Skin Cancer Detection using Machine Learning Classification Models

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Abstract: In recent years, computer-aided analysis techniques have emerged as valuable tools in assisting dermatologists by providing objective and efficient analysis of skin cancer images. This paper utilizes the combination of the Contourlet Transform (CT) and Local Binary Pattern (LBP) techniques for accurately recognizing borders, contrast changes, and shapes of skin cancer images. These results often contain many features, leading to high computational costs and potential over-fitting issues. Hence, we applied Particle Swarm Optimization (PSO) to select the most informative and discriminating features, reducing the dimensionality while retaining important information for accurate classification. After reducing the feature set with PSO, we applied these sets to Machine learning classification algorithms: Support Vector Machine (SVM), Random Forest (RF), and Neural Net- works (NN). The results show that SVM has the lowest time complexity of 0.0458 seconds, followed by the Neural Network at 0.08730 seconds, and the Random Forest model has the highest time complexity of 0.1622 seconds. The SVM and Neural Network models are faster to train than the Random Forest model, making them more suitable for real-time or latency-sensitive applications. We also compared our proposed model with the state-of-the-art models and obtained the accuracy of 86.9%, which is the highest among the models.

Keywords: Skin cancer, Contourlet Transform (CT), Particle Swarm Optimization (PSO).

1. Introduction

The escalating worldwide public health issue of skin cancer is a pressing concern, with millions of individuals being impacted annually. In order to attain a successful outcome, prompt identification and precise diagnosis are imperative. Dermatologists can utilize computer-aided analytical techniques [1] to examine images of skin cancer. Despite the considerable progress made in the area of skin cancer detection, the current feature extraction and classification approach to skin cancer images is limited [2]. Previous research has mainly focused on CT's individual applications, but incorporating other trans- forms like LBP for additional feature extraction may enhance classification performance. Selecting the best features from skin cancer images through optimization techniques [3] is critical for improving the efficiency and effectiveness of the detection system. Once an image's optimum input feature set is identified, classification methods should be employed further to enhance the detection process regarding time and space complexity.

The main contribution of this work is as follows:

- To enhance the manual feature extraction process, we adopted an improved combination of CT and LBP image transform techniques to accurately recognise borders, contrast changes, and shapes of skin cancer images from the International Skin Imaging Collaboration (ISIC) data set.

- We applied advanced PSO to optimise the feature extraction process to convert the initial 224×224 images into a reduced set of input data vectors.

- The reduced set of input feature vectors is applied to 3 advanced ML classification methods: SVM, RF, and NN for skin cancer detection. These models were evaluated based on various metrics, including accuracy, precision, recall, and F1-score, as well as the time and space complexity of each model's training process.

This work has been arranged as follows: Here is the format for this paper. Preview is covered in Section II. The suggested techniques are the subject of Section III. Results from the simulation and discussion information are included in Section IV. In conclusion, section V makes a note of the conclusion.

2. Preliminaries

A. Skin cancer

There are three primary types of skin cancer lesions [4]: Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC), and Melanoma. BCC is prevalent in regions exposed to the sun, SCC is characterised by firmness, and Melanoma [5] is associated with aggressiveness. Different types of skin cancer lesions exhibit distinct features and characteristics, which aid in their identification and diagnosis. Here are some key features of the three main

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types of skin cancer shown in Table-I. Dermatologists employ the ABCDE rule to assess which type of cancer moles and lesions. For instance, Melanoma was identified using the ABCDE rule [6], as shown in Table II. While these features and identification methods provide valuable guidance, it is essential to consult a dermatologist for a definitive diagnosis.

Table 1: Key Features Of The Three Main Types Of Skin Cancer Lesions

Skin cancer lesions	Appearance	Borders	Texture	Symptoms
Basal cell carcinoma (BCC)	Pearly, brown scar-like lesion	Smooth and rolled	A shiny small blood vessels on the surface	Do not cause pain but can bleed
Squamous cell carcinoma (SCC)	A firm, red, a flat, scaly, crusty lesion	Irregular, raised, rough	A rough, scaly surface	Tender, painful, or itchy and may bleed easily
Melanoma	An asymmetrical with irregular borders, uneven color distribution	A rare, notched, or blurred rather than smooth and well defined	Shades of brown, black, blue, red, or white, exceeding 0.24 inches in diameter	Changes in the size, shape, color of a mole over time are potential indicators

Table II. Abcde Rule To Assess Melanoma

Property	Details
Asymmetry (A)	Asymmetric, meaning one half of the lesion does not match the other half.
Borders (B)	Irregular, poorly defined, or scalloped borders
Colour (C)	Varied colours within a lesion, such as shades of brown, black, or red
Diameter (D)	The lesions larger than 0.24 inches in diameter
Evolution (E)	Changes in size, shape, colour, or elevation over time

B. Contourlet Transform (CT)

The Contourlet Transform [7] [8] is a sophisticated, multi-faceted image transform that operates on multiple scales and directions. It is widely utilized in various image processing tasks, including but not limited to image compression, denoising, and feature extraction. This transform builds upon the fundamental principles of the Wavelet Transform, but goes a step further by incorporating directional information. The Contourlet Transform involves a series of steps, which are hereby elucidated below in a more academic fashion:

- **Preprocessing:** To analyze an input image, ensure it is preprocessed, possibly resizing or denoising, to improve its quality.

- **Decomposition into Sub bands:** The Contourlet Transform involves decomposing an image into sub bands using a filter bank, which is crucial for determining the properties of the extracted features.

- **Directional Filter Banks:** The Contourlet Transform employs directional filter banks, unlike the standard Wavelet Transform, which uses only horizontal and vertical filters, enabling the representation of contours in the image.

- **Sub band Decomposition:** The image is divided into multiple sub bands, each containing specific frequency and direction information, resulting in a more accurate representation of the data.

- **Quantization and Feature Extraction:** Obtaining sub bands allows for quantization or feature extraction techniques, such as histogram-based statistics and texture analysis, depending on the specific application.

- **Feature Selection:** Feature selection is a method used to select the most relevant features for a task, which can reduce dimensionality and enhance the efficiency of subsequent processing steps.

C. Local Binary Pattern (LBP)

As a textural descriptor, the Local Binary Pattern (LBP) [9] is well known for its remarkable discriminating power. It compares the Grey level of each pixel in an image with that of its surrounding pixels to assign a binary number to each pixel. Neighbouring pixels that have a greater Grey level than the centre pixel in a preset patch are assigned a value of unity, while neighbouring pixels with a lower Grey level are assigned a value of zero. Consequently, a binary number is allocated to the centre pixel. Using a 3×3 patch, the original LBP operator generates an 8-digit binary number by using the neighbouring pixels. Following labelling every pixel in an image, a histogram with 256 bins and the LBP feature map are produced. Each bin in the LBP histogram represents a distinct feature that may be used as a feature vector for classification.

D. Particle Swarm Optimization (PSO)

CT images often contain numerous features, leading to high computational costs and over-fitting issues. PSO [10], a meta- heuristic optimization algorithm inspired by bird flocking or fish schooling, aims to select informative and discriminative features for accurate classification. PSO [11] searches for an optimal subset of features, with each particle representing a potential feature subset.

The particles are binary vectors with values representing different feature subsets. The fitness function evaluates each particle's performance, and based on these evaluations, particles adjust their positions within the search space.

Two factors guide the movement Personal Best (pBest): A particle has found the best solution (feature subset) so far. Global Best (gBest): The best solution among all the particles in the swarm. Particles are attracted to their pBest and gBest positions, and acceleration coefficients and random factors control this movement. The optimization process involves multiple iterations where particles continue to move and update their statuses. The strategy aims to converge to an optimal solution, i.e., the best feature subset that maximizes the classification performance. The PSO optimization terminates after a predefined number of iterations or when a convergence criterion is met. After the PSO optimization, the particle that achieved the best feature subset is selected as the final reduced feature subset.

E. Classification algorithms

With the reduced feature subset obtained from PSO, a classification algorithm [12] such as SVM, Random forest, Neural network is trained using this subset as input features. The reduced feature space typically results in faster training and improved generalization performance since it reduces the risk of over-fitting. By leveraging the PSO optimizer to select the most informative features from CT images, the feature reduction process helps improve the efficiency and accuracy of classification algorithms. It enables more focused and efficient training, essential for handling large-scale medical image data sets and improving the overall performance of computer-aided diagnosis systems for CT image analysis.

*1) **Support Vector Machines (SVM):*** Initially referred to as support-vector networks, support-vector machines (SVMs) [13]. Using the idea of non-linearly mapping vectors to a high-dimensional feature space and creating a linear decision surface (hyperplane) inside it, support vector machines (SVMs) are a type of binary classification technique. Due to the hyperplane's optimality as a maximal margin classifier with regard to the training data, support vector machines (SVMs) are effective in handling both separable and non-separable issues. Structural Risk Minimization (SRM) is the idea that SVMs follow, and it gives them improved generalisation capabilities. SVMs were swiftly used for classification and regression issues due to their significant benefits. Moreover, SVMs have always been problematic because to their limited sample sizes, non-linear issues, and the curse of dimensionality.

*2) **Random forest (RF):*** Random Forests [14] is a machine learning ensemble learning algorithm that uses multiple decision trees to create robust, accurate models, reducing variance and over-fitting in classification and regression tasks. This generates bootstrap samples by randomly selecting data points, which are then used to train a distinct decision tree. They consider a random subset of features, introducing diversity and reducing the likelihood of a dominant feature. Decision Tree construction involves growing multiple trees using bootstrap samples and random feature subsets. Voting or averaging is used for classification and regression tasks. Ensemble aggregation reduces over-fitting and improves generalization performance, with randomness in feature selection and bootstrapping introducing diversity for a robust model.

*3) **Neural network (NN):*** Neural networks [15] [16], which are machine learning algorithms, have been inspired by the human brain and are currently utilized in diverse domains such as natural language processing, image and speech recognition. They are classified as transformers, which operate by modifying input data through activation functions and weighted connections. The architecture of the network comprises of input, hidden, and output layers, consisting of weight initialization and loss function. During the feed forward process, input data is multiplied by weights and subsequently passed through activation functions. Optimization methods like stochastic gradient descent, are applied to iteratively adjust weights to minimize loss function and enhance prediction precision. The network undergoes numerous iterations of training, loss calculation, and back propagation to refine weights and biases. Regularization and hyper-parameter tuning are also executed to prevent overfitting and enhance generalization.
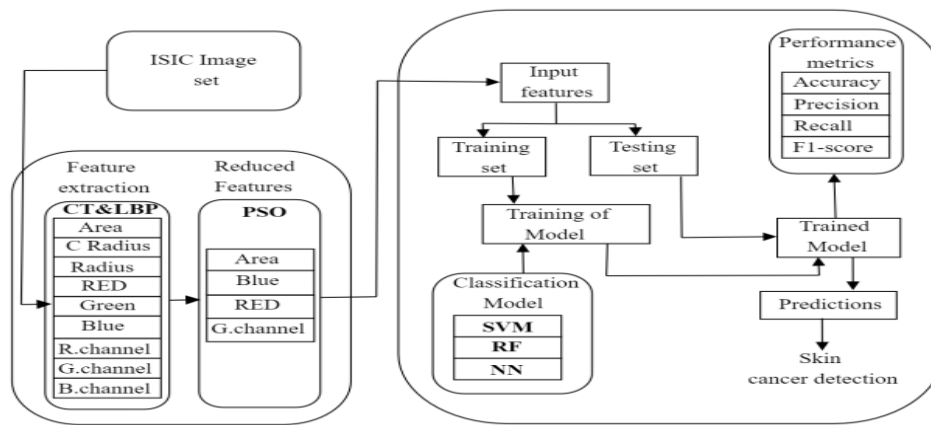
Fig. 1. Block diagram.

Table III. Image File Properties

Image File	Radius	Area	Contour Radius	Color Features	Green Channel	Red Channel	Blue Channel
(1).jpg	123	2533.5	28.39	[170 161 188]	135.72	130.73	162.00
(10).jpg	10	94	5.47	[181 167 221]	151.45	142.93	203.205
(100).jpg	361	128722	202.41	[159 157 223]	161.72	160.82	228.54
(101).jpg	374	249447	281.78	[138 130 195]	137.99	141.28	199.43
(102).jpg	15	157.5	7.08	[147 139 170]	128.27	125.96	162.17
(103).jpg	175	29871	97.51	[129 128 200]	119.43	115.25	203.72
(104).jpg	374	268128	292.14	[107 92 153]	124.22	133.55	208.22
(105).jpg	130	12405.5	62.83	[161 144 181]	156.10	151.9	190.90
(106).jpg	123	19065	77.90	[156 152 193]	135.85	131.33	185.97

3. Proposed Method

This section presents our approach to feature extraction and reduction and classification of skin cancer images, as shown in Fig 1. We applied the ISIC image set for the image preprocessing tools like CT and LBP for feature extraction of an image. After obtaining an extensive feature set, we adopted PSO to obtain the reduced optimal feature set. We gave this reduced feature set as input to three classification algorithms: Support Vector Machine (SVM), Random Forest (RF), and Neural Networks (NN). Our goal was to evaluate the Performance of each classification algorithm using the reduced feature sets and determine the most effective approach for image classification.

4. Simulation Results and Its Discussion

For the simulations, we employed a Kaggle dataset [17] focused on skin cancer. This collection comprises a total of 2357 images depicting both malignant and benign oncological ailments. These images were derived from The International Skin Imaging Collaboration (ISIC). The sorting of the images was based on the classification provided by ISIC, and each subset was divided into an equal number of images, except for melanomas and moles, which exhibited a slight dominance in terms of the number of images. To better understand the distribution of images within this dataset, please refer to Table IV for a detailed breakdown of benign and malignant classifications.

Table IV. Image Dataset Distribution

Name of Disease	Training set(2357)	Test set(118)
Actinic Keratosis	114	16
Basal cell Carcinoma	376	16
Dermatofibroma	95	16
Melanoma	438	16
Nevus	357	16
Pigmented benign Keratosis	462	16
Seborrheic Keratosis	77	3
Squamous cell Carcinoma	181	16
Vascular Lesion	139	3

A. Extracted Features:

The provided data contains information about different images and their corresponding color channel features - Green, Red, and Blue Channels. As shown in Table III, the provided data gives us insights into the color characteristics

of different images [18]. The intensity values of the three color channels indicate the presence and dominance of specific colors in each image. These features are obtained after application of CT and LBP methods, and these can be useful for further image analysis tasks, such as color-based image segmentation, object recognition, and classification. Additionally, this data can be utilized as feature vectors for machine learning models to perform image-related tasks based on color channel information.

B. Particle Swarm Optimization for Feature reduction:

After applying PSO model [19] to obtain strong features, the number of features has been reduced from 9 to 4. From the Table V, the optimization process has successfully identified the most relevant and informative features, leading to a significant reduction in both time and space complexity. The time complexity reduction achieved is 0.00204, indicating that the optimized feature set allows for faster computation and processing compared to using all 9 features. This reduction in time complexity is crucial in enhancing the efficiency of the model or algorithm. Furthermore, the space complexity has been reduced by a factor of 5. This means that the optimized feature set requires much less memory, making it more memory-efficient and suitable for applications with limited resources. After the PSO feature reduction, the selected features are [Area, Green Channel, Blue, RED]. These features have been identified as the most influential in making predictions or decisions within the given context. By focusing on these key features, the models performance can be maintained or even improved, while simplifying the model and reducing potential over-fitting.

Table V. Results Of Pso

Number of features before reduction	9
Number of features after reduction	4
Time complexity reduction	0.002043724
Space complexity reduction	5
Selected features	[Area, Green Channel, Blue, RED]

C. Performance analysis of various Classification Models:

A smaller feature set was subjected to three classification models: Support Vector Machine (SVM), Random Forest (RF), and Neural Network (NN). The models were assessed using a number of metrics, such as accuracy, precision, recall, and F1-score, in addition to the temporal and spatial complexity of each model's training procedure, as indicated

in Table VI. The three models all attained the same F1-score, recall, accuracy, and precision. This implies that the models' prediction powers are similar for the specific skin cancer categorization job.

The time complexity of the model-training phase indicates the time taken to fit the model to the training data. The SVM has the lowest time complexity of 0.0458 seconds, followed by the Neural Network at 0.0873 seconds, and the Random Forest model with the highest time complexity of 0.1622 seconds. The SVM and Neural Network models are faster to train than the Random Forest, making them more suitable for real- time or latency-sensitive applications. The space complexity refers to the memory required to store the model and its associated parameters. The Neural Network model has the highest space complexity of 816 units, while the SVM and Random Forest models have the same space complexity of 448 units. This difference in space complexity could be attributed to the architecture and size of the Neural Network. Considering time and space complexity is essential, especially when deploying models to resource-constrained environments such as mobile devices or embedded systems. The SVM might be preferred in such cases due to its faster training time and lower memory requirements.

Table VI. Skin Cancer Classification Results

Model	Accuracy	Precision	Recall	F1-score	Time	Space
SVM	0.8696	0.7561	0.8696	0.8089	0.0458	448
RF	0.8696	0.7561	0.8696	0.8089	0.1622	448
NN	0.8696	0.7561	0.8696	0.8089	0.0873	816

1) Comparative analysis:

The suggested model and the current approaches for classifying skin cancer are contrasted in Table VII. As demonstrated by the references, the model performs better than the current machine learning and deep learning models, yielding the greatest test accuracy as well as noticeably better outcomes in other assessment metrics including precision, recall, and F1-score. These findings demonstrate how well our approach detects skin cancer.

Table VII. Comparison Of Proposed Model With State-Of-The-Art Models

Reference	Accuracy	Precision	Recall	F1-Score
[20]	79.5%	-	-	-
[21]	81.3%	0.7974	0.7866	-
[22]	83.9%	0.709	0.56	-

[23]	85.7%	0.756	0.816	-
Proposed model	86.9%	0.756	0.8696	0.8089

5. Conclusion

The Contourlet Transform, optimized with Particle Swarm Optimization (PSO), emerges as the most promising feature extraction mechanism for skin cancer detection, offering high accuracy and robustness in classification. This research work contributes to the growing body of knowledge in medical image analysis and provides valuable insights for the development of more reliable and precise diagnostic tools in the medical field.

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