IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Usage of Image Processing Techniques in Disease Detection and Classification through Bioinspired Machine Learning Approaches: A Review

Akshaya Kumar Mandal
Department of Computer Science, Assam University, A Central University of India
Assam, Silchar- 788011, Assam, India

Abstract: A self-learning disease detection model will be useful for identifying COVID-19, suspected individuals using chest X-rays, and other skin disorders using skin images of infected patients. To detect COVID-19 and skin diseases, some AI-based bio-inspired models employ chest X-rays and skin images. Skin infection is a common problem that we are currently facing 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) are approaches for skin disease diagnosis and classification through image processing. In this study, we discuss the many techniques that have been applied in the past for preprocessing, segmentation, feature extraction, and classification of several diseases. After comparing several approaches, we developed a new modeling framework for disease detection and classification through bioinspired machine-learning techniques will produce a more accurate results.

Index Terms - Image processing; Bioinspired Machine Learning (Bio-ML); Neural Networks; Swarm intelligence; Biomedical imaging.

1. Introduction

The skin is the human body's largest organ. The skin 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 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 [3]. The 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 [4].

Dermoscopic images are primarily evaluated in the traditional way of detecting skin diseases. Dermoscopic images of the skin are used by dermatologists to identify conditions including color regression, dots and globules, and the pigment network. Nevertheless, there are substantial drawbacks to this treatment, including the need for high-level morphological tools and the need for doctors to complete specific training to use dermoscopy image tools, which takes time and necessitates additional effort [5, 6]. In addition, there is typically a significant amount of visual variability as well as skin lesions with irregular shapes and textures since infectious and inflammatory skin conditions share patterns and characteristics. Dermatologists have had trouble seeing these minute differences with the naked eye, especially newer dermatologists.

The study of skin diseases is a major area of interest in the field 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. The procedure is sped up by 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 [2]. 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 pictures are used to diagnose, with professionals employing specific techniques to create the results. This approach to diagnosis has various disadvantages, including overlapping viral and chronic skin diseases and a high level of optical heterogeneity, making accurate diagnosis difficult. As a result, this paper reviews medical imaging techniques and artificial intelligence to provide an automated diagnostic approach for several skin lesion types using dermoscopic images. To analyze skin images, a bag-of-features approach based on a hybrid deep network was employed.

Artificial intelligence (AI) has recently made strides in a variety of fields, including the medical sector and medical image processing. As a result, AI has gained promise as a tool for creating techniques for medicinal image interpretation. Deep learning networks which have distinctive characteristics and the capacity to learn visual representation on their own have demonstrated effectiveness in picture analysis as a possible AI solution. As a result, the development of computer-aided diagnostic (CAD) systems based on smart technologies is critical to assisting dermatologists in reliably and quickly detecting skin diseases, minimizing the pressure on healthcare systems, and reducing wait times for clinical dermoscopic screens [7].

The study and development of algorithms' ability to absorb new information, form assumptions, and make predictions depending on their environment are known as "bioinspired machine learning"(Bio-ML). It is the result of a variety of complementary methodologies used by the group, which range from probabilistic modeling to dimensionality reduction to computer models with biological inspiration. The earliest description of an abstract computer, commonly known as a Turing machine, was published in 1936, which is when the principles behind biological computing were originally introduced [1]. Recent developments in deep learning, like driverless automobiles, have already impacted the daily lives of many smartphone users and may soon change those of others as well. Since biological ideas like neuronal inhibition, which inspired dropout regularization strategies or temporal synaptic integration, were introduced, these algorithms—which are inspired by neuronal networks—have undergone several improvements (such as increased algorithm stability and decreased energy consumption by hardware devices).

Bioinspired machine learning (Bio-ML) in particular has outperformed other traditional approaches in the diagnosis of human diseases [8]. In this article presents an overview of a CAD system for diagnosing skin problems using multi-modality data fusion techniques. This study is focused on diagnosing digital photos in addition to studying metadata. To get a reliable, accurate, and timely skin-disease diagnosis, multi-deep learning models are used for the feature extraction from digital images, which are classified using various machine-learning approaches. As a consequence, this article helps researchers design bioinspired-based machine learning systems that rely 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 for more accurate diagnosis in metadata and digital images.

This paper's most comprehensive review framework is as follows: Part 2 reviews existing bio-ML techniques with a brief overview of current work for skin lesion classification and identification; Section 3 covers research goals and challenges; and Section 4 presents the analytical findings of the reviewed paper with proposed approaches. Lastly, Section 5 gives the conclusion and future work with useful references.

2. REVIEW OF EXISTING BIO-ML METHODS

In the last 20 years, the social insect metaphor for problem-solving has grown in popularity. This technique focuses on flexibility, robustness, distributed ness, and simple direct or indirect interactions between agents. Its successful applications in robotics, communication networks, and combinatorial optimization are all expanding rapidly. Swarm intelligence, defined as the emergent collective intelligence of groupings of simple organisms, is a fresh and exciting way for developing a kind of artificial intelligence that is piquing the attention of an increasing number of researchers. In this section, we discussed how to use bio-inspired machine learning algorithms on images from the Skin Disease Database to identify and classify diseases using several image processing methods. Pre-processing, segmenting skin lesions, feature extraction, and finally, skin disease categorization is the basic steps in the categorization of skin diseases [41]. The flow diagram and procedure for classifying skin diseases and chest X-rays photos are shown in Figure 1. 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 [27]. Consequently, the main objective is to evaluate previous approaches and provide a fresh approach to classifying skin diseases. As a result, skin disease classification becomes increasingly significant, as seen in Figure 2.

2.1 Neural Networks Approaches

Medical image-based diagnosis is only one of the diverse fields where neural networks have seen significant growth in their application 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 [20, 21]. Convolutional neural networks (CNNs) are widely considered the de facto standard in this field [22, 23] due to the extraordinarily good results they have achieved in medical image analysis and classification. CNN has been employed for several classification tasks related to medical diagnoses, such as lung disease [24], the detection of malarial parasites in thin blood smear images [25], breast cancer detection [26], wireless endoscopy images [27], interstitial lung disease [28], CAD-based diagnosis in chest radiography [29], the diagnosis of skin cancer by classification [30], and the automatic diagnosis of various chest diseases using chest X-ray image classification [31]. The diagnosis, treatment, and management of COVID-19 have been the focus of several experimental and research projects since the COVID-19 outbreak in December 2019.

To classify images, Chakraborty et al. [13] suggested an artificial neural network assisted with meta-heuristics. Angioma, basal cell cancer, and lentigo simplex have all been taken into consideration in this article. The images came from a dataset created by the International Skin Imaging Collaboration (ISIC). Non-dominated Sorting Genetic Algorithm-II, a well-liked multi-objective optimization technique, is used to train the ANN (NNNSGA II), producing superior outcomes than the previous techniques with 87.92% accuracy. To train the classifier, many features have been retrieved. The developed framework has been compared against two other well-known meta-heuristic-based classifiers, NN-PSO (ANN trained with particle swarm optimization) and NN-GA (ANN trained with a genetic algorithm). The proposed NN-NSGA-II model with distinct properties is superior, as evidenced by the experimental results. Properties are superior, as evidenced by the experimental results.

In three common skin disease methods, ALEnezi [14] proposed computer vision-based techniques for identifying 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 utilized 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.

Fig.1. Classifying skin diseases and chest X-rays photos

To identify coronavirus disease 2019 (COVID-19) from chest CT scans, Li et al. [15] proposed a mechanism for doing so. To separate community-acquired pneumonia (CAP) from chest CT scans, a deep learning model is being created to identify coronavirus illness 2019 (COVID-19). Based on our research, it is possible to distinguish COVID-19 from a cough using a machine learning method that makes use of a neural network model.

A method for identifying the disease that most commonly affects brinjal plants, white mould, was presented by Venkataramana et al. [16]. This disease may be classified and predicted using the deep learning integration method. They use the support vector machine (SVM) for classification and the convolutional neural network (CNN) for prediction. The suggested system outperforms previous methods by a factor of 99.4%, and the infections it predicts are very effective.

Gouda et al. [17] recommend using image-enhancing methods to brighten and remove noise from the lesion image. Resnet50, InceptionV3, and ResNet Inception were all trained on the top edge of the preprocessed lesion medical images to reduce overfitting and boost the general capabilities of the suggested DL techniques. Using the lesion image dataset from ISIC 2018, the performance of the proposed system was assessed. In Inception's proposed approach, the model's total accuracy rate is 85.7%, which is on par with that of skilled dermatologists.

A two-step strategy to describe skin conditions was proposed by Gautam et al. [18]: after pre-processing the images, a crucial element of the image is then extracted. The pre-processed images are then analyzed using the CNN model at various levels. The research's 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 is to create a mobile application that accepts skin photographs as input and generates comprehensive sickness data based on the analysis.

After image preprocessing, image features are collected and used to predict the disease diagnosis [19]. The number of retrieved features determines the method's accuracy. These traits are inputted into a feed-forward ANN for testing and training. Nine different ailments are categorized here with an accuracy rate of 90%.

A technique of image clustering using navi for classification was proposed by Pollap et al. [32] 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%.

Table 1. Evaluation and Comparison of networks approaches for disease detection

Authors	Name of disease	Objective	Classifier	Database	Evolution matrices	Draw back
Chakraborty et al. [13]	angioma, basal cell carcinoma and lentigo simplex	To develop ANN for multiskin disease	ANN	ISIC	Accuracy	Small dataset
ALEnezi [14]	eczema, melanoma, psoriasis	To develop ANN-SVM for multi skin disease	ANN-SVM	websites	Accuracy	High complexity
Li et al. [15]	Covid-19	To develop ANN for covid-19 detection	ANN	CT-scan images from websites	Accuracy	Prediction rate was low
Venkataramana et al. [16]	Brinjal Plant Disease	To develop CNN for plant disease detection	CNN	PlantVillage	Accuracy	High Complexity
Gouda et al. [17]	Skin Cancer	To develop CNN for plant disease detection	CNN	ISIC2018 dataset	Accuracy	Small dataset
Gautam et al. [18]	skin diseases	To develop CNN for skin diseases detection	CNN	HAM10000 ISIC	Accuracy	High Complexity
Yasir et al. [19]	Dermatological	To develop ANN for plant disease detection	ANN	Sir Salimullah Medical College and Mitford Hospital, Dhaka, Bangladesh, Department of Dermatology	Accuracy	Small dataset
Pollap et al. [32]	skin disease	To develop CNN-SVM for plant disease detection	CNN-SVM	Dermatology Service of Hospital Pedro Hispano (Matosinhos, Portugal)	Accuracy	Dataset size is small

2.2 Swarm Intelligence Approaches

Researchers in almost all branches of science, medicine, engineering, and industry have been interested in swarm intelligence for the past 20 years. Although the idea of a swarm implies diversity, stochasticity, unpredictability, and messiness, the idea of intelligence suggests that the method of problem-solving is successful in some manner. Information-processing units inside a swarm can be animate, mechanical, computational, mathematical, insects, birds, people, array elements, robots, isolated workstations, and even imaginary entities. 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 [42]. 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 technique presented in this study by Lkin et al. [33] demonstrates the considerable potential of CAD systems for dermatologists as a trustworthy, quick, and more accurate detection tool for deadly skin cancer types, such as malignant melanoma. To identify or monitor skin conditions, many programs, including SkinVision, MoleScope, Miiskin, MoleMapper, and UMSkinCheck, have recently been developed. The proposed hybSVM approach, which can diagnose melanoma with high accuracy, may be easily integrated into these apps via a web API, for example. Dermatologists can use the recommended method simultaneously via a web interface.

The method presented by Fahad et al. [34] is based on the ant colony optimization algorithm, which combines the benefits of the wrapper- and filter-based techniques. 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. The proposed technique differentiates the most crucial subset of features with enhanced prediction accuracy when compared to existing algorithms, as demonstrated by equivalent or higher classification performance for smaller and bigger benchmark datasets. Using the provided classifiers, the suggested method has an average accuracy of up to 72.69%.

A Cuckoo Search-trained neural network (NN) that can detect chronic kidney disease (CKD) at an early stage was proposed by Chatterjee et al. [35]. This issue has been resolved by using CS to train the neural network, which tries to minimize the root mean squared error involved during the training phase. Local search-based learning algorithms have the potential to become stuck in local optima. The multilayer perceptron feed forward network classifier and the NN-GA classifier was used to compare the performance of the NN-CS-based model. The experimental results show that when CS is used to train NN, its performance increases significantly, and its accuracy, precision, recall, and F-measure are, respectively, 99.2%, 99.4%, 100%, and 99.6%.

The deep belief network (DBN) is trained using the Rider-Cuckoo Search Algorithm (Rider-CSA) proposed by Cristin et al. [36]. The Rider optimization algorithm (ROA) is combined with CSA to produce the Rider-CSA. A classification technique is used by the proposed 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. The results showed that, with a maximum accuracy of 0.877, a sensitivity of 0.862, and a specificity of 0.877, the recommended Rider CSA exceeded other current techniques.

The most accurate analysis of skin cancer was provided by Lakshmi et al. [37] using Improved Cuckoo Optimization. The results showed that the proposed technology performed better than the other related approaches on several metrics. An improved cuckoo search optimization-based melanoma image segmentation method is trained using a variety of metrics, which leads to higher accuracy and lower error in the given picture datasets. The proposed Improved Cuckoo Search Optimization approach was applied to the ISIC directory, and the results were distinguished using diverse techniques such as genetic algorithms, artificial neural networks, elephant herding optimization, and particle swarm optimization. The new findings show that the suggested improved algorithm is capable of detecting skin cancer. It demonstrates that the technique's enhanced state affects standard quantity processes such as accuracy (99.26%), specificity (99.73%), and sensitivity (99.56%).

According to Khan et al. [38], skin lesion images are first filtered with a Gaussian filter to eliminate noise before being separated using an enhanced K-mean clustering and a special hybrid super-feature vector. To categorize the data, an SVM is employed. The DERMIS dataset, which includes 397 images of skin cancer, of which 251 were nevi and 146 were melanoma, was used to evaluate their proposed technique, with an accuracy rate of 96%.

Automatic diagnosis and detection tools, according to Narin [40], are crucial for limiting the spread of COVID-19. In addition to the "reverse transcription-polymerase chain reaction (RT-PCR)" test that is advised, further diagnosis and detection technologies are required. Automated diagnosis and detection methods based on X-ray and CT images are brought to light as a result of the COVID-19 virus's attack on the lungs. In this study, a high-performance detection system was developed employing three different CNN models (ResNet50, ResNet101, and InceptionResNetV2) with X-ray images from three different classes (COVID-19, normal, and pneumonia). Particle swarm optimization (PSO) and the ant colony algorithm (ACO), two feature selection methods, were applied, and the outcomes of each were examined. Support vector machines (SVM) and a k-nearest neighbor (k-NN) classifier were used in the 10-fold cross-validation procedure to obtain the results. The greatest performance for overall accuracy using the SVM approach without feature selection was 99.83%. Once the feature selection procedure was completed using the SVMACPSO method, the maximum performance was 99.86%.

3. RESEARCH DIRECTIONS AND ISSUES

Readers should anticipate seeing a significant amount of research on this topic shortly given the recent trend of applying image processing techniques via bioinspired machine learning algorithms to detect skin diseases. But, as was already said, there are considerable challenges in this area that need to be resolved. For resolving the problems and attaining appropriate results for skin disease diagnostics, there are a few methods. In the following, we present our opinions and future research directions based on insights from the literature in the areas of skin disease diagnostics and other domains (such as computer vision and pattern recognition).

Collect a substantial volume of labeled disease data: To obtain remarkable performance in disease detection, deep neural networks usually need vast volumes of data for training. So far, in practice, only a modest quantity of data about diseases is typical. We might address this problem in several ways to find solutions. On the other hand, hiring knowledgeable physicians to manually detect skin disease would be costly and time-consuming. On the other hand, it is feasible to efficiently label large amounts of data for skin disease detection tasks using automatic or semi-automatic data labeling approaches, such as those created by Gautam et al. [18], Pollap et al. [32], and Lakshmi et al. [37]. Also, it is possible to comprehensively merge the current publicly available skin datasets to create a sizable skin image dataset for testing deep learning techniques, comparable to ImageNet in the computer vision industry. Shades of Gray and max-RGB are two examples of color constancy techniques that may be used to address the issue of noisy input from various sources while also enhancing the performance of deep learning models. To rectify the influence of lighting on dermoscopy photos, these methods can be utilized as picture preprocessing techniques.

Increase the selection of clinical image data: As science advances, some dermatological treatments are being offered by deep learning algorithms in regions with a lack of medical resources. The availability of clinical images of patients of diverse ages and ethnicities must be increased to further enhance the algorithms' efficacy. Several studies employing deep learning to diagnose skin diseases have reportedly concentrated on classifying or segmenting certain skin problems [17, 18, 32, and 33]. Without identifying any subgroups, a trained algorithm can only decide if a lesion is more likely to be a certain type of skin disease, such as a nevus or melanoma. Conversely, a skilled pathologist can identify each given image from a broad spectrum of differential diagnoses and decide if a skin lesion belongs to any likely subtype of skin disease. It is urgently needed to develop a deep learning-based system for detecting skin diseases that are more reliable and capable of evaluating different kinds of skin lesions. To reduce the false-positive rate when using deep learning algorithms in actual clinical practice, it is necessary to increase the present databases of skin imaging data to cover a variety of cutaneous malignancies and normal skin types. As it was previously mentioned, fair-skinned people represent the majority of cases in the present databases of skin diseases rather than dark-skinned people; nonetheless, it is equally necessary to include skin data from the dark-skinned population to enhance the diversity of these datasets. Using existing datasets for skin diseases, some deep learning approaches performed superbly. Yet further testing on more challenging datasets is required to see how beneficial the algorithms are. To demonstrate the therapeutic value of deep neural networks in aiding the diagnosis of skin diseases, prospective clinical studies are especially necessary. For the creation of general and complex datasets, increasing data diversity is advantageous.

Therefore, deep learning algorithms may be effectively taught and thoroughly verified on these datasets before being used to solve real-world issues.

Table 2. Evaluation and Comparison of swarm intelligence approaches for disease detection

Authors	Name of disease	Objective	Classifier	Database	Evolution matrices	Draw back
İlkin et al. [33]	skin cancer	To develop Bacterial colony for skin diseases detection	Bacterial colony	ISIC	Accuracy	Processing time is high
Fahad et al. [34]	Liver, Iris, Diabetes, Lung-cancer	To develop ACO for skin diseases detection	ACO	UCI	Accuracy	High Complexity
Chatterjee et al. [35]	Kidney Disease	To develop NN-CS for skin diseases detection	NN-CS	UCI	Accuracy	Dataset size is small
Cristin et al. [36]	plant disease	To develop Rider-CSA for skin diseases detection	Rider-CSA	PlantVillage	Accuracy	Dataset size is small
Lakshmi et al. [37]	Skin Cancer	To develop ECSO for skin diseases detection	ECSO	ISIC	Accuracy	Processing time is high
Khan et al. [38]	skin	To develop SVM for skin diseases detection	SVM	ISIC	Accuracy	High Complexity
Narin [40]	Covid-19	To develop SVM-PSO for skin diseases detection	SVM-PSO	Italian Medical and Interventional Radiology Society	Accuracy	Processing time is high

Include more clinical information to assist in the detection of diseases: For detecting skin conditions, deep learning models are often given just dermoscopy or digital images. Nevertheless, in clinical settings, an accurate diagnosis also depends on the history of the skin lesion, the patient's risk profile, and a thorough skin examination. As a result, dermatologists routinely add additional clinical data to their diagnosis of skin cancers. The performance of dermatologists significantly improved, according to the authors of [14], who examined the impact of including additional details and close-up images for skin condition diagnosis. Deep learning algorithms may also be used to incorporate new clinical data into the process of identifying skin diseases. Unorganized documents from the present medical record may also be analyzed using methods like document analysis [19], CNN [18], and NN [18] and employed in the diagnosis procedure. To establish multi-view paradigms for the tasks of skin disease diagnosis, skin pictures and supporting medical information can be combined. Multi-view models may be used to identify illnesses of the skin, according to recent research. Moreover, it is believed that adding human experience to current deep learning algorithms may improve diagnosis performance even more.

Combine manual and deep neural network extracted data: To tackle specific skin disease detection tasks with high performance, hand-crafted features are commonly retrieved using less powerful traditional machine learning models. They are more easily and less expensively obtained with relatively little tagged data. Although handcrafted features often have poor generalization qualities and perform badly when compared to features obtained manually from massive amounts of data using deep neural networks, they can be used to enhance traditional feature analysis approaches. Decorrelated color spaces, for instance, may be investigated to see how they affect the segmentation of skin images and the detection of borderlines. Skin lesions' topography, growth, and geometrical features provide crucial information for identifying skin diseases. Integrating these features with those collected through deep-learning methods can help to improve the performance of existing deep-learning techniques. As a result, it would be useful to combine handcrafted features with deep features in the process of skin disease detection. In this approach, we may not only train a deep network with less labeled data but also obtain superior performance. Use ECSO to generate more data for deep learning. The capacity of ECSO [37] to produce realistic synthetic images for a variety of applications has piqued the interest of the computer vision community. The images may then be used as extra labeled data to train deep learning models, which frequently outperform models trained with limited preliminary information. When large-scale labeled datasets are not available, the characteristic of ECSOs can be incredibly useful in the process of identifying skin diseases. There have reportedly been a few studies in the literature that employ ECSO to identify skin conditions [36, 37]. Nonetheless, extra care should be used while employing ECSOs for medicinal purposes. We all know that ECSOs is not investigating the original distribution of pictures but rather are aiming to replicate genuine ones. As a result, images made using CSS may be very different from the originals. As a result, it is possible to train a deep learning model using images made with machine learning applications and then refine the resulting model using only the images.

Application of bioinspired techniques and domain adaptation for the diagnosis of diseases: Challenges brought on by a lack of extensive labeled data have been addressed using bioinspired methods and domain adaptability. A complex deep learning model is learned using data from a source domain where large-scale labeled data (such as nature images) is accessible using bioinspired techniques or domain adaptation. After then, the model is improved using data from the target domain, where there aren't many labeled data points (e.g., skin disease images). According to the previous paragraph, substantial research has enhanced the effectiveness of deep learning systems in disease detection approaches by using bioinspired techniques or classification techniques [17, 18, and 33]. It is plain that bioinspired approaches allow traditional deep learning algorithms to achieve promising outcomes even with a limited amount of labeled data. A method for employing deep learning is to extract feature representations using pre-trained models, and then learn from these features. For instance, Deep models were developed by Yasir et al. [19] to extract features, which were then used to train higher-level features via deep learning. Another approach to employing bioinspired techniques is to freeze a section of a deep network and train the remaining parts. It is generally accepted that a deep network's early layers choose similar filters for image data types. As a consequence, one may simply form and freeze the parameter values for the first layer from other networks that have been trained on similar tasks. After then, the remaining network is trained normally with a small amount of labeled data. Recent advances [37] in transfer learning within machine learning may help deep learning for skin disease detection become successful.

Create semi-supervised neural networks approaches for diagnosing diseases: Large volumes of labeled data are often needed to train a deep-learning model for disease diagnosis (skin disease). Nevertheless, because expert knowledge is necessary and the labeling process takes time, collecting huge volumes of labeled data is expensive. On the other hand, it is significantly easier and less expensive to gather massive volumes of unlabeled skin data. Semi-supervised learning aims to considerably alleviate the problems brought about by a lack of large-scale labeled data by allowing a model to use the available unlabeled data. In a few studies [13–16], semi-supervised learning has been used for the identification of skin issues. Semi-supervised deep learning has recently gained increased attention in the field of computer vision, and a few effective models with excellent performance have been created [17–19, 32]. It could be possible to interpret these models and create semi-supervised deep-learning models, particularly for the identification of skin diseases.

Investigate the use of swarm intelligence approaches for disease diagnosis: In recent years, swarm intelligence approaches (SIA) [33-38] have achieved performance in several areas, including skin cancer [37], plant disease [36], and kidney disease [35]. The success of bioinspired algorithms has been largely attributed to their strong function approximation abilities. SIA can be used to solve them since many medical decision-making challenges are sequential. The findings of various researches that employed SIA to tackle medical image processing problems were favorable [33, 35, and 37]. As far as we are aware, no research has employed SIA to identify skin conditions. SIA thus has the potential to be an effective tool for identifying skin issues.

Possible explanations for bioinspired algorithm predictions: Explainability is a significant impediment to the use of bioinspired techniques in clinical diagnostic settings. Instead of relying just on a confidence score to forecast the occurrence of skin infections, bioinspired algorithms require a detailed rationale for their predictions. The ABCDE criteria (asymmetry, border, color, diameter, and evolution) or the 7-point skin lesion malignancy checklist (pigment network, regression structures, pigmentation, vascular structures, streaks, spots, and globules, and blue-whitish veil) are two alternative treatments to this problem [39].

4. ANALYSIS OF RESULTS

A non-exclusive correlation of recent results is included in this phase. This is a summary of the present relationship between each class's findings. In the statistics that follow, the assessment percentage of current investigations from 2000 to 2023 is shown Figure 3 and 5. In this article, neural networks and swarm intelligence are studied for the diagnosis of skin diseases. Methods for a variety of parameters, including accuracy, time, and complexity, are included in Tables 3 and 4(Figure 2 and 4). This review article discusses neural network-based methods. ALEnezi [14] proposed a method for detecting skin problems detected diseases such as eczema, melanoma, and psoriasis with 100% accuracy. Swarm intelligence-based solutions have been addressed, according to Chatterjee et al. [35], by using CS to train the neural network, which attempts to lower the root mean squared error sustained throughout the training phase. Experimental results show that neural networks trained with CS perform significantly better and are 99.2% accurate.

Table 3. Comparison and evaluation of neural networks approaches for disease detection

Authors	Accuracy	Time	Complexity	Diseased detected	Minimum Size of image
Chakraborty et al. [13]	87.92%	medium	medium	Skin	100 × 100
ALEnezi [14]	100%	high	high	Skin	100 × 100
Li et al. [15]	96%	medium	medium	Covid-19	100 × 100
Venkataramana et al. [16]	99.4%	high	high	Brinjal Plant Disease	100 × 100
Gouda et al. [17]	85.7%	medium	medium	Skin	100 × 100
Gautam et al. [18]	98%	high	high	Skin	100 × 100
Yasir et al. [19]	90%	medium	medium	Dermatological	100 × 100
Pollap et al. [32]	82%	high	high	skin disease	100 × 100

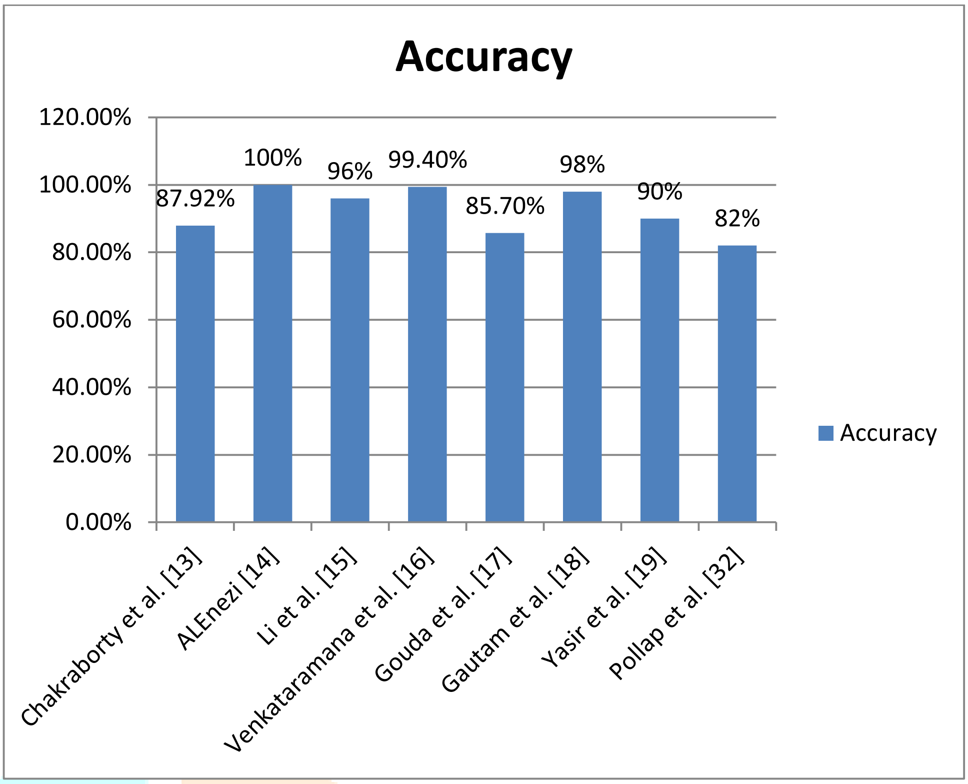

Fig.2. Comparison of Accuracy achieved neural networks approaches

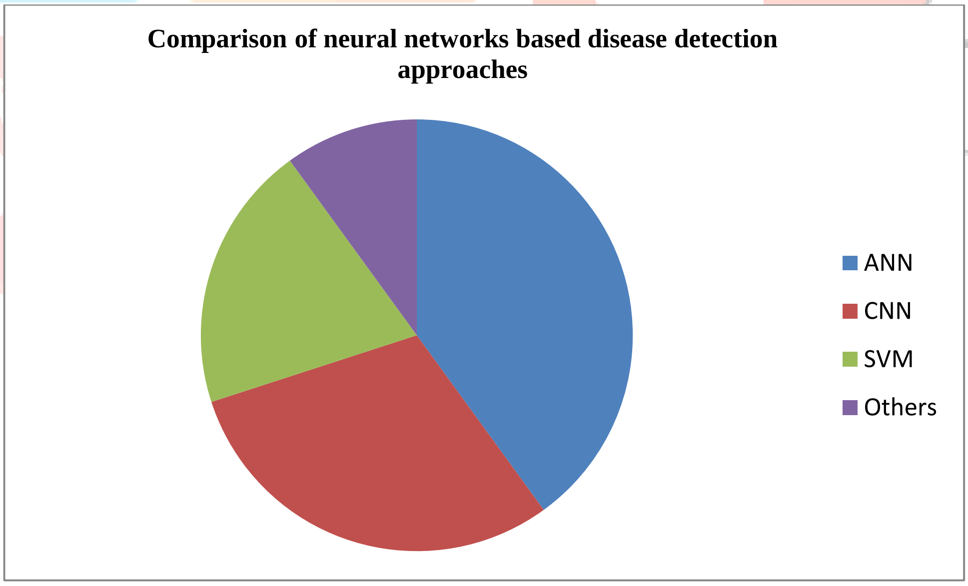

Fig.3. Neural networks based disease detection approaches

Table 4. Comparison and evaluation of swarm intelligence approaches for disease detection

Authors	Accuracy	Time	Complexity	Diseased detected	Minimum Size of image
İlkin et al. [33]	97.56 %	high	high	skin cancer	100 × 100
Fahad et al. [34]	72.69 %	high	high	Iris, Liver	100 × 100
Chatterjee et al. [35]	99.2%	medium	medium	Kidney Disease	100 × 100
Cristin et al. [36]	87.7%	medium	medium	plant disease	100 × 100
Lakshmi et al. [37]	99.26 %	high	high	Skin Cancer	100 × 100
Khan et al. [38]	96%	high	high	skin	100 × 100
Narin [40]	99.86 %	medium	medium	COVID-19	100 × 100

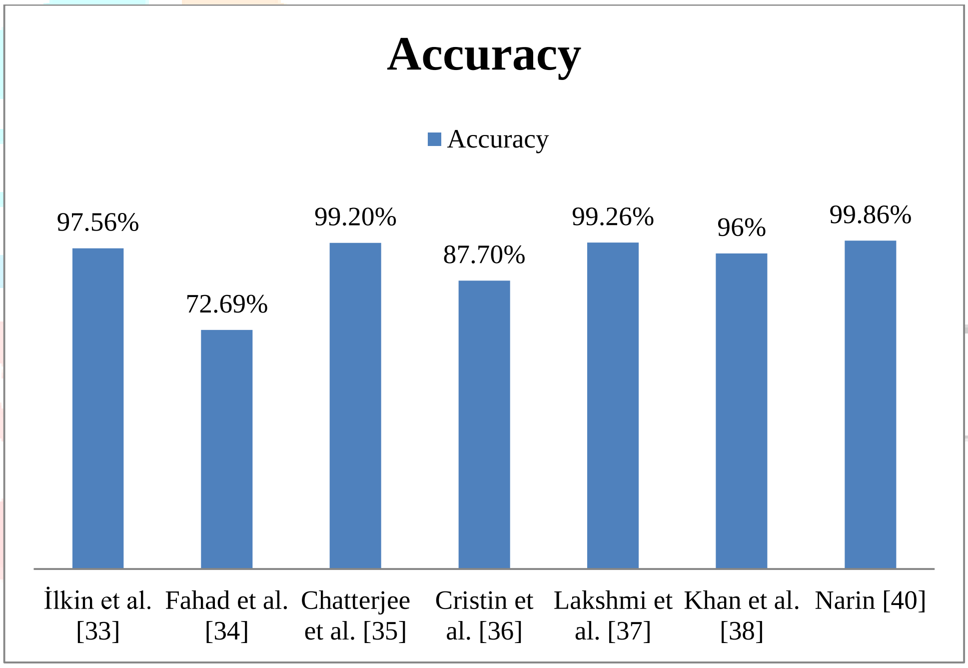

Fig.4. Comparison of Accuracy achieved swarm intelligence approaches

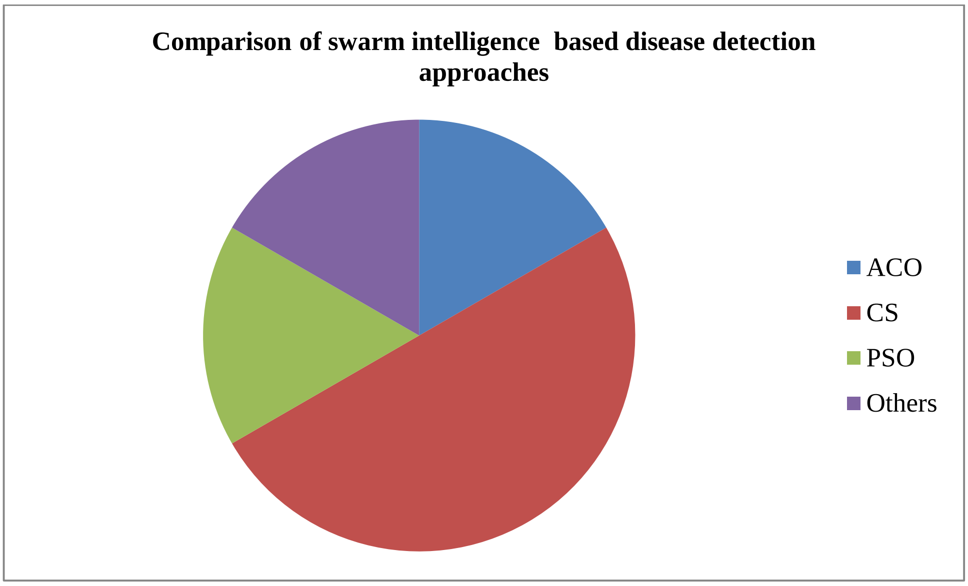

Fig.5. Swarm intelligence based disease detection approaches

5. CONCLUDING DISCUSSION AND FUTURE WORK

In this article, we present a summary of the latest innovations in disease detection using image processing techniques and machine learning algorithms with a bioinspired approach. The first thing we'll do is go through the technical aspects of skin disease. Second, alternative image processing techniques for identifying and classifying diseases using bio-inspired machine learning algorithms applied to chest X-rays and skin disease database images and analyze image processing applications for illness detection based on particular tasks such as segmentation, classification, and multi-task learning. The remaining challenges in disease diagnosis using image processing techniques in disease detection and classification by bioinspired machine learning algorithms are then discussed, along with possible future research directions. We conclude by summarizing the entire article.

Compared to previous pertinent literature reviews, this one offers a thorough analysis of the subject of skin disease and COVID-19 diagnostics, with a focus on modern applications of image processing methods employing bio-inspired machine learning approaches. The fundamental concepts in the field of skin disease diagnosis and detecting COVID-19 using chest X-rays and digital skin images and the challenges faced in this field are intuitively understood via the content of this article. Further, people who are interested in working in this field in the future should look into a variety of different methods for resolving these problems.

The advantages of employing digital skin images and chest X-rays to automatically identify diseases are enormous. On the other hand, accurate diagnosis emphasizes the necessity of reliable automated diagnosis methods that may be used in the diagnostic process by both expert and inexperienced physicians. According to the article, various bioinspired machine-learning approaches have been presented with equivalent or higher diagnosis performance on experimental skin disease and chest X-ray datasets. We should be conscious of the fact that a computer-aided COVID-19 and skin disease diagnosis system should be extensively examined before it is employed for actual clinical diagnoses.

In summary, it is essential to propose a bioinspired machine learning approach in the future to classify the types of skin diseases. Therefore, an automatic classification of skin-related diseases can be detected using a deep neural network-based approach. Also, by using this innovative technique, the system can enhance accuracy and reduce the time and complexity of the identification of skin diseases.

Conflict of Interest: The authors affirm that they have no financial 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.

Funding: The authors received no specific funding for this project.

References

[1] Turing, A. M. (1936). On computable numbers, with an application to the Entscheidungsproblem. *J. of Math*, *58*(345-363), 5.

[2] Shanthi, T.; Sabeenian, R.S.; Anand, R. Automatic Diagnosis of Skin Diseases Using Convolution Neural Network. Microprocess. Microsyst. 2020, 76, 103074.

[3] American Cancer Society. Key Statistics for Melanoma Skin Cancer. 2022. Available online: https://www.cancer.org/cancer/ melanoma-skin-cancer/about/key-statistics.html (accessed on 27 October 2022).

[4] Wei, L.-S.; Gan, Q.; Ji, T. Skin Disease Recognition Method Based on Image Color and Texture Features. Comput. Math. Methods Med. 2018, 2018, 8145713.

[5] Amarathunga, A.A.L.C.; Ellawala, E.P.W.C.; Abeysekara, G.N.; Amalraj, C.R.J. Expert System for Diagnosis Of Skin Diseases. Int. J. Sci. Technol. Res. 2015, 4, 174–178.

[6] Bajwa, M.N.; Muta, K.; Malik, M.I.; Siddiqui, S.A.; Braun, S.A.; Homey, B.; Dengel, A.; Ahmed, S. Computer-Aided Diagnosis of Skin Diseases Using Deep Neural Networks. Appl. Sci. 2020, 10, 2488.

[7] Monisha, M.; Suresh, A.; Rashmi, M.R. Artificial Intelligence Based Skin Classification Using GMM. J. Med. Syst. 2019, 43, 3.

[8] Kassem, M.A.; Hosny, K.M.; Damaševiˇcius, R.; Eltoukhy, M.M. Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis: A Systematic Review. Diagnostics 2021, 11, 1390.

[9] LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. Nature 2015, 521, 444.

[10] Hosny, K.M.; Kassem, M.A.; Fouad, M.M. Classification of Skin Lesions into Seven Classes Using Transfer Learning with AlexNet. J. Digit Imaging 2020, 33, 1325–1334.

[11] Wu, H.; Yin, H.; Chen, H.; Sun, M.; Liu, X.; Yu, Y.; Tang, Y.; Long, H.; Zhang, B.; Zhang, J.; et al. A Deep Learning, Image-Based Approach for Automated Diagnosis for Inflammatory Skin Diseases. Ann. Transl. Med. 2020, 8, 581.

[12] Khan, M.A.; Akram, T.; Sharif, M.; Kadry, S.; Nam, Y. Computer decision support system for skin cancer localization and classification. Comput. Mater. Contin. 2021, 68, 1041–1064.

[13] Chakraborty, S., Mali, K., Chatterjee, S., Banerjee, S., Mazumdar, K. G., Debnath, M., ... & Roy, K. (2017, August). Detection of skin disease using metaheuristic supported artificial neural networks. In *2017 8th Annual Industrial Automation and Electromechanical Engineering Conference (IEMECON)* (pp. 224-229). IEEE.

[14] ALEnezi, N. S. A. (2019). A method of skin disease detection using image processing and machine learning. *Procedia Computer Science*, *163*, 85-92.

[15] Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., ... & Xia, J. (2020). Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy. *Radiology*, *296*(2), E65-E71.

[16] Venkataramana, A., Kumar, K. S., Suganthi, N., & Rajeswari, R. (2022). Prediction of Brinjal Plant Disease Using Support Vector Machine and Convolutional Neural Network Algorithm Based on Deep Learning. Journal of Mobile Multimedia, 771-788.

[17] Gouda, W., Sama, N. U., Al-Waakid, G., Humayun, M., & Jhanjhi, N. Z. (2022, June). Detection of skin cancer based on skin lesion images using deep learning. In *Healthcare* (Vol. 10, No. 7, p. 1183). MDPI.

[18] Gautam, V., Trivedi, N. K., Anand, A., Tiwari, R., Zaguia, A., Koundal, D., & Jain, S. Early Skin Disease Identification Using Deep Neural Network.

[19] Yasir, R., Rahman, M. A., & Ahmed, N. (2014, December). Dermatological disease detection using image processing and artificial neural network. In *8th International Conference on Electrical and Computer Engineering* (pp. 687-690). IEEE.

[20] Lundervold, A. S., & Lundervold, A. (2019). An overview of deep learning in medical imaging focusing on MRI. Zeitschrift für Medizinische Physik, 29(2), 102-127.

[21] Ahmad, M. (2021). Ground truth labeling and samples selection for hyperspectral image classification. Optik, 230, 166267.

[22] Kayalibay, B., Jensen, G., & van der Smagt, P. (2017). CNN-based segmentation of medical imaging data. arXiv preprint arXiv:1701.03056.

[23] Li, Q., Cai, W., Wang, X., Zhou, Y., Feng, D. D., & Chen, M. (2014, December). Medical image classification with convolutional neural network. In 2014 13th international conference on control automation robotics & vision (ICARCV) (pp. 844-848). IEEE.

[24] Umer, M., Sadiq, S., Ahmad, M., Ullah, S., Choi, G. S., & Mehmood, A. (2020). A novel stacked CNN for malarial parasite detection in thin blood smear images. *IEEE Access*, *8*, 93782-93792.
[25] Rouhi, R., Jafari, M., Kasaei, S., & Keshavarzian, P. (2015). Benign and malignant breast tumors classification based on region growing and CNN segmentation. Expert Systems with Applications, 42(3), 990-1002.
[26] Sharif, M., Attique Khan, M., Rashid, M., Yasmin, M., Afza, F., & Tanik, U. J. (2021). Deep CNN and geometric features-based gastrointestinal tract diseases detection and classification from wireless capsule endoscopy images. *Journal of Experimental & Theoretical Artificial Intelligence*, *33*(4), 577-599.
[27] Asada, N., Doi, K., MacMahon, H., Montner, S. M., Giger, M. L., Abe, C., & Wu, Y. U. Z. H. E. N. G. (1990). Potential usefulness of an artificial neural network for differential diagnosis of interstitial lung diseases: pilot study. Radiology, 177(3), 857-860.
[28] Katsuragawa, S., & Doi, K. (2007). Computer-aided diagnosis in chest radiography. Computerized Medical Imaging and Graphics, 31(4-5), 212-223.
[29] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. nature, 542(7639), 115-118.
[30] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. nature, 542(7639), 115-118.
[31] Dong, Y., Pan, Y., Zhang, J., & Xu, W. (2017, July). Learning to read chest X-ray images from 16000+ examples using CNN. In 2017 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE) (pp. 51-57). IEEE.
[32] Połap, D., Winnicka, A., Serwata, K., Kęsik, K., & Woźniak, M. (2018). An intelligent system for monitoring skin diseases. Sensors, 18(8), 2552.
[33] İlkin, S., Gençtürk, T. H., Gülağız, F. K., Özcan, H., Altuncu, M. A., & Şahin, S. (2021). hybSVM: Bacterial colony optimization algorithm based SVM for malignant melanoma detection. *Engineering Science and Technology, an International Journal*, *24*(5), 1059-1071.
[34] Fahad, L. G., Tahir, S. F., Shahzad, W., Hassan, M., Alquhayz, H., & Hassan, R. (2020). Ant colony optimization-based streaming feature selection: an application to the medical image diagnosis. *Scientific Programming*, *2020*, 1-10.
[35] Chatterjee, S., Banerjee, S., Basu, P., Debnath, M., & Sen, S. (2017, April). Cuckoo search coupled artificial neural network in detection of chronic kidney disease. In 2017 1st International conference on electronics, materials engineering and nano-technology (IEMENTech) (pp. 1-4). IEEE.
[36] Cristin, R., Kumar, B. S., Priya, C., & Karthick, K. (2020). Deep neural network based Rider-Cuckoo Search Algorithm for plant disease detection. *Artificial intelligence review*, *53*, 4993-5018.
[37] Lakshmi, S.A., Anandavelu, K., (2022). Enhanced Cuckoo Search Optimization Technique for Skin Cancer Diagnosis Application. *Intelligent Automation & Soft Computing*, 35, 3403-3413.
[38] Khan, M. Q., Hussain, A., Rehman, S. U., Khan, U., Maqsood, M., Mehmood, K., & Khan, M. A. (2019). Classification of melanoma and nevus in digital images for diagnosis of skin cancer. *IEEE Access*, 7, 90132-90144.
[39] Goyal, M., Knackstedt, T., Yan, S., Oakley, A., Hassanpour, S.: Artificial intelligence-based image classification for diagnosis of skin cancer: Challenges and opportunities. arXiv preprint arXiv:1911.11872 (2019)
[40] Narin, A. (2021). Accurate detection of COVID-19 using deep features based on X-Ray images and feature selection methods. Computers in Biology and Medicine, 137, 104771.
[41] Mandal, A. K., Sarma, P. K. D., & Dehuri, S. Machine Learning Approaches and Particle Swarm Optimization Based Clustering for the Human Monkeypox Viruses: A Study. In International Conference on Innovations in Intelligent Computing and Communications, Springer, Cham, 313--332, (2022).
[42] Mandal, A. K., & Dehuri, S. A survey on ant colony optimization for solving some of the selected np-hard problem. In International Conference on Biologically Inspired Techniques in Many-Criteria Decision Making, Springer, Cham, 85--100, (2020).