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Image-based Skin Disease Detection and Classification through Bioinspired Machine Learning Approaches

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Abstract— A self-learning disease detection model will be useful for identifying skin infections in suspected individuals using skin images of infected patients. To detect skin diseases, some AI-based bioinspired models employ skin images. Skin infection is a common problem that is currently faced due to various reasons, such as food, water, environmental factors, and many others. Skin infections such as psoriasis, skin cancer, monkeypox, and tomato flu, among others, have a lower death rate but a significant impact on quality of life. Neural Networks (NNs) and Swarm intelligence (SI) based approaches are employed for skin disease diagnosis and classification through image processing. In this paper, the convolutional neural networks-based Cuckoo search algorithm (CNN-CS) is trained using the well-known multi-objective optimization technique cuckoo search. The performance of the suggested CNN-CS model is evaluated by comparing it with three commonly used metaheuristic-based classifiers: CNN-GA, CNN-BAT, and CNN-PSO. This comparison was based on various measures, including accuracy, precision, recall, and F1-score. These measures are calculated using the confusion matrices from the testing phase. The results of the experiments revealed that the proposed model has outperformed the others, achieving an accuracy of 97.72%.

Keywords- Neural networks; Image Processing; Bioinspired Machine Learning (Bio-ML); Swarm intelligence, Skin Disease.

I. INTRODUCTION

The skin is the largest organ in the human body. It also controls body temperature and fights against germs, infections, sensitivities, and infectious disorders. Skin illnesses include monkeypox, dermatitis, chickenpox, psoriasis, smallpox, rosacea, cowpox, ringworm, measles, tomato fever, and many others. Figure 1 depicts a skin disease marked by circular to oval-shaped red scaling plaques on the skin. Certain diseases, on the other hand, might severely harm and deform an individual as a result of symptoms such as pain or itching. In addition, dermatitis caused by such illnesses can affect a person's health and sense of self [1]. Majority of people think that some skin conditions don't pose any substantial problems. Even though most people make an effort to manage these skin issues in their way, if a certain skin disease cannot be treated with existing treatments, the disease will only get worse. In addition, the individual may be ignorant of the severity of their skin disease [2].

Skin disease research is in the forefront and gains prominent focus of medical image processing. The two most prevalent diseases, skin cancer, and monkeypox cause millions of illnesses and deaths worldwide each year. Dermatologists are helped by machine-learning-based techniques for detection and classification of skin diseases. The procedure is speed up with use of image processing, which extracts distinguishing characteristics from the images. To enhance and boost the diagnostic performance of dermoscopy, many dermoscopy techniques have been created. Dermoscopy is a non-invasive technique for imaging the skin. The clarity of skin spots is aided by the ability to get a magnified and lit image of a particular area of skin [3]. It enhances the visual effect of a skin lesion by removing surface reflectivity. According to clinical data and statistics, skin illnesses harm the lives of millions of people globally. These diseases may have an impact on a patient's health and life, as well as raise the expense of healthcare services. It is more difficult to treat the effects of such diseases when they are identified later. Typically, dermoscopic image are used to diagnose, with professionals employing specific techniques to detect the illness. These diagnostic approaches have several drawbacks, including the overlap of viral and chronic skin illnesses and high optical variance, both of which face accurate diagnosis difficulties. As a result, this paper discusses medical imaging techniques and bioinspired machine learning approaches to provide an automated diagnostic approach for several skin

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lesion types using dermoscopic images. To analyze skin images, a bag-of-features selection approach was employed based on a hybrid deep learning network.

Figure 1. Sample Skin Disease images from Dataset (Photo credit:www.google.com/indiaTVnews)

In the field of human disease detection, bioinspired machine learning (Bio-ML) methods has outperformed traditional approaches [4]. This paper describes a bioinspired system that uses multi-modality data fusion approaches to diagnose skin issues. The research focuses on the diagnosis of digital images as well as the evaluation of metadata. A combination of multi-deep learning models is used to extract features from digital images with the goal of providing a reliable, accurate, and speedy diagnosis of skin-related issues. These extracted characteristics are then classified using multiple machine-learning methods. As a consequence, this article helps researchers design bioinspired-based machine learning systems that founded on a reliable image processing model of numerous extracted features to assist doctors in real-time skin disease identification. The present research concludes by outlining medical image analysis techniques based on the convolutional neural networks-based cuckoo search algorithm (CNN-CS). It is trained using the well-known multi-objective optimization technique cuckoo search. The proposed model is compared with three additional popular metaheuristic-based classifiers, Convolutional Neural Networks-based Genetic algorithm (CNN-GA), Convolutional Neural Networks-based Bat algorithm (CNN-BAT), and Convolutional Neural Networks-based Particle Swarm Optimization algorithm (CNN-PSO), in terms of performance evaluation metrics. The experiments showed that the proposed CNN-CS model outperformed other models, with an overall accuracy of 97.72%.

II. RELATED WORKS

In the last 30 years, the application of social insects as a metaphor for problem-solving has gained significant attraction. This approach highlights attributes like adaptability, robustness, distribution, and the direct or indirect interactions between agents. Its applications in robotics, communication networks, and combinatorial optimization are all expanding successfully and rapidly. Swarm intelligence, defined as the emergent collective intelligence of groupings of living organisms, is a fresh and exciting way for developing a kind of artificial intelligence technique that is piquing the attention of researchers. In this section, application of bio-inspired machine learning algorithms on images from the skin disease database to identify and classify diseases using several image processing methods are discussed [5, 6]. Pre-processing, segmenting skin lesions, feature extraction, and image enhancement are basic steps for identification and categorization of skin diseases [7]. The flow diagram and procedure for classifying images of skin diseases are shown in Figure 2. Skin conditions are a common problem today. Because of this, it is crucial to recognize skin diseases, which are more difficult to do than other conditions [8]. Consequently, the main objective is to evaluate previous approaches and propose a new approach to classify skin diseases. As a result, skin disease classification becomes increasingly significant, as seen in Figure 3.

A. *Neural Networks Approaches*

Medical image-based diagnosis is only one of the diverse fields where neural networks have seen significant growth in their applications in healthcare. Neural network models have demonstrated significant performance in computer vision problems requiring the processing of medical images. Artificial neural networks (ANNs) exceeded several existing models and image analysis approaches [9, 10]. Convolutional neural networks (CNNs) are widely considered the de facto standard in this field [11, 12] due to the extraordinarily good results; this method was used in medical image analysis and classification. CNN has been employed for several classification tasks related to medical diagnoses, such as wireless endoscopy images [8], lung disease [13], breast cancer detection [14], the detection of malarial parasites in thin blood smear images [15], interstitial lung disease [16], the automatic diagnosis of various chest diseases using chest X-ray image classification [17], CAD-based diagnosis in chest radiography [18] and the diagnosis of skin cancer by classification [19]. Since the COVID-19 pandemic in December 2019, the diagnosis, treatment, and medication for skin disease have been the focus of several researches.

Chakraborty et al. [20] proposed an approach for classifying images using an artificial neural network combined with meta-heuristics approaches. The study focused on diagnosing angioma, basal cell cancer, and lentigo simplex. The image dataset utilized in the research was obtained from the ISIC. To train the artificial neural network (ANN), they employed the Non-dominated Sorting Genetic Algorithm-II, a widely recognized technique for multi-objective optimization.

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This strategy yielded better results compared to previous techniques, achieving an accuracy of 87.92%. The training of the classifier involved extracting a variety of features. Their proposed model was compared against two other popular meta-heuristic-based classifiers: NN-PSO and NN-GA. The experimental results demonstrated the superiority of the proposed model with its distinct properties. Their suggested methods were validated as superior, as indicated by the experimental findings.

A common skin disease detection method proposed by ALEnezi [21] based on computer vision techniques to identify skin illnesses. Their solution uses color image inputs. The image is then resized using pre-trained convolutional neural networks to extract features. Following that, a multiclass SVM was used to categorize the feature. Because Saudi Arabia has a very hot climate, this research will be useful in diagnosing skin disorders there. The technology successfully and correctly detects skin illnesses like eczema, melanoma, and psoriasis.

A two-step strategy to describe skin conditions was proposed by Gautam et al. [22]: after pre-processing the images, a crucial element of the image is extracted. The pre-processed images are then analyzed using the CNN model at various levels. The proposed method is quick and easy, and up to 98% of the time, it yields accurate results when used with different sorts of illnesses. The ultimate goal of their research was to create a mobile application that accepts skin photographs as input and generates comprehensive data related to sickness based on analysis.

A technique of image clustering using sensors for classification was proposed by Pollap et al. [23] in "An intelligent system for monitoring skin disease." To locate crucial areas in a photograph, they used the SIFT method. For classification and segmentation, they subsequently used CNN and SVM. Their precision is 82%, and their accuracy is 84%.

Figure 2. Classifying skin diseases images (Image credit: www.google.com/SciDev.Net

B. Swarm Intelligence Approaches

Researchers in almost all branches of science, medicine, engineering, and industry have been interested in swarm intelligence for the past 30 years. The idea of a swarm inherently encompasses traits such as diversity, randomness, unpredictability, and complexity. In contrast, the concept of intelligence implies that the problem-solving approach efficiently utilizes these characteristics to achieve success. Information-processing units inside a swarm can be animated, mechanical, computational, mathematical model according to behavior of insects and bird’s populations. There must be an interaction between the units, regardless of the connection's various attributes. Systems including ant and termite colonies, fish schools, bird flocks, and herds of land animals have all been addressed by swarm intelligence [24, 40 and 41]. Swarm intelligence also applies to some human-made items, such as multi-robot systems and computer software developed to address optimization and data analysis problems.

The method presented by Fahad et al. [25] is constructed based on the ant colony optimization algorithm, which includes the benefits of the filter- and wrapper-based approaches. When additional characteristics are added to the model, the incremental method reduces the processing cost. While training a classifier, choosing a subset of features lowers the computational cost, which is especially helpful for data with a variety of attributes. As compared to current methods, their proposed method is more accurate and predicts the most important characteristics, as demonstrated by equivalent or higher classification performance for smaller and

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bigger benchmark datasets. Based on the classifiers used, the suggested method has an average accuracy of up to 72.69%.

The deep belief network (DBN) is trained using the Rider-Cuckoo Search Algorithm (Rider-CSA) proposed by Cristin et al. [26]. In this work, Rider optimization algorithm (ROA) is combined with CSA to produce the Rider-CSA. Their proposed classification technique is used by the Rider-CSA-based DBN to find plant diseases. Using the criteria for sensitivity, accuracy, and specificity as well as the Plant Village database, the recommended approach is put into practice. This approach exhibits maximum accuracy 0.877, sensitivity 0.862, and specificity 0.877. The recommended Rider CSA outperformed other current techniques.

Lakshmi et al. [27] conducted a comprehensive study on skin cancer analysis, utilizing an enhanced cuckoo optimization technique. The outcomes of their research demonstrated superior performance in comparison to other relevant methods, across multiple evaluation metrics. Their refined approach leveraged cuckoo search optimization to enhance the accuracy and precision of melanoma image segmentation, yielding exceptional results across diverse image datasets. The efficacy of the enhanced cuckoo search optimization was evaluated using the ISIC image collection datasets. Comparative analysis was made against a range of techniques, including genetic algorithms, artificial neural networks, elephant herding optimization, and particle swarm optimization. The results revealed that their proposed approach enhancement displayed a remarkable ability to identify skin cancer accurately. Their research findings show the efficacy of their proposed algorithm has achieved remarkable detection accuracy of 99.26%. Furthermore, the algorithm showcased exceptional specificity at 99.73% and sensitivity at 99.56% in detecting skin cancer.

III. BIOINSPIRED OPTIMIZATION

Optimization is the most well-known mathematical problem in science and engineering applications. Bioinspired optimization approaches are usually used to discover the best solution. Currently optimization is an active research topic. It offers models for resolving optimization issues that demand a significant amount of computational power and might be stochastic or deterministic. Techniques based on bio-inspiration are used in contemporary research, technology, and structures. It is sparked by findings in adaptation, practices, and salvation that have evolved physiologically over millions of years. Beginning in the early 1980s and continuing into the 2010s, the field of "bioinspired computing" has been applied in investigating a variety of natural phenomena. By 2020, a significant increase is observed in the number of unique algorithms that had been successfully defined. Various artificial intelligence (AI) problem-solving algorithms have been developed as a result of growing understanding of nature and biological processes. The component of artificial evolution which is incorporated for arriving at a decision includes two primary methods: Swarm intelligence and evolutionary computation algorithms. The term "evolutionary computation" refers to algorithms that are constructed using concept of the survival of the fittest and "swarm intelligence" refers to distributed problem-solving algorithms that were inspired by the coordinated team intelligence of swarms or the group behaviors of insect enclaves and other species inhabitants. As a result, the proposed method for the prediction of skin disease should employ a bioinspired optimization approach to achieve higher efficacies.

- Based on the literature review, the proposed approach will produce more accurate results.

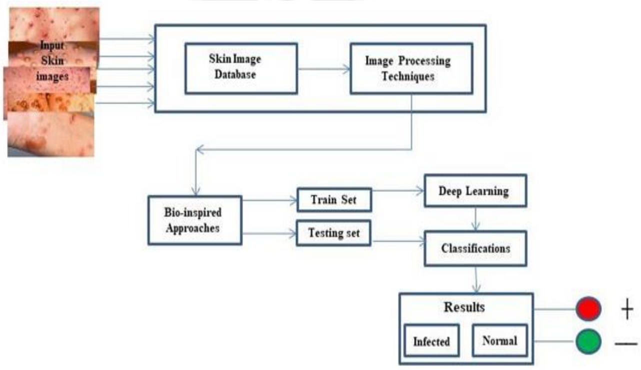

Figure 3. Proposed approach to the skin disease detection process

A. Genetic algorithm

In 1992, J.H. Holland designed one of the metaheuristic algorithms that are most well-known today [28]. Chromosome representation, fitness selection, and physiologically inspired operators are a few of its elements. Selection, mutation, and crossover are the three biologically inspired procedures. The GA's fundamental principle is to mix the most effective answers from earlier investigations of the answer space with fresh ones. GA is carried out in the following steps in a computing environment [40]:

1. Creating a starting population of chromosomes at random using a heuristic method.
   1.1 The possible response is determined by the population's chromosomes.
2. The fitness of each chromosome is computed.
3. Applied genetic operations: mutation, crossover, and selection.
4. Recalculate each chromosome's fitness value using data from this expanding population.

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5. When the maximum number of iterations has been reached or all chromosomes have been mapped to the same intersection, the process should be stopped.

B. Bat Search algorithm

The Bat Algorithm represents a contemporary and state-of-the-art meta-heuristic approach inspired by how bats employ echolocation. Echolocation enables bats to navigate obstacles, locate prey, and discover concealed habitats within darkness, granting them a perception of distance. The distinct characteristics of bats, emitting prolonged, high-frequency sound pulses and subsequently interpreting echoes rebounding off nearby objects; serve as the fundamental inspiration for the Bat Algorithm. This algorithm encapsulates crucial attributes such as frequency (F), position (P), velocity (Vi), loudness (lu), and pulse rate (pr) for each bat under consideration in its framework. These features aid in problem solving and the pursuit of the intended goal [29]. The step of bat algorithm as follows [40]:

1. Set the parameters Vi, F, lu, and pr to their initial values.
2. While (t < maxiteration):
3. Generate new solutions by modifying F, Vi, and location.
4. If (random > pr):
5. Select one of the finest solutions.
6. If (random < lu && f(xi) < f(x1)):
7. Apply the proposed approach, increasing the 'pr' parameter while decreasing 'lu'.
8. End if.
9. Determine the bats and identify the current best position.
10. End for.
11. Calculate G_{best} solution (position).

C. PSO algorithm

It is a bioinspired algorithm that draws inspiration from the movement patterns of fish and flock of birds as they look for food or resources. A swarm is a colony or group of whole particles, whereas a particle is an individual. Each particle had a random initialization and goes in search of a workable solution. To achieve the best or ideal result, each particle modifies its position and velocity. Based on the best particle candidates who are closest to the solution, the particle's position is updated [7]. A detailed description of the PSO algorithm's operation is provided below [40]:

1. In the search space, fix the starting place and speed of each particle.
2. Determine each particle's fitness using the objective or fitness function. If the fitness value is higher than the best fitness value (G_{best}), the new value equals G_{best}.
3. Calculate the velocity and location of each particle using the formula

   Position= $p_i^{t+1} = p_i^t + v_i^{t+1}$

   Velocity (Vi) = $v_i^{t+1} = w.\ v_i^t + c_1 r_1 (p_b^t - p_i^t) + c_2 r_2 (g_b^t - p_i^t)$

   Where, p_i^t represents Particle position.

   v_i^t represents particle velocity.

   Cognitive and social factors are represented by c_1 and c_2, r_1 r_2 are arbitrary values between 0 and 1.
4. Evaluate the fitness by applying the fitness function.
5. Identify the present best position.
6. Update (t) = t+1 (where, t indicates the iteration).
7. Display the current Gbest and the velocity V.
8. If the specified condition is satisfied, stop;
9. Otherwise, the processes are continuing then go to step 3.

D. Cuckoo Search algorithm

This strategy is inspired by the cuckoo bird's behavior, where it lays eggs mimicking those of other species to have them raised by the host. In 2009, Yang and Deb devised the cuckoo search algorithm, representing new solutions as cuckoo eggs [30]. This approach aims to replace suboptimal solutions in nests with potentially superior ones. Instead of a basic random walk, the method incorporates a Levy flight mechanism that employs a Levy- flight probability distribution to determine step lengths, enhancing the exploration process [40]:

$$P_i^{t+1} = P_i^t + \alpha \oplus \text{Levy}(\lambda),\ i = 1, 2, 3, \ \dots, n.$$

α = step size
λ = Levy exponent
$\oplus$ = Entry wise multiplication
P_i^t = position of nest

The CS algorithm provides four fundamental rules:

1. Cuckoos lay single eggs in randomly selected nests.
2. In the subsequent generation, find superior nests containing the best eggs (solutions).
3. Cuckoo birds visit multiple host nests.
4. Host birds have the possibility of discovering a cuckoo egg.

   4.1. If host bird discover cuckoo’s egg can decide to remove the egg.

   4.2. Otherwise construct a new nest any elsewhere.

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IV. DESCRIPTION OF THE DATASETS AND METHODS

The datasets for the research undertaken in the paper is compiled by downloading images of infected skins images from various websites (examples: ISIC [38], other news sources in Kerala and Odisha, India [39]). The collection has 700 images to represent each skin diseases (monkeypox, chickenpox, smallpox, cowpox, and measles, and others from various websites [37-39]. A few sample images of the dataset thus prepared are shown in Figure 2.

- **Methodology**: This section provides a full explanation of the methodology used by the suggested system for identifying, extracting, and categorizing images of skin infections. The method will be very useful for identifying tomato flu and monkeypox. Preprocessing, feature extraction, and classification are just a few of the several components that make up the skin infection detection architecture (SIDA) proposed in this work and are shown in a block diagram of the system in Figure 3.
- **Preprocessing:** An effective skin disease detection system needs to address a few key issues. Creating a database and standardizing image dimensions are two examples. The next section provides additional information about image scaling techniques.
- **Image Resizing:** The size of the image can be increased or decreased based on the image records stored in the database. All images will have the same number of features if one combines the size of images. Also, reducing the image's size speeds up system performance by cutting down the processing time. The reduced image is 299×299 pixels in size, whereas the original was 300×325 pixels.
- **Feature Extraction:** Convolutional neural networks (CNN) are stacks of layers that combine linear and nonlinear processes. There are four basic building blocks: a convolutional layer, a pooling layer, a nonlinear rectified linear units (ReLU) layer connected to a standard multilayer neural network known as the fully connected layer, and a loss layer at the backend. The exceptional performance of CNN in fields like visual tasks and image processing is well known [31]. To imitate the 2012 ImageNet for the Large Scale Visual Recognition Competition, Krizhevsky et al. [31] created the deep CNN model AlexNet (ILSVRC-2012). AlexNet is composed of five convolutional layers, each followed by a nonlinear ReLU layer. Furthermore, max-pooling layers exist in the first, second, and fifth levels, as shown in Figure 5. Two normalization layers follow the first and second convolutional layers. At the top of the model, the softmax layer is followed by two completely linked layers. AlexNet was trained using over 700 images from seven different classes. The feature extraction process is demonstrated using a trained convolutional neural network since it is the simplest and most reliable technique to employ deep learning.
- **Classification:** The task of image classification is to categorize images. It is done by using a Gray Level Co-occurrence Matrix and a Support Vector Machine (GLCM-SVM) after feature extraction. Using the retrieved features from the training data, a GLCM-SVM can train a classifier [32].

V. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed approach is executed on a Windows 10 operating environment, utilizing a system equipped with an Intel(R) Core(TM) i7-9700 processor operating at 3.00 GHz and 16 GB RAM. The implementation is carried out using a Python application, and the outcomes are visualized in Figure 4. The process involves preprocessing of input images, followed by feature extraction using a relevant Convolutional Neural Network (CNN). Ultimately, classification is performed through the GLCM-SVM classifier. The study employs a dataset of 700 skin images depicting diverse dermatological conditions [37-39], and the experimental findings are represented in the confusion matrix depicted in Figure 6.

Table I. Comparison of CNN-CS performance measures with CNN-GA, CNN-BAT and CNN-PSO

	Accuracy	precision	Recall	F1-measure
CNN-GA	90.56	88.26	93.64	90.87
CNN-BAT	84.58	93.47	82.69	87.75
CNN-PSO	90.01	86.16	85.58	85.87
CNN-CS	97.72	91.53	86.14	88.76

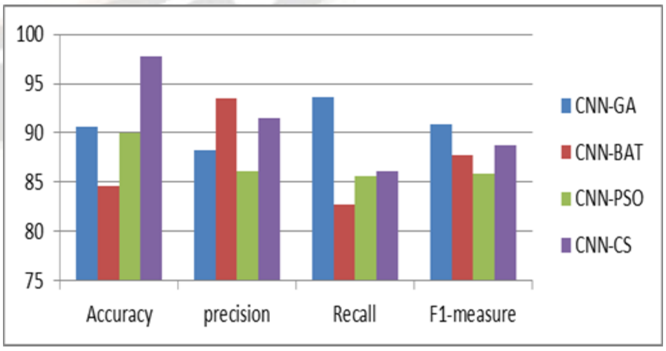

Figure 4. Comparison of obtained results: CNN-CS with CNN-PSO, CNN-BAT, and CNN-GA

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The suggested method detects distinct skin diseases. For this implementation 560 images are used for training, and 140 are used for validation. The proposed method classifies two separate skin illnesses, using the CNN-CS model. In terms of performance parameters like accuracy, precision, recall, and F1-measure [33, 34], the proposed technique employing CNN-CS outperforms CNN-GA, CNN-BAT and NN-PSO. The experimental settings for CNN-CS are comparable to those in LSTM-CS [35], and NN-CS [36] respectively. The performance indicators of the suggested models are derived from the confusion matrices acquired during several rounds of testing. The comparative analysis is outlined in Table 1, while Figure 4 graphically represents the outcome of the experiment.

Table 2. Comparison of CNN-CS performance measures with LSTM-CS [35] and NN-CS [36]

	Accuracy	precision	Recall	F1-measure
LSTM-CS [50]	97.59	95.87	97.09	96.48
NN-CS [51]	88.24	82.56	88.87	85.60
CNN-CS	97.72	91.53	86.14	88.76

As shown in Table 2, the CNN-CS model performed well, with an accuracy of 97.72%, precision 91.53%, recall 86.14%, and F1-measure 88.76%. The CNN-CS model, on the other hand, outperformed both the LSTM-CS [35] and NN-CS [36] models, obtaining the greatest accuracy 97.72%. This increase in accuracy is a remarkable result of the suggested method. The CNN-CS model has beaten all other models compared in the study in terms of accuracy and its ability to correctly categorize the several of skin diseases under investigation. Figure 5 depicts an illustration of the comparison outcomes.

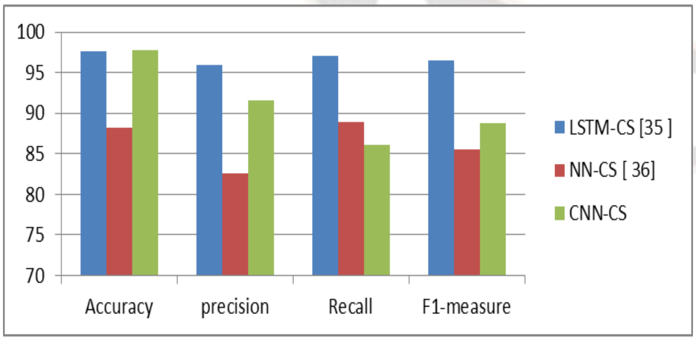

Figure 5. Comparison of obtained results: CNN-CS with LSTM-CS [35] and NN-CS [36]

The performance of the CNN-CS approach on a class-by-class basis was analyzed using the confusion matrix shown in Figure 6. The results indicate that our CNN-CS technique effectively categorizes images into eight distinct classes, as evident from the analysis of experimental datasets. Notably, the approach demonstrates excellent discrimination between tomato flu and monkeypox, chickenpox, smallpox, cowpox, and measles normal images. However, it still struggles to achieve perfect accuracy in distinguishing between the viruses that cause measles and chickenpox. This difficulty could be attributed to the presence of similar characteristics in both classes, as observed in the images of the database process and visualizations shown in Figure 2.

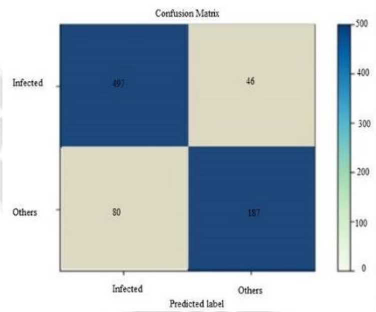

Figure 6. Confusion matrix of CNN-CS

ROC performance curves were used to evaluate how well the proposed classification model performed on the skin image dataset. The following classifiers are used in this work: (a) CNN-CS, (b) CNN-GA, (c) CNN-BAT, and (d) CNN-PSO. These graphs show the accuracy of each classifier in classifying each category of skin diseases. Curves closer to the upper-left corner imply better class separation accuracy, notably in the CNN-CS classifier. Furthermore, the Area under the Curve (AUC) value evaluates the model's ability to distinguish between distinct diseases in the dataset. Figure 7 depicts all the classifiers, which demonstrate similar behaviors. In this article, we assigned disease categories to the skin image dataset from diverse sources, encompassing Kaggle skin images, the ISIC benchmark skin image dataset, and images from Indian news sources in Kerala, Tamil Nadu, and Orissa [37-39]. These assignments were structured as follows: class 0: skin image dataset, class 1: smallpox, class 2: chickenpox, class 3: tomato flu, class 4: measles, class 5: cowpox, class 6: monkeypox, and class 7: normal skin images. Across the four distinct classifiers, the findings from the proposed model CNN-CS generate the highest classification performance. Conversely, classifiers CNN-PSO exhibited the lowest area under the curve (AUC). Notably, the CSC classifier achieved an overall accuracy of 97.72% and hence effectively demonstrating its enhanced detection capabilities compared to well-established classifiers based on bioinspired approaches.

VI. CONCLUSION

In this article, latest innovations in skin disease detection using image processing techniques and machine learning algorithms with bioinspired approaches are presented. Here at first, the technical aspects of skin diseases are studied. Second, alternative image processing techniques for identifying and classifying diseases using bio-inspired machine learning algorithms are applied to skin disease database images and analyzing image processing applications for illness detection based on particular tasks such as segmentation, classification, and multi-task learning.

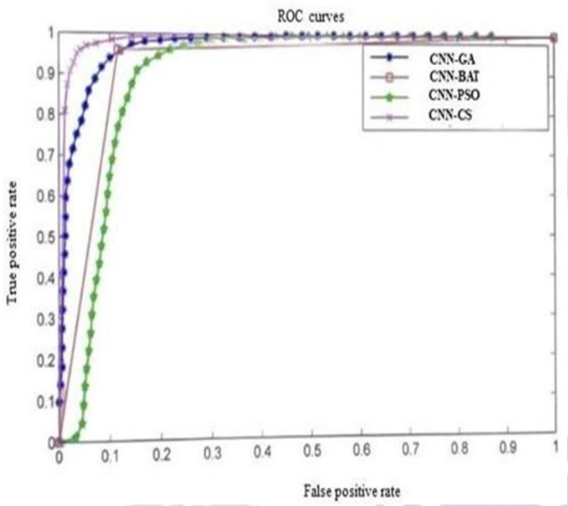

Figure 7. Receiver operating characteristic curves of the models CNN-CS, CNN-PSO, CNN-BAT and CNN-GA

In conclusion, the proposed model CNN-CS is compared with three additional popular metaheuristic-based classifiers, CNN-GA, CNN-BAT, and CNN-PSO, in terms of performance evaluation metrics based on testing phase confusion matrices, such as accuracy, precision, recall, and F1-measure. The experiments showed that the proposed CNN-CS model outperformed the other models, with an overall accuracy of 97.72 % that can be used to classify skin diseases. By adding more functionality that offers complete information about skin diseases under one roof, the scope may be further extended and creating a user-friendly smartphone application that caters to both the general public and medical professionals, offering easy skin disease detection and extensive information on various skin issues.

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CONFLICT OF INTEREST

The writers confirm that they have no financial interests or interpersonal conflicts that may have seemed to influence the research presented in this article. This article complies with ethical standards since none of the writers conducted any experiments using human subjects.

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