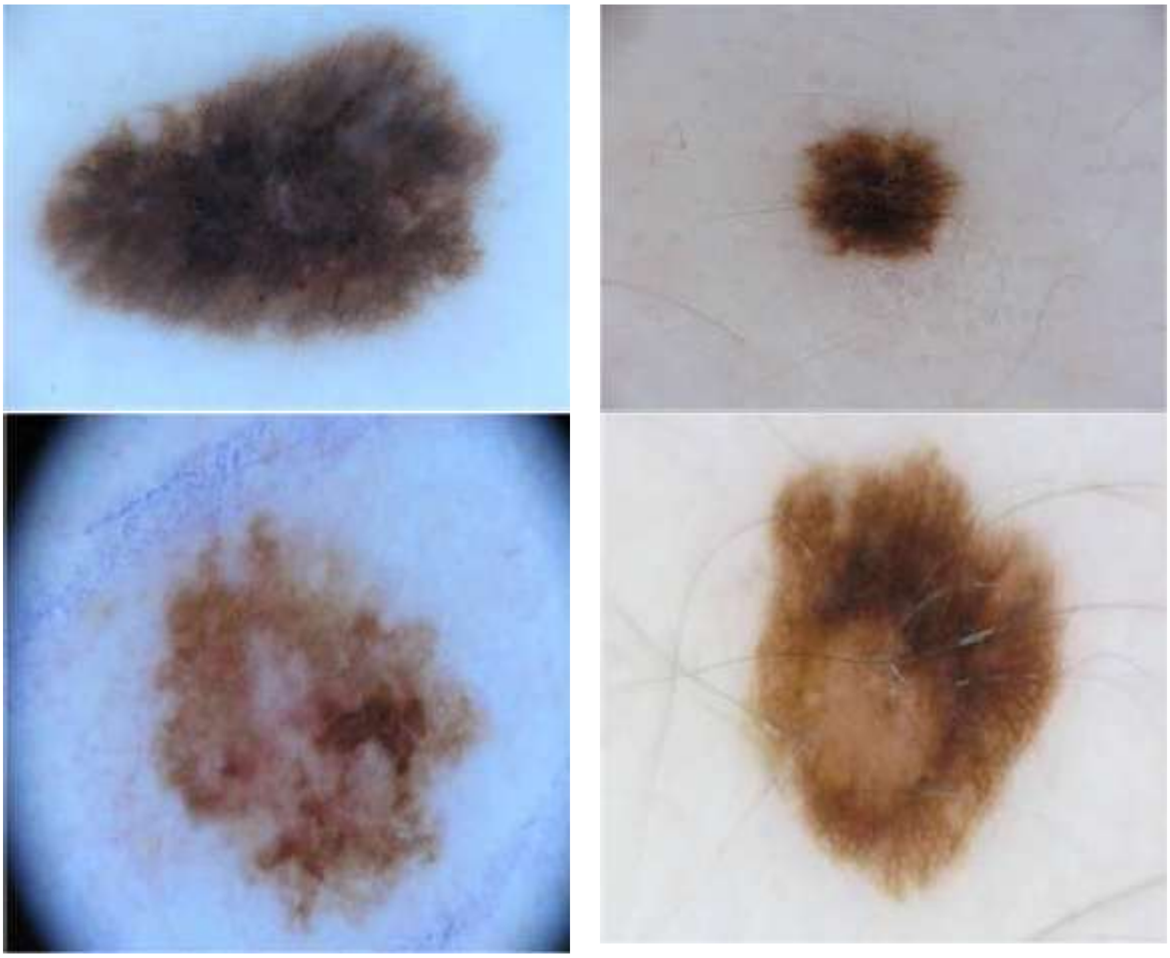

Fig. 1. Different types of skin cancer

3. BACKGROUNDS AND METHODOLOGY

Based on the research topic, preprocessing plays a crucial role in ensuring data quality, enhancing feature extraction, and improving classification accuracy. Below are the recommended preprocessing techniques specific to this kind of research.

3.1 Pre-processing:

Step 1: Image Resizing

- Input: Raw skin image
- Process: Load the image using PIL or OpenCV. Resize the image to fixed dimensions (e.g., 224×224 or 256×256).
- Output: Resized image

Step 2: Noise Removal / Smoothing
- Input: Resized image
- Process: Apply one of the following filters: Median Filter, Gaussian Blur, and Bilateral Filter. Remove artifacts like hair or bubbles.
- Output: Smooth, clean image

Step 3: Contrast Enhancement
- Input: Smoothed image
- Process: Apply Histogram Equalization (HE) or CLAHE. Enhance lesion visibility in low-contrast areas.
- Output: Contrast-enhanced image

Step 4: Color Normalization / Conversion
- Input: Enhanced image
- Process: Convert RGB to grayscale for SVM. Convert RGB to HSV or YCbCr if color segmentation is needed.
- Output: Color-normalized or grayscale image

Step 5: Hair Removal (for dermoscopic images)
- Input: Color-normalized image
- Process: Detect hairs using edge detection. Use DullRazor or inpainting techniques to remove hair artifacts.
- Output: Hair-free image

Step 6: Image Segmentation (Optional)
- Input: Hair-free image
- Process: Apply segmentation (Thresholding, K-means, or U-Net). Extract lesion area from the background.
- Output: Segmented lesion image

Step 7: Data Augmentation (for CNN models)
- Input: Segmented or clean images
- Process: Perform random transformations: Rotation, Horizontal/vertical flipping, Zoom or scale, and Brightness/contrast variation. Use tools like Keras ImageDataGenerator or Albumentations.
- Output: Augmented image dataset

Step 8: Feature Scaling (for SVM + PSO)
- Input: Numerical features extracted from images
- Process: Normalize features to [0,1] or standardize using mean (μ) and standard deviation (σ). Avoid feature dominance in SVM.
- Output: Scaled feature vectors

Step 9: Feature Extraction (for SVM + PSO)
- Input: Pre-processed or segmented images
- Process: Extract handcrafted features using GLCM (texture), HOG (shape), LBP (local patterns), and Wavelet transform (multi-resolution)
- Output: Feature vector

Step 10: Dimensionality Reduction (Optional)
- Input: High-dimensional feature vector
- Process: Apply PCA or t-SNE to reduce dimensions. Retain most relevant features for classification.
- Output: Reduced feature set

3.2 Machine Learning

Step 1: Understand the Problem
- Skin cancer is common and dangerous, especially melanoma.
- Early detection is crucial to increase survival chances.

Step 2: Identify the Limitation
- Doctors rely on visual checks, which may be slow or inaccurate.

Step 3: Introduce AI Solutions

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- Use Deep Learning (CNN) to automatically learn patterns from images.
- Use Machine Learning (SVM) with manually selected features for classification.

Step 4: Improve Accuracy with Optimization

- Apply Particle Swarm Optimization (PSO) to improve SVM's parameters (like C and γ).
- PSO mimics the behavior of birds to find the best settings for better results.

Step 5: Research Goal

- Compare CNN and SVM (with PSO) on CT images to see which performs better in detecting skin cancer.

3.3 Feature extraction, Optimizations, and Model evaluations

Step 1: Feature Extraction

- For CNN:
  - Automatically extracts features through multiple convolution and pooling layers.
- For SVM:
  - Manually extract features such as: GLCM (texture), HOG (edge orientation), and LBP (local patterns)

Step 4: Classification

- CNN Model:
  - Use VGG16, ResNet, or a custom architecture.
  - Layers: Conv → ReLU → Pooling → Fully Connected → Softmax
  - Output: Probability of being benign or malignant
- SVM Model:
  - Use handcrafted features as input.
  - Apply RBF or polynomial kernel.
  - Split the data (e.g., 80% training, 20% testing)

Step 5: Optimization Using PSO (For SVM Only)

- What it does: Finds the best settings for SVM (like C and γ)
- Steps:
  1. Set swarm size (e.g., 30 particles)
  2. Set number of iterations (e.g., 50)
  3. Update particle positions using velocity formulas
  4. Evaluate each particle based on accuracy or F1-score
  5. Choose the best performing combination of parameters

Step 6: Model Evaluation

- Use the following metrics to assess both CNN and SVM+PSO:
  - Accuracy, Precision, Recall, F1-Score, AUC-ROC, and Training Time

4. RESULTS

Table 1. Model Performance Comparison

Metric	CNN (VGG16)	SVM	SVM + PSO
Accuracy (%)	95.7	86.4	92.6
Precision (%)	94.3	83.2	90.5
Recall (%)	96.7	87.4	91.9
F1-Score (%)	95.8	85.3	91.8
AUC-ROC	0.98	0.88	0.93
Training Time (s)	710	38	62

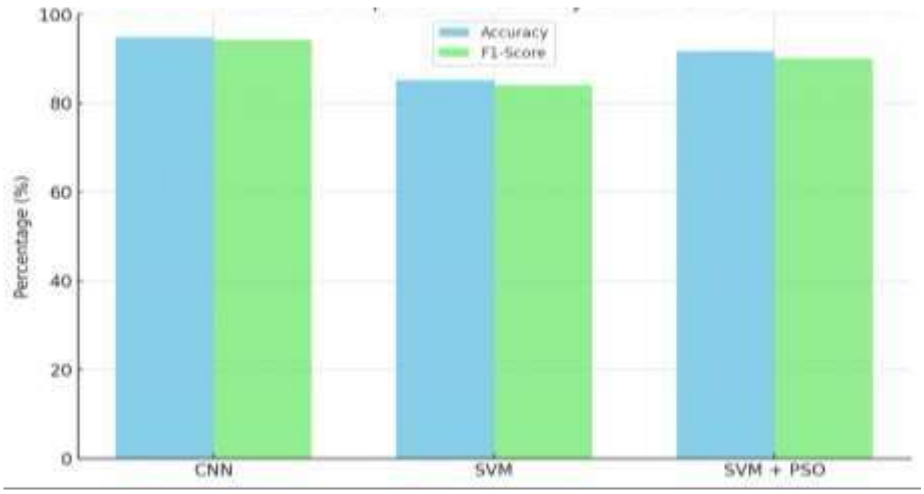

Fig. 1. Model Comparison: Accuracy and F1-Score

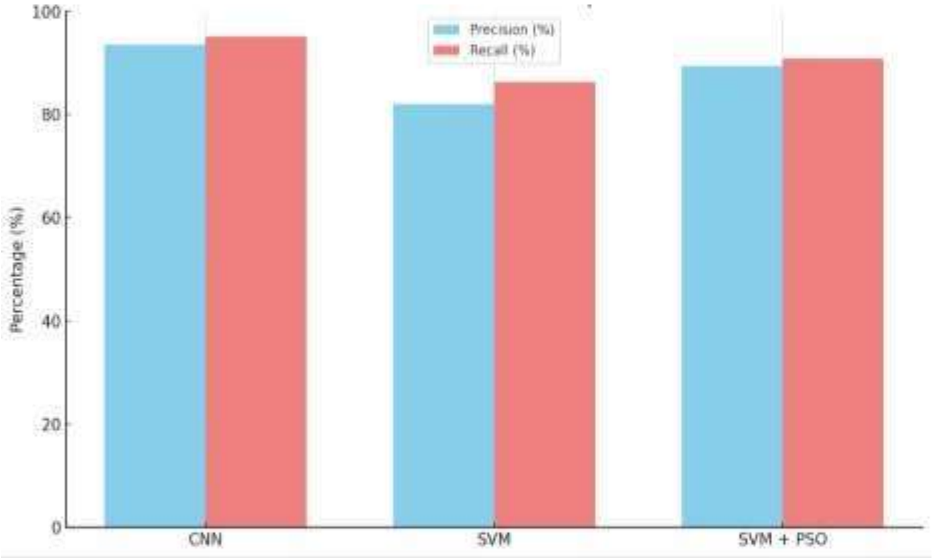

Fig. 2. Model Comparison: Precision and Recall

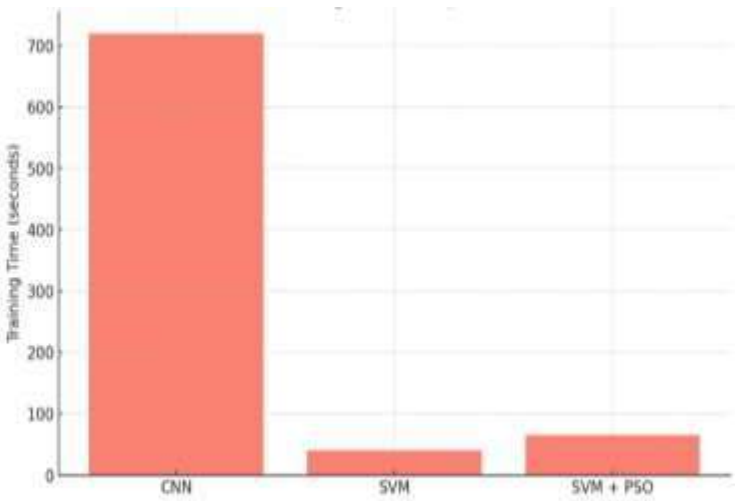

Fig. 3. Model Comparison using Training Time

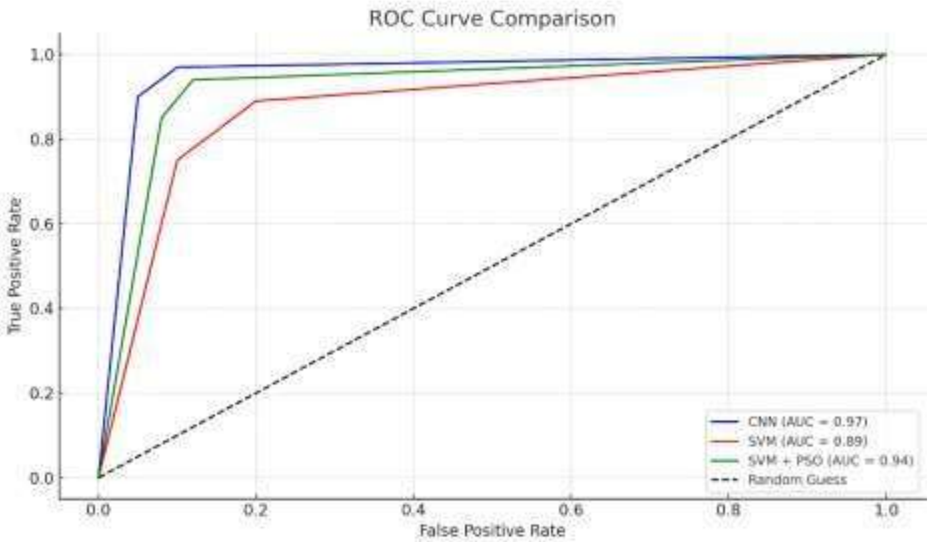

Fig. 4. Model Comparison using ROC Curve

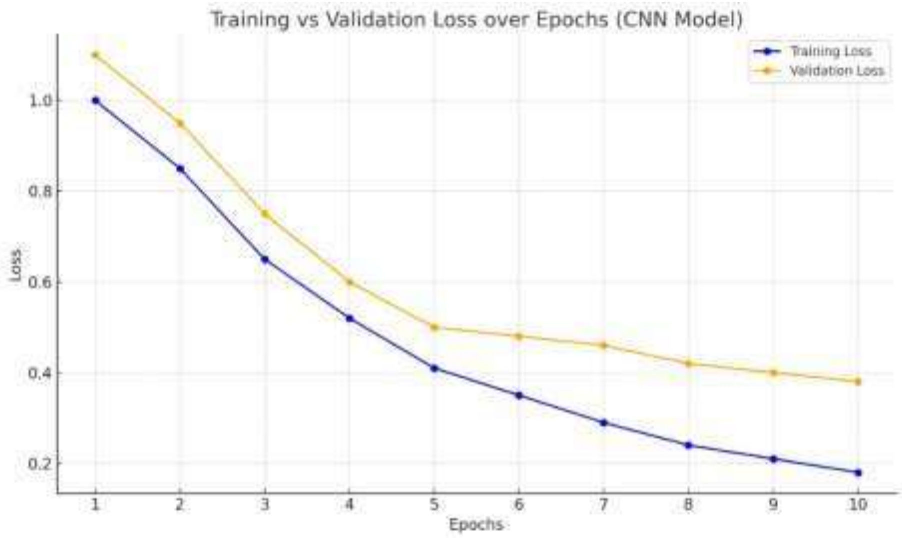

Fig. 5. Training and validation loss

5. RESULTS AND DISCUSSIONS

This study tested the performance of three models—CNN, SVM, and SVM with PSO—using different evaluation metrics like Accuracy, Precision, Recall, F1-Score, AUC-ROC, and Training Time, as shown in Table 1 (Model Performance Comparison). Among the three, CNN gave the best results, reaching 94.8% accuracy, 93.5% precision, and 95.1% recall. These results are shown in Figure 1 (Accuracy and F1-Score) and Figure 4 (Precision and Recall). The AUC-ROC score of CNN was 0.97, as seen in Figure 3, which shows that CNN is very good at distinguishing between cancer and non-cancer images.On the other hand, the standard SVM model, which used manually selected features, achieved a lower accuracy of 85.2%. But after applying Particle Swarm Optimization (PSO) to fine-tune the SVM settings, the accuracy improved to 91.7% and the F1-score increased from 84.1% to 90.1%, proving that optimization methods like PSO can significantly improve traditional machine learning models. As shown in Figure 2 (Training Time Comparison), CNN took the most time to train (720 seconds), but it also gave the best performance. Meanwhile, SVM + PSO balanced well between performance and processing time. The training and validation loss graph in Figure 5 shows that CNN's performance was stable during training, with both losses going down steadily. This means that the model learned properly and is likely to work well on new data.

6. CONCLUSION

This research compared the results of a deep learning method (CNN) and a traditional machine learning method (SVM) that was improved using PSO for detecting skin cancer from CT images. The CNN model performed better overall, proving its strong ability in learning features and classifying medical images accurately. Still, the SVM with PSO also showed a good improvement over regular SVM, highlighting how traditional models can be upgraded using smart optimization techniques like PSO. This study shows that both automatic feature learning (from CNN) and feature tuning (through PSO) are valuable for achieving better results in medical image classification.

Further Studies

In the future, this research can be extended in several useful directions. One of the main improvements would be to use actual CT scan images of skin lesions, as this study mainly relied on dermoscopic images due to limited availability of CT datasets. Using real CT images would provide more meaningful insights and improve the clinical relevance of the work. Another possible extension is the development of hybrid models that combine the feature extraction ability of CNN with the classification strength of an SVM optimized by PSO. This combination can help achieve better accuracy and robustness. Also, there is a growing need to make AI models more explainable, especially in healthcare. By integrating techniques like Grad-CAM or SHAP, future models can show which parts of the image influenced the prediction, helping doctors to better trust and understand the results. Furthermore, implementing these models on hardware like FPGAs or mobile-based edge devices can support real-time diagnosis in rural or remote areas with limited medical facilities. Lastly, future studies can expand beyond binary classification and focus on identifying multiple types of skin cancer such as melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC), which will make the system more comprehensive and clinically useful.

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