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# Skin Melanoma Diagnosis Using Machine Learning and Deep Learning with Optimization Techniques: Survey

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**Abstract**. Skin cancer is regarded as one of the most perilous forms of cancer and is recognized as a leading contributor to mortality worldwide. The likelihood of fatalities can be diminished significantly if skin cancer is identified at an early stage. Among the various types of skin cancer, melanoma stands out due to its remarkably high fatality rates. This is primarily attributed to its propensity to metastasize to other bodily regions if not promptly detected and treated. The process of diagnosing melanoma is notably intricate, even for seasoned dermatologists, primarily due to the extensive morphological diversity observed in patients' moles. Consequently, the automated diagnosis of melanoma presents a formidable challenge that necessitates the development of proficient computational techniques capable of facilitating diagnosis, thereby assisting dermatologists in their decision-making process. In this study, we meticulously examined the most recent scientific papers on melanoma diagnosis, specifically focusing on applying deep learning and machine learning techniques in conjunction with optimization techniques.

## 1 Introduction

One of the most prevalent forms of cancer is skin cancer, which starts when skin cells proliferate uncontrollably. UV radiation from sunlamps and tanning beds can trigger it, which leads to the proliferation of skin cells and the formation of malignant tumors. One of the main causes of death in the globe is skin cancer. According to data released by Americans, 97,160 individuals received a skin cancer diagnosis in 2023, accounting for 5.0% of all cancer cases reported in the country, while 7990 people lost their lives to the disease, representing 1.3% of all skin cancer-related fatalities in the country. [1]
Melanoma is a skin cancer that is extremely lethal and spreads quickly all over the world. This type of skin cancer is extremely deadly because it spreads quickly to lymph nodes even before the disease is detected. In the United States, 76,380 new cases of melanoma and 10,130 deaths were predicted for 2016. In the United States, this takes more than one life per hour. Consequently, melanoma incidence is rising globally.[2] Thankfully, early detection of melanoma contributes to effective treatment, with an estimated 98% of cases lasting five years or more. [3]
A more modern kind of visual examination called dermoscopy removes surface reflection while also magnifying the skin. According to research, a person may diagnose patients with dermoscopy with 75%–84% accuracy with the right training. To increase dermoscopic expertise's scalability, procedural algorithms like the "ABCD rule",”[4]

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The "ABCD" rule, which is a subset of guidelines for melanoma identification, is as follows [5]:
• Asymmetry (A): A lesion's one moiety differs from its other moiety.
• Border irregularity (B): It is common for melanoma lesions to have asymmetric borders that are hard to characterize. The edges of the non-cancerous moles are uniformly smooth.
• Color (C): Malignant moles exhibit an uneven distribution of color or many colors, such as blue, black, brown, etc. Typically, benign moles are only one shade of tan or brown.
• Diameter (D): The diameter of melanoma lesions is frequently larger than six millimeters


**Fig 1. ABCD's of Melanoma**

Due to the poor contrast of skin lesions, the large intraclass variance of melanomas, the high degree of visual resemblance between melanoma and non-melanoma lesions, and the presence of numerous artifacts in the picture, automated melanoma detection in dermoscopy images is an extremely difficult task. [6]
The best option for detecting and classifying cancer is the Computer-Aided Diagnosis (CAD) system, which reduces human labor and time while having extremely high classification accuracy. Several techniques based on machine learning (ML) and deep learning (DL) have been utilized to create reliable skin-lesion categorization systems.[7].
This article examines the most current studies that employed various deep learning and machine learning techniques together with optimization algorithms to properly identify skin cancer. The basis for creating deep learning and machine learning with optimization algorithms for skin cancer diagnosis that is more precise, effective, and efficient may be laid by this review paper.

## 2 Machine learning

Machine learning (ML) is a branch of artificial intelligence that uses mathematical models to identify patterns and relationships in data. It can be used to annotate or unannotated datasets and is divided into supervised and unsupervised algorithms. ML approaches include regression analysis, classification, association analysis, and clustering, each with a separate algorithm for decision-making tasks. Machine science enables systems to learn and make decisions from data without explicit programming, improving performance through experience. Medical systems have benefited from ML techniques to improve diagnostic accuracy by analyzing medical images of suspicious places on the skin. Machine learning systems can evaluate and classify these places based on attributes extracted from the trained data.

### 2.1 Machine learning with optimization algorithms

To successfully treat skin cancer, early diagnosis is essential. Machine learning algorithms can help with this process, reducing the morbidity and death load associated with the disease [8]. The weights and parameters of machine learning models may be optimized using optimization algorithms to improve the classification performance of skin cancer photos
as in figure 2.[9] The following studies demonstrate melanoma diagnoses using machine learning and optimization algorithms.

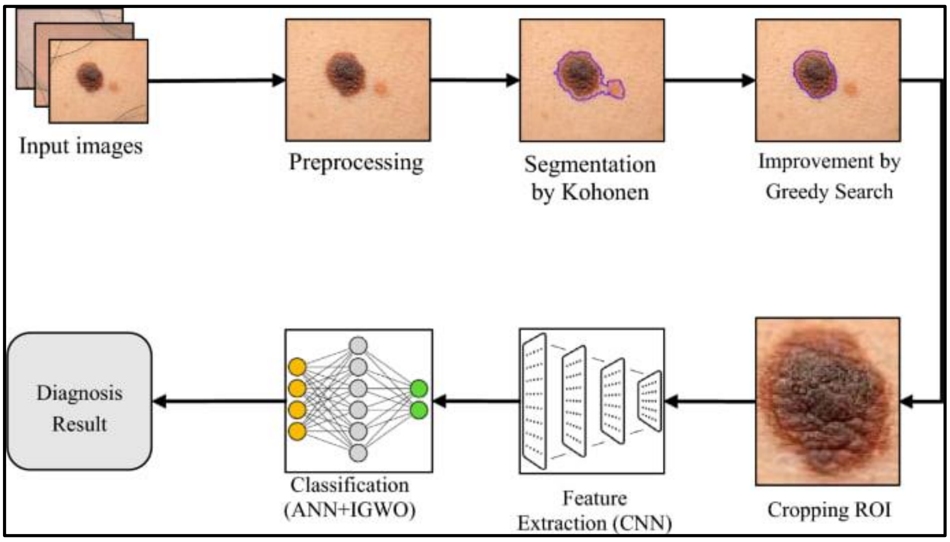


**Fig 2.** Machine learning with optimization algorithms.

#### *2.1.1 Bacterial colony (BCO-SVM) method*

This method suggested a classification system dubbed hybSVM to diagnose malignant melanoma, which combines the SVM algorithm with the Bacterial Colony Optimization technique. The Bacterial Colony algorithm improves the SVM algorithm's effectiveness in melanoma identification. The Feature Space Locally Linear Clustering FSLIC clustering method datasets are used in the study to test the hybSVM algorithm. This method achieves high accuracy in melanoma detection with 98% AUC on ISIC and PH2 datasets and enhances classification performance with enhanced SVM. However, it may be computationally intensive and not universally applicable.[10]

#### *2.1.2 Firefly optimization technique (FA-BNN)*

This method suggested a neural network-based automated technique for categorizing skin cancer. The Firefly optimization approach (FA) is used by the authors to modify the neural network's parameters. The steps involved in pre-processing, which included morphological operations including bottom hat filtering and dilatation utilizing the disk as an object, were employed to enhance the segmentation of the cancer region from the skin in the article. The authors divide the picture into the skin and mole areas using the fuzzy c-means segmentation technique, and then they employ cropping to isolate the mole region and segment it separately. The system achieved an accuracy of 94.5% using the PH2

dataset. By using Firefly optimization for feature selection in neural networks, the novel method increases the accuracy of classification. Its application may be limited by its intricacy and specificity, which are contingent upon the quality of the dataset.[11]

#### *2.1.3 Modified cat optimization algorithm (MCOA- non-convex boundaries) method*

The modified cat rate optimization algorithm (MCOA), which is based on extracting non-convex boundaries and changes in pixel size, shape, and image intensity on the skin surface, was intended to be used at an early stage of melanoma detection. Using the non-convex borders of the diseased region as a guide, MCOA can identify skin cancer early on and stop it from spreading. The non-convex borders of melanoma in skin scans are obtained by MCOA through the extraction of image characteristics. Using MCOA and HAM10000 datasets, an accuracy of 85% was achieved in melanoma detection. The Modified CAT Optimization Algorithm has a high degree of accuracy and is useful for early melanoma identification; however, practical applications may find it challenging due to its complexity, and its performance may differ based on the dataset utilized.[12].

#### *2.1.4 Ant colony optimization (ACO-Genetic Algorithm GA with TSVM) method*

It is a hybrid intelligent ACO-GA algorithm for picture segmentation and a Transductive Support Vector Machine TSVM classifier for illness identification as an automated method for detecting various types of dermatological conditions. The ACO-GA algorithm is used by the algorithm to determine the best cluster centers and to categorize the photos. To precisely identify dermatological illnesses, the TSVM classifier contrasts testing samples with training samples with a 95% accuracy rate. The study makes use of 812 colored skin photographs from the dermatology department at Khulna Medical College, While the novel combination of ACO, GA, and TSVM improves the accuracy of skin illness diagnosis, it may also increase algorithm complexity and limit the applicability of the algorithm to other skin disorders.[13].

#### *2.1.5 (MTLABC) - multi-layer perceptron (NN MLP) method*

Algorithm (MTLABC) for multi-layer perceptron NN training using the dermoscopy dataset ISIC, which consists of 996 lesion pictures (85% for training and 15% for testing). After applying image processing techniques (hair removal, segmentation using Otsu's thresholding, picture enhancement, and feature extraction using GLCM features and color moments features), the tests are carried out on the dataset. The suggested system performs at 75.12%. Although the novel hybrid method improves the classification accuracy of melanoma photos by integrating Artificial Bee Colony based on learning, it still has issues with dataset specificity and algorithm complexity. [14].

#### *2.1.6 Artificial Bee Colony (ABC) with segmentation method*

The Artificial Bee Colony (ABC), an artificial swarm intelligence technique for melanoma detection in skin tumor lesions. The ABC algorithm helps physicians diagnose malignant melanoma with the least amount of time and effort required since it is quick, easy to use, and versatile. Segmenting the lesion's areas and using the ABC approach for the values of distinctive principles, enables the automated categorization of skin malignancies. Images from the PH2 dataset are used in the article. With a 94.88%-93.11% increase in accuracy. The creative use of swarm intelligence in dermatology provides accurate differentiation between healthy and diseased moles, which is essential for the early identification of skin cancer. However, in real-world medical contexts, its complexity and dataset specificity could provide difficulties.[15]

#### *2.1.7 Three methods metaheuristic (PSO), (SA), (ANN, and SVM)*

Using three metaheuristic methods, they identified the best feature sets for detecting deadly malignant melanoma pictures from the MED-NODE: simulated annealing (SA), Ant colony optimization (ACO), and particle swarm optimization (PSO). Support vector machines (SVM) and artificial neural networks (ANN) are used to classify lesions as malignant or benign; the method's best classification accuracy result was 87.69%. By utilizing PSO, ACO, and SA to efficiently decrease feature sets, the technique improves classifier performance. It detects melanoma with a high degree of classification accuracy. However, certain dataset specificity and metaheuristic algorithms play a major role in its efficacy, which impacts generalizability.[16]

#### *2.1.8 Particle swarm optimization (PSO) - multi-layer perceptron (NN MLP) method*

They proposed a Multi-Layer Perceptron (MLP) with optimized network parameters using the Particle Swarm Optimization (PSO) algorithm for detecting malignant melanoma. The MED-NODE dataset is used for segmentation, feature extraction, classification, and result analysis. Image preprocessing techniques are used, followed by an adaptive snake approach for segmentation and a genetic algorithm for dimensionality reduction. The system achieves an accuracy of 85.9%, the technique makes use of PSO for parameter optimization, which enhances classification performance and achieves high melanoma detection accuracy. Nevertheless, its practical usability may be affected by the dataset's properties and implementation complexity.[17]

### *2.1.9 Particle swarm optimization (PSO-SVM) method*

Particle swarm optimization it is a method hybrid approach based on Particle Swarm Optimization and Support Vector Machine (PSO-SVM) for the automatic detection of skin cancer (melanoma) using Histo-pathological pictures. The wavelet coefficients' energy from the wavelet packet decomposition and characteristics taken from the grayscale picture histogram co-occurrence matrix are used by the system. A genuine dataset from the Southern Pathology Laboratory in Wollongong, New South Wales, Australia, is used to assess the system's performance. The evaluation's findings indicate a classification accuracy of 87.13%. Combining PSO with SVM, the advanced hybrid technique has good accuracy rates for identifying melanoma; nevertheless, its implementation may be complicated and dependent on the quality and variety of the dataset.[18]

### *2.1.10 (PSO), and (WOA-PNN) method*

Particle swarm optimization PSO, Whale Optimization WOA-PNN focused on precise skin cancer diagnosis using dermoscopy pictures. The technique involves obtaining, analyzing, and cleaning up images using a Gabor filter. The pre-processed pictures are segmented using a Fuzzy C-Means algorithm, a Gabor Response Co-occurrence Matrix extracts melanoma parameters, and characteristics are optimized using a hybrid Particle Swarm Optimization (PSO)-Whale Optimization method (WOA). The Probabilistic Neural Network classifier helps identify features and categorize skin lesion phases. The new strategy achieves an accuracy of 97.83%. The dataset used includes images from PH2, Dermis, Dermquest, and Kaggle. Skin cancer identification is made more accurate by the hybrid optimization efficiency of PSO and WOA, which also improves high accuracy when using the PNN classifier. Computational load, however, may rise due to intricate algorithm integration and possible overfitting risk.[19]

### *2.1.11 Particle Swarm Optimization (HLPSO-SVM, KNN) method*

It is a unique technique to improve the efficiency of several phases of autonomous skin lesion diagnosis, which is based on Particle Swarm Optimization (PSO). First of all, the first method uses a PSO-based algorithm called HLPSO to optimize a network's hyper-parameters at a fixed depth of three. Conversely, the second technique makes use of features that are extracted from an image, namely those that are associated with color, form, and texture. Furthermore, a recently suggested descriptor is presented, and an ensemble model (SVM, KNN) is utilized, demonstrating a recognition rate of 0.8825 for data utilized in the ISIC dataset and 0.8427 for hold-out assessment. The approach, which combines PSO, clustering ensemble, and deep learning, improves the precision of melanoma diagnosis; yet, it has drawbacks, including data dependency and computational complexity.[20]

### *2.1.12 World Cup Optimization (WCO-ANN) method*

It is a novel approach to image-based melanoma malignancy detection. An MLP neural network (ANN) is optimized using the World Cup Optimization technique to simulate global FIFA competitions. Problem constraints are used by the multi-layer perceptron network (MLP), and the root mean square error is minimized via the WCO method. According to experimental findings, the suggested strategy considerably boosts the efficiency of the conventional MLP algorithm. 92% on the Australian Cancer Database (ACD) was attained. By using a novel method to optimize neural network parameters, this program may be able to increase classification accuracy. It might provide a specialty remedy for medical diagnosis. Its novelty and intricacy, meanwhile, could make comprehension and application difficult. The effectiveness of the algorithm for additional tasks related to medical imaging or skin cancer is not discussed.[21]

### *2.1.13 World Cup Optimization (WCO-SVM) method*

A new computer-aided detection system for skin cancer was published, which utilized a support vector machine (SVM) approach in conjunction with a meta-heuristic algorithm known as the World Cup Optimization (WCO) algorithm. Image segmentation is one of the many applications that have seen success with the WCO method, a global optimization technique. With 92.64% for ACS photos and 87.5% for ISIC images, the suggested approach has the highest correct detection rate. the approach incorporates a meta-heuristic algorithm, which may increase SVM classification accuracy. However, practical applications may find it challenging because of its intricacy, and data quality may have an impact on how effective it is.[22]

#### *2.1.14 (DRFO-Fuzzy K-mean) method*

Developed the Red Fox Optimization algorithm and offered a unique optimal pipeline approach for the accurate diagnosis of melanoma from dermoscopy images using Kernel Fuzzy C-means. This article uses photo preprocessing, segmentation, feature extraction, and classification to diagnose melanoma. A recently developed version of the Red Fox Optimization (DRFO) Algorithm improves feature selection and classification to yield a result with a greater accuracy of 90.5% on the ISIC 2020 dataset. Red Fox Optimization improves classification accuracy, and Kernel Fuzzy C-means is used in the advanced clustering technique for precisely segmenting skin lesion images. However, the algorithm's suitability for various applications may be impacted by its complexity and dataset-specific performance.[23]

#### *2.1.15 Golden jackal optimization (GJO -Otsu segmentation) method*

It is a very effective method for image segmentation related to skin cancer. The opposition-based golden jackal optimizer (IGJO), an improved variant of the golden jackal optimization (GJO) algorithm, is used in this method. Using Otsu's approach as the objective function, the IGJO algorithm is especially used to handle the multilevel thresholding problem in skin cancer picture segmentation. Skin scans from the International Skin Imaging Collaboration (ISIC) collection are used in the study publication. The novel Segmentation Approach makes use of a sophisticated version of GJO. Its ability to analyze imaging effectively suggests the possibility of early diagnosis. However, its dataset specificity and computational complexity might make it less useful in real-world scenarios.[24]

**Table 1**. List of reviewed research**.**

| Ref NO | Author and year | Data – set | Methods | Accuracy |
|---|---|---|---|---|
| 1 | Sümeyya _ Ilkin, Tugˇrul Hakan Gençtürk, Fidan Kaya Gülagˇız, Hikmetcan Özcan, Mehmet Ali Altuncu, Suhap S ahin 2021 | ISIC<br>PH2 | Bacterial colony BCO-SVM | 97%<br>98% |
| 2 | M. Sundar Prakash Balaji, S. Saravanan , M. Chandrasekar ,G. Rajkumar and S. Kamalraj 2020 | PH2 | Firefly optimization technique FA-BNN | 94.5% |
| 3 | N. Prabhakaran 2023 | HAM10000 | modified cat optimization algorithm MCOA-non-convex boundaries | 85% |
| 4 | Md. Humayan Ahmed, Romana Rahman Ema, and Tajul Islam 2019 | 812 colored skin photographs | Ant colony optimization ACO-Genetic Algorithm GA with TSVM | 95% |

| | | | | |
|---|---|---|---|---|
| 5 | Radhwan Ali Abdulghani Saleh, and Rustu Akay 2019 | ISIC | Teaching Learning Based Artificial Bee Colony MTLABC- multi-layer perceptron NN MLP | 75.12% |
| 6 | Mohanad Aljanabi, Jameel Kaduim Abed, H.J. Abd, Ahmed Hussein Duhis, Ammar O. Abdallh, and Nadia Alan 2020 | PH2 | Artificial Bee Colony ABC with segmentation | 93.01-94.88 |
| 7 | Soumen Mukherjee, Soumen Mukherjee, and Madhusudan Roy 2021 | MED-NODE | particle swarm optimization PSO, simulated annealing SA, Ant colony-ANN, SVM | 87.69% |
| 8 | Soumen Mukherjee, Arunabha Adhikari, and Madhusudan Roy 2019 | MED-NODE | particle swarm optimization PSO- multi-layer perceptron NN MLP | 85.9% |
| 9 | Maen Takruri, Mohamed Khaled Abu Mahmoud, and Adel Al-Jumaily 2019 | obtained from the Southern Pathology Laboratory in Wollongong NSW, Australia | particle swarm optimization PSO-SVM | 87.13% |
| 10 | J. Jaculin Femi, and T. Jaya 2023 | PH2 Dermis, Dermquest Kaggle | particle swarm optimization PSO, Whale Optimization WOA-PNN | 97.83% |
| 11 | Teck Yan Tan, Li Zhang, and Chee Peng Lim 2019 | ISIC | Particle Swarm Optimization HLPSO-SVM, KNN | 0.8427 0.8825 |

| | | | | |
|---|---|---|---|---|
| 12 | Navid Razmjooy, Fatima Rashid Sheykhahmad, Noradin Ghadimi 2018 | ACD | World Cup Optimization WCO-ANN | 92% |
| 13 | Dezhong Bi, Dongxia Zhu, Fatima Rashid Sheykhahmad, and Mingqi Qiao 2021 | ACS ISIC | World Cup Optimization WCO-SVM | 92.64% 87.5% |
| 14 | Zexian Fu, Jing An, Qiuyu Yang, Haojun Yuan, Yuhang Sun, and Homayoun Ebrahimian 2022 | ISIC | Developed Red Fox Optimization algorithm.DRFO-Fuzzy K-mean | 90.5% |
| 15 | Essam H. Houssein, Doaa A. Abdelkareem, Marwa M. Emam, Mohamed Abdel Hameed, and Mina Younan 2022 | ISIC | Golden jackal optimization GJO-Otsu segmentation | 91% |

Noticed that models used the concept of machine learning to diagnose skin cancer using ANN, and BNN. KNN, MLP, SVM, Fuzzy K-mean and Otsu segmentation with different optimization algorithms such as BCO, FA, COA, ACO, ABC, RFO, WCO, and PSO Where it was applied to various datasets, and the highest accuracy obtained was 98%. Machine learning using optimization algorithms can improve the accuracy of skin cancer diagnosis and reduce time. However, challenges include data quality as high-quality images can hinder learning skin cancer-related features. Differentiating between diseases: Some skin diseases may resemble skin cancer, making differentiation difficult. In addition, data diversity. Models must be trained on diverse data to recognize a wide range of conditions, as cancerous tumors vary in shape, size, and color.

## 3 Deep learning

Deep learning, a branch of artificial intelligence uses multilayered neural networks to learn intricate tasks like pattern recognition, prediction, and categorization. The difficult task of skin lesion picture segmentation in computer vision has been completed by it. Because deep learning can do picture categorization, object detection, restoration, and captioning, it can be used in medical imaging. Unsupervised learning methods like Bayesian deep learning can be used to tackle the problem of the limited amount of annotated data accessible in medical imaging. Due to low contrasts and hazy boundaries, deep learning can reliably identify characteristics crucial for the categorization of skin lesions.

### 3.1 Deep learning and optimization algorithms

The use of optimization algorithms with deep learning techniques plays a crucial role in improving the accuracy of skin cancer diagnosis. By combining deep learning with optimization algorithms as in figure 3, the performance of the models can be improved, however, there are still some challenges that need to be addressed when using machine learning for skin cancer detection. These include the limited size of skin cancer datasets, data imbalance, difficulty in handling large lesions, the complexity of feature engineering, and lack of interpretability of deep learning model[25]. The following studies demonstrate melanoma diagnoses using deep learning and optimization algorithms

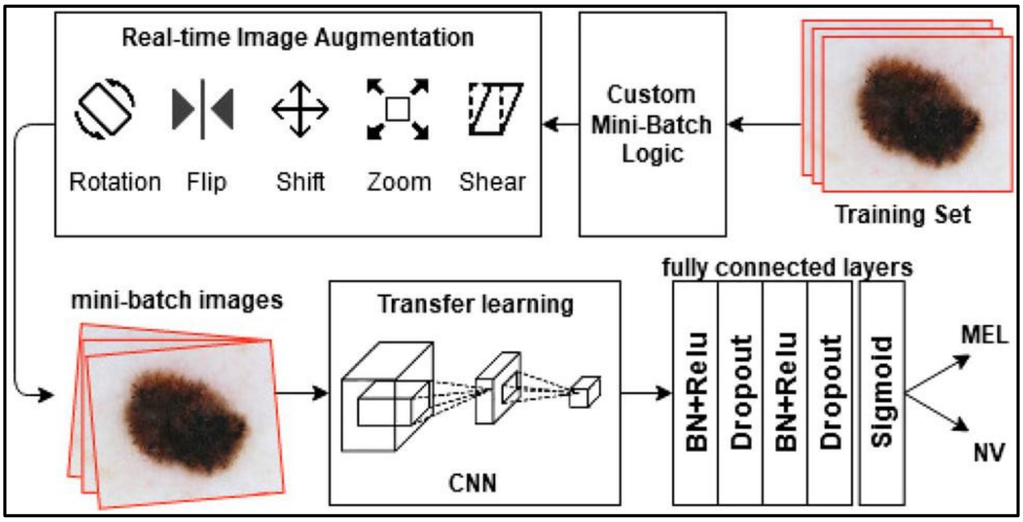


**Fig (3):** Deep learning and optimization algorithms.

### *3.1.1 (GA-CNN) with (HAM10000, ISIC2018 data-set) method*

This method it is an enhanced Convolutional Neural Network (CNN) model for the early identification of skin lesions, with the best hyperparameters chosen by a genetic algorithm (GA). As measured by assessment criteria like PREC, SN, F-score, ACC, SP, and the DICE coefficient, the improved CNN model performs admirably. Physicians may use the model as a cost-effective tool for early skin lesion diagnosis. With the HAM10000 dataset, the improved CNN model yielded 98.66% accuracy, while with the ISIC 2018 dataset, it reached 95.96% accuracy. These algorithms can help in early detection, lessen the workload for dermatologists, and automate the diagnosis procedure. They can be used to identify different skin malignancies or medical disorders, and they are affordable and transferable. Nonetheless, issues with data limits, algorithm complexity, interpretability, clinical validation, and ethical and legal issues must be taken into account. The quality and quantity of available data may have an impact on these algorithms' efficacy and accuracy.[26]

### *3.1.2 (GOW-CNN) method*

It is a hyperparameter-optimized convolution neural net (AHON) to identify skin cancer types using the Grey Wolf Optimization (GWO) algorithm. The GWO approach improves the CNN architecture by selecting necessary hyperparameters, incorporating proper picture preparation, color-to-grayscale image conversion, and Gaussian filtering techniques. The GWO-based CNN model performs better in testing accuracy (98.33%) than both the PSO and GA models. It shows competitive efficacy in detecting skin cancer, achieving a low testing loss of about 0.17%. Comparing it to PSO and GA, the ISIC skin lesion multiclass dataset's constraints, the model's complexity, and the fact that it is specialized for skin cancer diagnosis all restrict its efficacy.[27]

### *3.1.3 (PSO-GA with CNN) method*

After training the ISIC dataset, extracted deep characteristics from the photos using the convolutional neural network (CNN) model called EfficientNet. The deep characteristics were selected using genetic algorithms (GA) and particle swarm optimization (PSO). Following selection, a variety of feature combinations were constructed using the selected features. Utilizing the Support Vector Machine (SVM) technique, each selected feature set was categorized. The performance of the recommended model was evaluated and found to be 89.17% based on the accuracy rate. The paper presents a high-accuracy skin cancer diagnostic methodology combining CNN, GA, PSO, and advanced data classification methods, but faces challenges due to model intricacy, computing requirements, data sensitivity, and expert validation[28]

#### *3.1.4 (WOA-CNN) method*

This method it is a novel approach for early skin cancer screening utilizing image processing and machine vision methods. This method uses an enhanced deep learning neural network (DLCNN) and an enhanced whale optimization algorithm(WOA), On two independent datasets Dermquest and DermIS. The technique tries to increase diagnostic accuracy by extracting different information from skin pictures using concatenated neural network layers. in this study we noted highly accurate and proficient in handling complex dermatological imaging data; it is optimized for the diagnosis of skin cancer. Nevertheless, there are several disadvantages, such as the necessity for additional validation in actual clinical situations, data dependency, computational intensity, and implementation complexity.[29]

#### *3.1.5 (GOA-AexNet) method*

This method it is a devised a revolutionary non-destructive testing approach that leads to better diagnostic results, Utilizing the AlexNet and Extreme Learning Machine network. By optimizing the process using a more sophisticated Grasshopper optimization algorithm (GOA), the technique is improved even further. With an impressive 98% accuracy, the suggested technique performs better than the others and shows more efficacy when utilizing the PH2 dataset. The hybrid skin cancer detection model, which combines deep learning and sophisticated optimization, shows good diagnostic accuracy but has difficulties with validation in real-world scenarios, high processing requirements, data dependency, generalization, and complexity.[30]

#### *3.1.6 (PSO-CNN) with (ISIC data-set) method*

This method is particles, particle Swarm Optimization (PSO) was employed to reduce the number of undesirable background patches within the ROI. The ROI lesion region was segmented and characteristics were extracted using the Speed-up Robust characteristics (SURF) technique. Using these characteristics, a Convolutional Neural Network (CNN) model was developed. PSO was employed as a filter by CNN to increase classification precision. On the ISIC-2016 Dataset, the suggested approach produced a diagnostic accuracy of 99.46%. The model increases the accuracy of disease prediction and classification, maximizes CNN performance, and boosts diagnostic effectiveness; nevertheless, it has drawbacks in terms of computational complexity, overfitting risk, model complexity, dependence on data quality, and generalizability. [31]

#### *3.1.7 (GA-CNN) with (ISIC photos) method*

In this method Genetic Algorithms (GA) were employed in the creation of the convolutional neural network architecture (CNN) that they proposed. Finding the best neural network architecture for classifying melanoma is the aim. An updated subset of ISIC photos. Using a genetic algorithm, the convolutional neural network design allows the population to develop over time to reach optimal fitness. Our hybrid approach to building melanoma-detecting CNNs reaches 94% accuracy. Genetic algorithms are used in the melanoma classification process to achieve excellent accuracy, using an automatic network architecture that adjusts to changing interactions. However, their early low accuracy, complexity, processing requirements, overfitting, and need for validation on larger datasets are drawbacks.[32]

#### *3.1.8 (BES- SqueezeNet) method*

It is a new approach for identifying if skin lesions are melanoma or benign. A novel hybrid convolutional neural network architecture and bald eagle search (BES) optimization are put forth. A Squeeze Net architecture's hyperparameters are optimized using the BES algorithm. With an overall accuracy of 98.37% on ISIC 2020, the suggested melanoma skin cancer prediction model was successful. The model managed class imbalance and used sophisticated optimization strategies to attain high accuracy metrics. But complexity, computational power, limited accuracy at first, reliance on data preprocessing, and additional validation requirements are some of the obstacles it encounters.[33]

#### *3.1.9 (GA-CNN) and a segmentation algorithm method*

It is a convolutional neural network (CNN) design using genetic algorithms (GA) and ensemble learning for melanoma diagnosis. The architecture is created using a genetic algorithm that identifies the best ensemble members, and the diagnosis is made by merging individual forecasts. The approach also includes data augmentation, transfer learning, and a segmentation algorithm. The segmentation approach outperformed U-Net and R2U-Net in two datasets PH2, DERM-LIB, and HAM10000, achieving 90%, 85%, and 79%. The model uses a genetic approach for optimization along with numerous CNNs to reliably diagnose melanoma. However, there are several difficulties, such as the necessity for clinical validation, dependence on data quality, overfitting risk, complex architecture, and high computing resource demand.[34] .

#### *3.1.10 (PSO-CNN) with (HAM1000 data-set) method*

This method it is a technique for classifying skin diseases while maintaining information security that combines particle swarm optimization (PSO) with an ensemble of pre-trained convolutional neural networks (PSOCNN). 10,015 samples from the HAM1000 (human against machine) dataset, are divided into seven different groups to evaluate the suggested architecture. It is a multiclass skin lesion categorization issue in this instance. This technique achieved 97.82% accuracy. The model successfully manages class imbalance and ensures information security by achieving high accuracy in multiclass skin lesion categorization. However, it has to deal with complexity, resource intensity, and computational complexity. It also has a risk of over fitting and is highly dependent on the quality and preparation of the data.[35].

#### *3.1.11 (PSO-CNN) with (PH2 data-set) method*

It is an intelligent system for diagnosing skin cancer utilizing deep learning models and enhanced particle swarm optimization (PSO). The researchers generate textures using more effective texture descriptors (GLRLM, LBP, and HOG), extract more distinct form and color features, and suggest two PSO versions for feature selection. For the categorization of lesions, they also employ ensemble classifiers and deep CNN models. The study used the PH2 dataset, Accuracy the precision was 98%. The improved PSO algorithm provides extensive feature extraction, personalized parameter settings, and strong feature optimization. The intricacy, computational load, over fitting risk, and requirement for significant adjustment are some of its disadvantages. Due to its intricacy and abundance of characteristics, [36].

#### *3.1.12 (SLI-GWO)-CNN method*

This method employed a hybrid classifier that incorporates Convolutional Neural Network (CNN) and Neural Network (NN) architectures, to categorize melanoma as benign or malignant. The Sea Lion Integrated Grey Wolf Algorithm (SLI-GWO) approach was used in the study to optimize CNN's weight and starting rate. Higher Order Uniform Moment Induced- Local Binary Patterns (HOSMI-LBP) features are combined with GLCM features in the suggested model to extract features. Using the PH2 and ISIC datasets, the researchers were able to attain a 95% and 90% accuracy rate. The model provides a thorough method of melanoma detection using analysis of skin lesions more accurately, it makes use of a hybrid classification algorithm and an optimized CNN architecture. It can overfit, though, and is complicated and computationally demanding. Its clinical applicability requires more validation. [3]

#### *3.1.13 (GA, PSO-Inception-v3 and DenseNet-201) method*

In this method examined how well the GA, PSO, and DE algorithms performed when it came to fine-tuning the hyper-parameters of previously trained models. The combination of features from the DenseNet-201 and Inception-v3 models for the ISIC2018 and ISIC2017 datasets produced the best results. Additionally, the research indicates that deep network design and hyper-parameter optimization can enhance classification performance, achieving an accuracy of 90.1% on the ISIC 2018 dataset and 81.6% on the ISIC 2017 dataset. The study uses metaheuristic techniques to optimize the architecture and hyper-parameters of deep neural networks for the categorization of skin lesions. High accuracy was attained in the tests of the optimized CNNs, while there are still issues with hyper-parameter optimization complexity.[38]

### *3.1.14 (GSO-FNN) method*

This method which uses fractal neural networks to identify malignant melanoma to classify skin lesions for prognostication and effective therapy. This will replace the Gold Standard excision biopsy, which is currently used to diagnose this condition, with a deep learning technique. Malignant melanoma may now be classified and predicted with an accuracy of 98.4 utilizing the PH2, HAM10000, and ISIC datasets, negating the need for costly processing and expert analysis. The technique accurately classifies malignant melanoma using various datasets, reducing processing costs and expert analysis time. However, its complexity, computing power, and high-quality image reliance limit its generalizability to other skin lesions and therapeutic contexts.[39].

### *3.1.15 (PSO,ACO,GTO-DCNN) method*

It is developed a profound learning methodology to handle the three main tasks: using metaheuristic algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Gorilla Troop Optimization (GTO), they selected characteristics through profound extraction of characteristics using transfer learning. A two-tier categorization was proposed, and the large collection of characteristics was optimized as a feature selector. The number of characteristics is whittled down to an appropriate range. On the HAM10000 dataset, the suggested approach produced accuracy values of 89.89% and 93.58%. This method outperforms state-of-the-art techniques. it is very flexible and scalable to many settings and datasets. Nevertheless, it encounters difficulties including the intricacy of the model, the computing demands, and the requirement for input dermoscopy photos of superior quality. [40]

**Table 2.** List of reviewed research.

| Ref No. | Author and year | Data – set | Methods | Accuracy |
|---|---|---|---|---|
| 16 | Omran Salih and Kevin Jan Duffy<br>2023 | HAM10000<br>ISIC2018 | GA-CNN | 98%<br>95% |
| 17 | Rasmiranjan Mohakud, and Rajashree Dash<br>2021 | ISIC | GOW-CNN | 98.33% |
| 18 | Erdal BAŞARAN, Agri Ibrahim, and Yüksel ÇELİK<br>2022 | ISIC | PSO-GA with CNN | 89.17% |
| 19 | Ni Zhanga, Yi-Xin Caia, Yong-Yong Wanga, Yi-Tao Tiana, Xiao-Li Wangb, and Benjamin Badami<br>2019 | Dermquest<br>DermIS | WOA-CNN | 90% |
| 20 | Gengluo Li, and Giorgos Jimenez<br>2022 | PH2 | GOA-AexNet | 98% |

| | | | | |
|---|---|---|---|---|
| 21 | Ankita Tyagi & Ritika Mehra 2020 | ISIC | PSO-CNN | 99.46% |
| 22 | Luigi Di Biasi, Fabiola De Marco, Alessia Auriemma Citarella, Paola Barra, Stefano Piotto Piotto, and Genoveffa Tortora 2023 | ISIC | GA-CNN | 94% |

| Ref No. | Author and year | Data – set | Methods | Accuracy |
|---|---|---|---|---|
| 23 | Gehad Ismail Sayed, Mona M. Soliman, and Aboul Ella Hassanien, 2021 | ISIC2020 | BES- SqueezeNet | 98,37% |
| 24 | Eduardo Pe´rez, and Sebastia´n Ventura 2021 | DERM-LIB<br>PH2<br>HAM1000 | GA-CNN | 90%<br>85%<br>79% |
| 25 | Hera Shaheen and Maheshwari Prasad Singh 2022 | HAM1000 | PSO-CNN | 97.82% |
| 26 | Teck Yan Tan, Li Zhang, Chee Peng Lim 2019 | PH2 | PSO-CNN | 98% |
| 27 | Abhinandan Kumar Tiwari, Manoj Kumar Mishra, Amiya Ranjan Panda, and Bikramaditya Panda in 2021 | ISIC<br>PH2 | (SLI-GWO)-CNN | 95%<br>90% |
| 28 | Farzad Golnoori, Farsad Zamani Boroujeni, and Amirhassan Monadjemi in 2023 | ISIC 2017<br>ISIC2018 | GA, PSO- Inception-v3 and DenseNet-201 | 81.6%<br>90.1% |
| 29 | S. P. Karuppiah, Adlin Sheeba, S. Padmakala, C. A. Subasini 2022 | PH2, HAM10000, ISIC datasets | GSO-FNN | 98.4% |
| 30 | Anupama Damarla, Dr Sumathi D 2022 | HAM10000 | PSO,ACO,GTO-DCNN | 89.89%<br>93.58% |

Some models used deep learning concepts by using the popular approaches DCNN, FNN, CNN, AlexNet, DenseNet, and SqueezeNet. With different optimization algorithms such as GA, PSO, GWO, WOA, BES, GSO, and GTO. Where it was applied to various datasets and the highest accuracy obtained was 99%. Deep learning with optimization algorithms is a promising technological advancement in skin cancer diagnosis, offering improved accuracy, automatic learning, fast analysis, and the ability to handle large data sets. However, it also has drawbacks, such as the need for large amounts of data, which can be difficult to obtain, making it difficult to understand decision-making processes and potential data bias. Additionally, the high costs associated with purchasing and maintaining hardware for training and running deep learning models may pose a challenge. Despite these challenges, deep learning remains a promising tool for improving healthcare quality.

## 4 Result discussion

Research on skin cancer and methods of treating it with diagnosis has seen significant advancements in recent years, particularly with the emergence of automated diagnosis systems using deep learning models. However, it is essential to consider the ethical implications associated with these technologies, especially in the context of healthcare.

One key ethical concern is patient privacy. Automated diagnosis systems often require access to large amounts of medical data, including sensitive information about individuals' health conditions. Safeguarding patient privacy and ensuring the secure handling of personal data is crucial to prevent unauthorized access or misuse of this information. Researchers and developers should prioritize implementing robust data protection measures, such as data anonymization and encryption, to mitigate privacy risks.

Another ethical consideration is the potential biases in the training data used to develop deep learning models for skin cancer diagnosis. Biases can arise if the training data predominantly represents certain demographics or skin types, leading to disparities in diagnosis accuracy across different population groups. It is crucial to address these biases and strive for diverse and representative training datasets to ensure fairness and equity in automated diagnosis systems. Regular audits and evaluations of the training data can help identify and mitigate biases that may negatively impact diagnosis outcomes.

Additionally, the interpretability of deep learning models used for skin cancer diagnosis raises ethical concerns. Deep learning models often operate as "black boxes," meaning that they provide accurate predictions but lack transparency in explaining how or why those predictions are made. This lack of interpretability can challenge the trust and understanding of healthcare professionals and patients. Researchers should focus on developing methods to enhance the interpretability of deep learning models, enabling clinicians to comprehend and validate the diagnostic decisions made by these systems. Explainable AI techniques, such as generating heat maps to highlight areas of concern in skin images, can aid in this regard.

Through such considerations, researchers can strive to create automated diagnosis systems that are not only accurate but also ethically sound and trusted by healthcare professionals and patients alike.

## 5 Conclusion

This research provides an analytical review of the literature on the diagnosis of melanoma and the categorization of skin cancer images. It provides a thorough analysis of the techniques and algorithms applied to the segmentation, processing, and classification of pictures related to skin cancer. It was investigated to use both deep learning with optimization algorithms and traditional machine learning techniques. We found that combining machine learning and deep learning with optimization methods can improve the precision of melanoma detection, potentially saving lives.

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