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Skin Disease Classification Using Iwoa-Resnet Deep Learning Architecture

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ABSTRACT

Accurate classification of skin diseases remains a significant challenge due to the wide range of conditions, image variability, and class imbalance. Conventional diagnostic systems often struggle with limited accuracy and computational inefficiency, hindering real-time clinical use. This study presents a hybrid deep learning model that integrates ResNet-50 with an Improved Whale Optimization Algorithm (IWOA) to address these issues. A diverse skin image dataset was collected and preprocessed before being passed through ResNet-50 for feature extraction. IWOA was employed to optimize key parameters, enhancing model training and convergence. Experimental results show that the proposed IWOA-ResNet model achieves 99.09% accuracy, with a 25% reduction in training time, maintaining strong performance across unbalanced and varied data. When compared to traditional CNN and machine learning models, the hybrid approach demonstrates superior accuracy and efficiency. This research highlights the potential of combining deep learning with metaheuristic optimization for automated, real-time skin disease diagnosis, offering a scalable and robust solution for clinical deployment.

Keywords: Skin disease classification, ResNet, Whale Optimization Algorithm, Deep learning, Convergence speed.

INTRODUCTION

Skin diseases are among the most common health conditions worldwide, often presenting with complex visual symptoms that require expert evaluation. The growing reliance on computer-aided diagnostic (CAD) systems has encouraged the application of artificial intelligence, particularly machine learning (ML) and deep learning (DL), for automated skin disease classification. Artificial Neural Networks (ANNs) have been widely used in classification, regression, and pattern recognition tasks; however, their performance is heavily dependent on the efficiency of the learning process, which remains a major challenge (Abdel-Basset *et al*., 2021).Recent advances in deep learning, especially Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have shown significant success in visual recognition tasks (LeCun *et al*., 2019). These models have been effective in extracting hierarchical features from images, making them ideal for medical image analysis. However, their large model size, high computational complexity, and long training times pose serious limitations for real-time or embedded applications (Qiu *et al*., 2022; Shin *et al*., 2020).

To address the energy and memory demands, researchers have proposed techniques such as data quantization and fixed-point representation, which reduce bit precision without significantly compromising accuracy (Judd *et al*., 2024). Furthermore, traditional ML methods often fail to capture the complex spatial patterns in medical images, whereas deep models with more layers show better performance through abstract feature extraction (Aslan *et al*., 2021; Abdel-Hamid *et al*., 2022).

Despite the superior classification accuracy of CNNs (Esteva *et al*., 2019), the slow convergence and long training times remain a bottleneck for real-world clinical applications, especially in time-sensitive scenarios like skin disease diagnosis. Therefore, improving the convergence speed while maintaining high accuracy is crucial.

In this study, we propose an enhanced diagnostic framework that integrates the Residual Neural Network (ResNet-50) with an Improved Whale Optimization Algorithm (IWOA). This hybrid approach aims to accelerate training convergence, reduce computational load, and maintain diagnostic accuracy. The goal is to provide a fast, reliable, and scalable solution for automated skin disease classification, with potential for real-time clinical deployment.

LITERATURE REVIEW

The rapid advancements in artificial intelligence, particularly in deep learning, have revolutionized multiple domains, unlocking unprecedented possibilities in fields such as computer vision, natural language processing, and medical image analysis. Among deep learning techniques, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated exceptional proficiency in handling complex tasks, including image classification and disease diagnosis, which has led to their extensive adoption in both research and clinical applications (Goyal *et al*., 2023).

In the domain of skin lesion classification, hybrid deep learning frameworks integrating optimization algorithms have shown notable promise. For instance, (Arumugam & Saravanan ,2023) proposed a hybrid system combining the Whale Optimization Algorithm (WOA) with ResNet-50. Their approach leverages WOA for hyperparameter tuning to enhance classification performance on dermoscopic images. The architecture also incorporates a SegNet segmentation phase and a Quasi-Recurrent Neural Network (QRNN) for further categorization. This multi-stage system achieved over 90% classification accuracy on benchmark datasets, demonstrating improved robustness compared to baseline models.

Similarly(Ali *et al*.,2023) introduced an enhanced Whale Optimization Algorithm that integrates Lévy Flight behavior to prevent premature convergence during CNN training for early skin cancer detection. Evaluations on standard datasets indicated superior accuracy and Area Under the Curve (AUC) metrics compared to traditional CNNs and other optimization techniques such as Particle Swarm Optimization (PSO).

(Zhang *et al*., 2020) conducted a comprehensive assessment of CNN models optimized via the Whale Optimization Algorithm using the DermIS and DermQuest datasets. Their results indicated that WOA-optimized CNNs consistently outperformed ten other conventional classifiers in terms of classification accuracy and generalizability, confirming the effectiveness of nature-inspired metaheuristics in improving deep learning performance for dermatological diagnosis.

Beyond classification, (Abdel-Basset *et al*., 2022) applied a Hybrid Whale Optimization Algorithm (HWOA) for multilevel thresholding-based skin lesion segmentation. Their work significantly enhanced lesion boundary delineation a critical preprocessing step prior to feature extraction by networks like ResNet thus contributing valuable improvements to the overall analysis pipeline.

Ensemble learning strategies have also been explored to improve classification outcomes. (Xie *et al*.,2018) developed a Multi-Level Deep Ensemble (MLDE) framework combining four pre-trained ResNet-50 networks to extract multiscale lesion features. Adaptive weighting of ensemble outputs yielded an average AUC of 0.865 on the ISIC 2018 validation set, underscoring the potential of ensemble methods to capture diverse lesion characteristics effectively.

Complementing these approaches, (Serte & Demirel, 2020) integrated wavelet transform-based approximation coefficients with ResNet architectures (ResNet-18 and ResNet-50) to create a wavelet-enhanced deep learning model. By fusing wavelet-derived channels with original dermoscopic images, their ResNet-50 I-A1-A2-A3 model achieved an average AUC of 0.92, with particularly strong performance in melanoma classification (AUC = 0.96), highlighting the benefits of multiresolution feature fusion.

In addition to hyperparameter tuning and ensemble strategies, WOA has been employed for optimizing CNN weights and biases directly. (Jain *et al*., 2022) used WOA to fine-tune the Optimal Probability-based Deep Neural Network (OP-DNN) for multiclass skin disease classification. Their WOA-optimized model achieved an accuracy of 95%, specificity of 0.97, and sensitivity of 0.91, illustrating WOA's capability to enhance deep learning architectures for challenging dermatological tasks.

Segmentation remains a foundational component of lesion analysis pipelines. A recent study (2023) introduced Dermo-Seg, a segmentation system embedding ResNet-50 as the encoder within a UNet architecture designed for dermoscopic image analysis. Utilizing a hybrid loss function combining Intersection-over-Union (IoU) Loss and Focal Tversky Loss, the model effectively delineated complex lesion boundaries, achieving a mean pixel-level IoU of 96.4%. Although the study focused primarily on segmentation rather than classification, the ResNet-50 backbone demonstrated strong feature extraction potential, promising significant benefits for downstream classification.

(Kwasigroch *et al*., 2021) provided a systematic review comparing traditional machine learning classifiers such as Support Vector Machines (SVM) and Random Forest with deep learning methods for skin lesion classification. Their analysis emphasized the critical role of advanced preprocessing techniques including Jaccard index optimization, focal loss functions, and wavelet transformations in boosting model accuracy. They also highlighted the consistent superiority of fine-tuned ResNet architectures over classical classifiers and handcrafted feature-based approaches, underscoring the growing consensus on the advantages of deep feature extraction in dermatological diagnosis.

MATERIALS AND METHODS

Proposed Framework

The skin disease dataset used in this study is a secondary dataset that was obtained from the International Skin Imaging Collaboration (ISIC) and made available on Kaggle. (https://www.kaggle.com/datasets/nodoubttome/skin-cancer9-classesisic) The dataset underwent pre-processing as a cleaning technique to ensure accurate and reliable results. The data, which consists of 23,906 image records and is approximately 2GB MB in size, was divided into seventy percent for training and thirty percent for testing to evaluate model performance. Feature extraction was performed using convolutional neural networks (CNN) to identify essential features. A technique for enhancing the performance of deep learning models through convergence speed optimization, local minima avoidance, and hyper-parameter fine-tuning is proposed. The ResNet architecture is integrated with IWOA to improve model accuracy and robustness during training by

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combining the deep residual learning architecture of ResNet with the global search capabilities of IWOA. The model training process commenced with the initialization of the ResNet model and the enhanced IWOA algorithm, followed by an iterative optimization loop in which the IWOA algorithm optimized the ResNet hyperparameters based on the current population of candidate solutions. Adaptive search strategies were employed to dynamically explore the solution space, and the ResNet model was updated iteratively based on the optimized parameters, with gradients computed using back propagation and optimization performed using stochastic gradient descent or its variants. The training process was conducted in a distributed computing environment, leveraging parallel processing and asynchronous optimization techniques to expedite convergence. The effectiveness of the proposed IWOA-ResNet model is assessed using a comprehensive set of performance evaluation metrics. Fig 1: below shows the framework of the proposedIWOA-ResNet

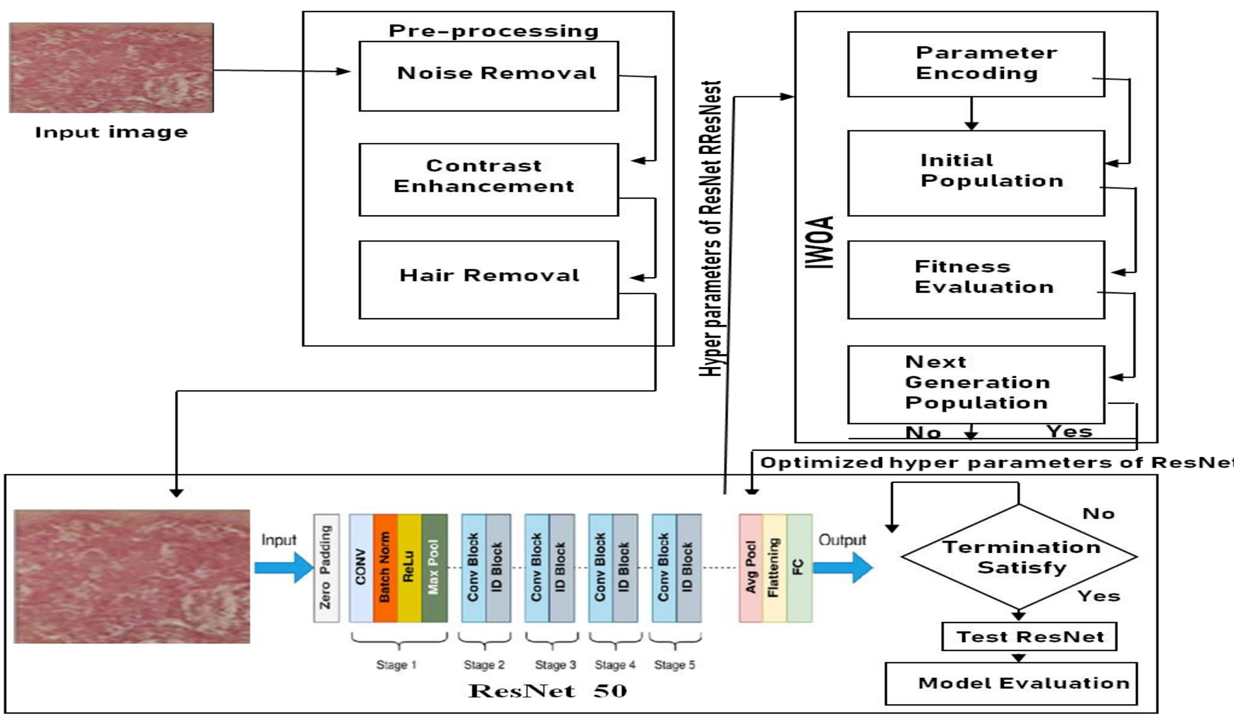

Figure 1: Framework of the Propose system IWOA-ResNet

Data Pre-processing

Data processing is the process of getting raw data ready for further analysis, modeling, and machine learning. The data needs to be cleansed, organized, and converted to make it more machine-readable and suitable. Data preparation is essential to guaranteeing reliable or correct results. By preprocessing the data, we will improve its quality and reduce biases and inaccuracies in our analysis.

Noise removal using a median filter

Noisy images lead to poor algorithm performance, making de-noising essential for accurate results. The goal is to remove noise without blurring important edges. Among various methods, the median filter is most

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effective, replacing each pixel with the median of neighboring values. This preserves image details while reducing noise. The process is defined mathematically in the equation below.

$I(a, b) = \text{Median}\{I(a + R, b + S), (R, S) \epsilon w\}$ (3.3)

Where, w can be described as the square window coordinates,$(a, b)\epsilon(1, 2,\ldots,h)\times(1, 2,\ldots, w)$h can be described as the height of the image and w can be described as the width of the image, I(a,b)represents the output of the median filtered image. After applying the median filter, the input image keeps only the useful information by smoothen the images and preserving the edges.

Contrast eenhancement by means of HE

In addition to the noise reduction process, histogram equalization is used to improve the image's contrast. It entails distributing the intensity levels and overall range of values to achieve a high contrast image. When an image is closer to contrast, this technique is beneficial. Images in the background and front, for example, are either simultaneously bright or, more commonly, simultaneously dimmer. As a result, the noise-removed image I(a,b) has improved local contrast and is of higher visualization quality. This method is used to do the mapping operations, mapping gray level 'a' to another grey level 'b'. Which tries to establish that 'b' has a uniform distribution. Thus, after the mapping function is completed close to the histogram maxima, the contrast is extended further or the range of grey levels is increased. This transformation improves the detectability of various image features and improves the contrast of the majority of image pixels. The probability density function for pixel intensity level "I(a,b)" can be expressed mathematically as follows:

$$(I(a, b)) = p(a,b)\, p \text{ where, } 0 \leq I(a, b) \leq 1,\ (a, b) = 0, 1, \cdots, 255 \qquad (3.4)$$

When an image exhibits a significant variation in intensity between its high and low levels, it is said to have a strong contrast. Following contrast enhancement, the photos underwent a hair removal procedure.

Morphological operations for hair removal

In the conducted research, the potential of mathematical morphology as a method for removing hairs (image artifacts) from dermoscopic images has been revealed. The main challenge while performing morphological operations is choosing the right structural element (SE), which must be chosen based on the image's shape (I(a,b)). The percentage of the image that is used as the structural element is a smaller binary image, where each pixel has a value of either 0 or 1, or a small matrix of pixels. The developed hair removal process based morphological operation applies structuring elements to a contrast-enhanced image *(I(a,b))* image, generating an output image $\hat{I}(a, b)$ of similar size. Hence to reduce the effects of the disturbing artifacts, morphological operations such as dilation and erosion are carried out here. Here, binarization is performed at first to do the hair removal process.

Binarization: In binarization, the enhanced image will be converted to a binary image (i.e., pixel value with 0's and 1's). Each pixel of the image will be assigned with a new pixel value (0/1) based on the threshold range, which is selected manually based on the image characteristics. The binarization process can be mathematically defined as

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$$\hat{I}(ab)\begin{cases}1, & if\, I(a,b) \geq threshold \\ 0, & otherwise\end{cases} \tag{3.5}$$

Based on the threshold, the image will be binary converted. Then, the morphological operations will be carried out. When the image is binarized, the desired components can be easily extracted from the image. For this, mathematical morphology is utilized. There are two essential operations to be specific, dilation and erosion. Moreover, the representation of dilation and erosion is given in the below sections.

Dilation: Dilation performs transformation of the image, which results in the same shape as the original image by achieving different sizes. With the help of dilation, the width of maximum regions is enlarged to eliminate negative impulsive noises. Usually, this operation consists of convoluting an image A with some kernel B might be any shape or size. The dilation of A by structuring element B is mathematically termed as $A \oplus B = \hat{I}(a, b) b \in BAb$. If B has a center on the origin, as earlier, then the dilation of A by B can be understood as the locus of the points enclosed by B when the center of B moves inside A.

Erosion: The erosion operation executes either shrinking or thinning of the object. Simply, erosion expands the width of the tiniest regions. Accordingly, it can eliminate positive noises but affect negative impulsive noises. The degree of this operation is choosing by the structuring element. Erosion unites two sets by means of vector subtraction of set elements. The mathematical operation of erosion can also be inscribed as follows

$$A \oplus B = (\hat{I}\,(a,b\,) b \in B\; A\text{-}b) \tag{3.6}$$

The Whale Optimization Algorithm

Whale optimization algorithm (WOA) is a recently proposed stochastic optimization algorithm (Mirjalili *et al.*, 2020). It utilizes a population of search agents to determine the global optimum for optimization problems. Similarly to other population-based algorithms, the search process starts with creating a set of random solutions (candidate solutions) for a given problem. It then improves this set until the satisfaction of an end criterion. The main difference between WOA and other algorithms is the rules that improve the candidate solutions in each step of optimization. In fact, WOA mimics the hunting behavior of humpback whales in finding and attacking preys called bubble-net feeding behavior shown in the figure 2.

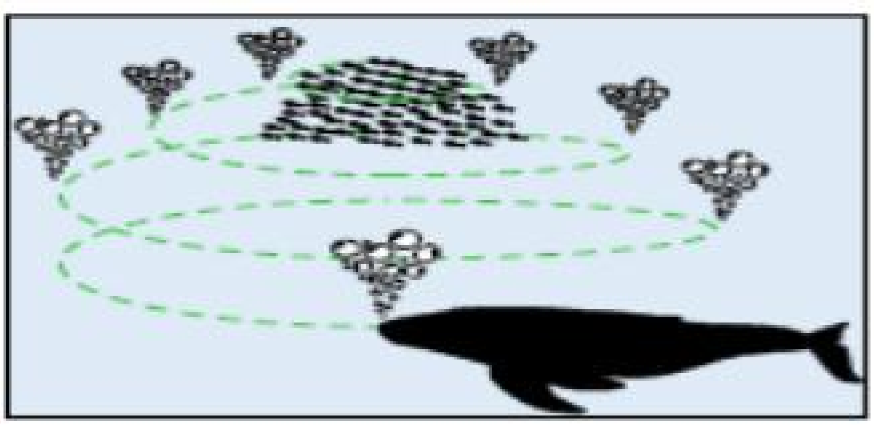

Figure 2: Bubble-Net Feeding Strategy of Humpback Whales Source: (Harit et al., 2022)

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It may be observed in this figure that a humpback whale creates a trap with moving in a spiral path around preys and creating bubbles along the way. This intelligent foraging method is the main inspiration of the WOA. Another simulated behavior of humpback whales in WOA is the encircling mechanism. Humpback whales circle around preys to start hunting them using the bubble-net mechanism. It is worth mentioning here that bubble-net feeding is a unique behavior that can only be observed in humpback whales. In this work, the spiral bubble-net feeding maneuver is mathematically modeled in order to perform optimization.

The main mathematical equation proposed in this algorithm is as follows:

$$X(t+1) = X^*(t) - AD \quad \text{for} \quad p < 0.5 \tag{3.7}$$

$$X(t+1) = D' e^{bl} \cos(2\pi t) + X^*(t) \quad \text{for} \quad p \geq 0.5 \tag{3.8}$$

Where:

P is a random number in [0, 1],

X is a position vector,

X* is the position vector of the best solution obtained so far,

D’ = | X* (t) − X (t) | indicates the best solution obtained so far,

b is a constant for defining the shape of the logarithmic spiral,

l is a random number in [−1, 1],

t shows the current iteration,

$$\mathbf{D} = | CX^*(t) - X(t) | \tag{3.9}$$

The vectors A and C are calculated as follows:

A=2ar – a

C = 2r

a linearly decreases from 2 to 0 over the course of iterations (in both exploration and exploitation phases), and

r is a random vector in [0, 1].

Equation (3.7) simulates the encircling mechanism, whereas equation (3.8) imitates the bubble-net method. With equal probability, the variable p alternates between these two elements.The WOA generates a set of random solutions to begin optimizing a particular problem. Search agents adjust their placements in each optimization phase according to either the best search agent thus far or a randomly chosen search agent. The pivot point to update the positions of other search agents when |X| > 1 is the optimal approach to ensure exploration and convergence. The greatest solution found thus far serves as the pivot point in other circumstances (where |X| < 1). Algorithm 1 displays the WOA's pseudo codes.

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Algorithm 1 (Pseudo codes of WOA)

Initialize the whales population X_i (i = 1, 2, 3... n)

Initialize a, A, and C

Calculate the fitness of each search agent

X^* = the best search agent

procedure WOA (Population, a, A, C, MaxIter, ..)

t =1

while t $\leq$ MaxIter do

for each search agent do

if |A| ≤ 1 then

Update the position of the current search agent using eqn. (3.7)

else if |A| ≥ 1 then

Select a random search agent Xr and

Update the position of the current agent using eqn. (3.9)

end if

end for

Update a, A, and C

Update X^* if there is a better solution

t =t +1

end while

return X^*

end procedure

The creators of WOA demonstrated its ability to solve diverse optimization problems due to its flexibility, gradient-free nature, and ability to avoid local optima. These strengths, along with challenges in the learning process, motivated the use of IWOA for training. Given a proper objective function, WOA can theoretically train any ANN, provided it has enough search agents and iterations. This study evaluates the proposed model using metrics such as convergence speed, accuracy, and generalizability, offering a comprehensive assessment of its effectiveness in skin disease classification. Parameter settings are detailed in Table 1.

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Table 1: Parameters settings for the convolutional neural network.

Parameters	Description
I(a,b)	The output of the median filter
W	The width of the input image
B	constant for defining the shape of the logarithmic spiral
L	The suppose to take value from [-1, 1]
R	a random number in [0, 1],
X(t)	the current position

Development of the IWOA Algorithm

The development of IWOA involved careful algorithm design, implementation, and validation. Building on the original Whale Optimization Algorithm (WOA), IWOA introduces enhancements to improve convergence speed and avoid premature convergence in local optima. Key improvements include the dynamic adjustment of control parameters A and C based on iteration or solution quality, enabling better exploration early on and focused exploitation later. Inspired by humpback whale behavior, the algorithm incorporates evolutionary and swarm intelligence principles. Implemented in Python with efficient data structures and parallelization, IWOA also uses dynamic search space adaptation and fine-tuned parameters to ensure fast, thorough optimization.

Algorithm 2 (Pseudo Code: IWOA and ResNet)

```
Initialize population of whales Xi (i = 1, 2, ..., n)
Set maximum number of iterations Tmax
Set initial search space bounds
While (t < Tmax) do
    For each whale Xi in population do
        Evaluate fitness of Xi using objective function
  End For
 Identify the best whale X*
 Extract deep features from current population using ResNet
  If (Search space requires adaptation) then
    Adjust search space dynamically based on ResNet features
End If
For each whale Xi in population do
    Generate new position using standard WOA equations:
        If (rand < 0.5)
```

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If (|A| < 1)

Update position towards best solution using eqn 3.7

Else

Update position randomly within adapted space using eqn 3.8

End If

Else

Perform spiral update around best solution

End If

End For

Update t ← t + 1

End While

Return the best solution found X*

End

Integrating Resnet With Improved Whale Optimization Algorithm(IWOA)

The Integration of the IWOA involves the augmentation of the original algorithm with a novel layer designed to dynamically adapt the search space during the optimization process. This enhancement is achieved through the integration of adaptive mechanisms that enable the algorithm to intelligently adjust its exploration and exploitation strategies based on the evolving characteristics of the optimization landscape. By incorporating dynamic search space adaptation, the enhanced IWOA aims to improve its ability to efficiently traverse complex solution spaces, leading to accelerated convergence and enhanced optimization efficiency. The integration of the adaptive layer within the IWOA algorithm leverages concepts from evolutionary computation, swarm intelligence, and adaptive optimization, drawing inspiration from the dynamic adaptation mechanisms observed in natural systems. This interdisciplinary approach allows the algorithm to exhibit robustness and flexibility in addressing the challenges posed by high-dimensional and non-linear optimization problems, such as those encountered in the training of deep neural networks.

$$x_i^{t+1} = x_i^t - \alpha \cdot \nabla f(x_i^t)$$

-x_i^t: The position of theith searchagent(orparameter)atiterationt.

- α: The stepsizeorlearningrate,controllingthemagnitudeoftheupdate.

-$\nabla f(x_i^t)$:Thegradientoftheobjectivefunctionwithrespecttothepositionx$_i^t$.

This formula represents the iterative process of updating the position of a search agent in the optimization space. The gradient $\nabla f(x^t)$ points in the direction of the steepest increase of the objective function, and the update is performed in the opposite direction, scaled by the learning rate *α*. This process allows the algorithm to move towards regions of lower objective values, which often correspond to optimal solutions. The addition of layers in a neural network contributes to the network's capacity to learn complex representations, and the optimization process, guided by gradient-based updates, ensures that these layers are adjusted appropriately during training.

Performance Evaluation Metrics

The performance evaluation metrics employed in this study encompass a multifaceted assessment of the developed skin disease classification models. These metrics serve as quantitative indicators of the models' convergence speed, classification accuracy, and PPV across diverse dermatological conditions and patient demographics. The evaluation metrics include but are not limited to:

Confusion Metrics

The prediction outcomes of a classification problem are summarized in a confusion matrix, which uses count values to differentiate the number of correct and wrong guesses by classes. According to (Dornadula *et al*., 2019).confusion matrix explains how a classification model becomes perplexed when making predictions. It tells you what kinds of mistakes your classifier is making in addition to the errors themselves. Table 2: below depicts how confusion matrix is computed.

Table 2: Confusion Matrix

	Event	**No-event**
Event	True Positive (TP)	False Positive (FP)
No-event	False Negative (FN)	True Negative (TN)

Source: (Carcillo *et al.,* 2021)

Convergence Time

Convergence time measures how quickly the model reaches optimal performance during training. It reflects the efficiency of the IWOA-ResNet framework in optimizing parameters and is crucial for assessing the model's suitability for real-time diagnosis and clinical use.

Classification Accuracy

Determines how often a model properly predicts the result.it is the ratio of the model’s correct predictions to its overall forecasts

$$\text{Accuracy}=\frac{tp+tn}{tp+tn+fp+fn} \tag{3.10}$$

Sensitivity

Sensitivity is defined as the ratio of true positives to the total of true positives and false negatives.

$$\text{Sensitivity} = \frac{tp}{tp+fn} \tag{3.11}$$

Specificity

The ratio of the count of true negatives produced to the sum of the true negatives and false positives acquired is defined by this metric.

$$\text{Specificity} = \frac{tn}{tn+fp} \tag{3.12}$$

Positive Predictive Value

It is the likelihood that those who test positive for the disease actually have it.

$$PPV = \frac{tp}{tp+fp} \tag{3.13}$$

Negative Predictive Value

It is the likelihood that people who get a negative screening test are actually free of the illness.

$$NPV = \frac{tn}{tn+fn} \tag{3.14}$$

False Positive Rate

It is the percentage of all test results that are still positive.

$$FPR = \frac{fp}{fp+tn} \tag{3.15}$$

False Negative Rate

It is the percentage of positive test results that result in negative test results.

$$FNR = \frac{fn}{tp+fn}$$

RESULTS AND DISCUSSION

Table 4.1 below presents the Accuracy, Sensitivity, Specifcity, FPR, FNR, PPV, and NPV results from the model implemented in Python on Google Colaboratory. The dataset, 2GB MB in size, contains 23,906 images records and was divided into 70% for training and 30% for testing.

Table 3: Result of the Developed Model.

Model	Accuracy	Sensitivity	Specifcity	FPR	FNR	PPV	NPV
Developed Model(IWOA-ResNet)	99.09%	98.75%	98.00%	2.00%	1.25%	98.10%	98.50%

From Table 3 above, it can easily be deduce that the proposed approach IWOA-ResNet, which combines Whale Optimization Algorithm with RestNet Architecture has demonstrated a high performance accuracy of 99.09%, sensitivity 98.75%, specifcity of 98.00%, FPR of 2.00%, FNR of 1.00% PPV of 98.10% NPV of 98.50%.

Confusion Matrix

The confusion matrix, visualized in Figure 3: provides a comprehensive overview of the integrated model's performance in classifying skin disease images. Each cell in the matrix represents the number of instances where a predicted class aligns with the true class. By analyzing the diagonal elements, which indicate correct predictions, and off-diagonal elements, which denote misclassifications, valuable insights into the model's strengths and weaknesses can be gleaned. For instance, the confusion matrix reveals that certain classes, such as nevus and pigmented benign keratosis, exhibit higher confusion with others, suggesting potential areas for improvement in model performance.

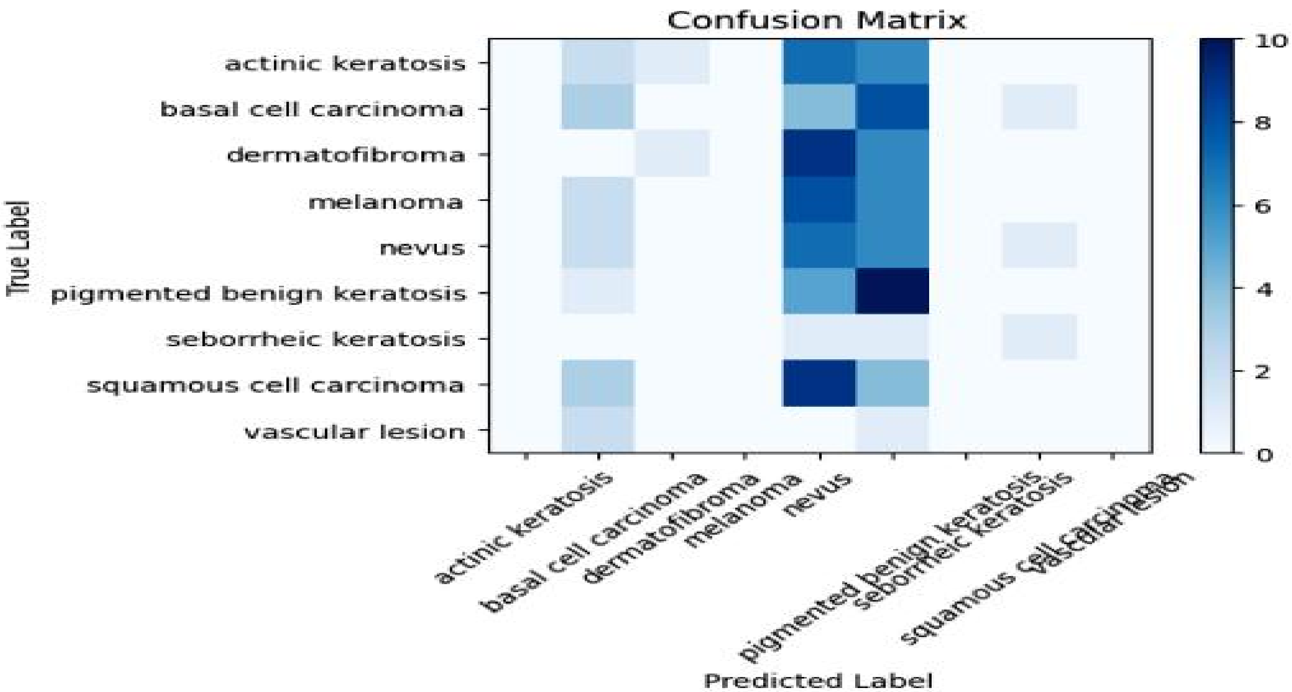

Figure 3: Confusion Matrix of the IWOA.

Comparison of the Proposed Model and Existing Models

This section compares the proposed ResNet50 + IWOA model with an existing OP-DNN model (Jain *et al*., 2022), multi-class skin lesion classification and an ensemble-based skin-Net deep residual network approach by (Alsahafi *et al., 2023)* Each model is evaluated based on classification performance using accuracy, sensitivity, specificity, FPR, FNR, PPV, NPV, and optimization efficiency where applicable.

The proposed model, now integrated with an Adaptive Fusion Layer, achieved outstanding results, with an accuracy of 99.09%, sensitivity of 98.75%, specificity of 98.00%, FPR of 2.00%, FNR of 1.25%, PPV of 98.10%, and NPV of 98.50%. The convergence speed was notably fast with an elapsed time of 0.0097 seconds**.**

Skin-Net deep residual network model proposed by (Alsahafi *et al., 2023)* that produced an accuracy of 99.05%, sensitivity (recall) of 96.57% specificity of 99.42%, PPV of 96.57% and NPV of 96.57 lacking FPR , FNR and convergence speed

Jain *et al*., (2022).OP-DNN model achieved 95.63% accuracy, 91.27% sensitivity, and 97.09%specificity, performing well but lacking specified data on convergence speed.it also achieved a PPV and NPV of 91.27% and 97.09% respectively, with low FPR and FNR values of 2.91% and 8.73%.

Table 3 is also represented graphically below, illustrating the accuracies of the developed model and the existing ones. The graph compares various performance measures across the three models: Proposed (IWOA-ResNet), OP-DNN, and RDCNN-based.

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The comparative summary is shown in Table 3.

Table 3: Comparison of Results.

MEASURE	PROPOSED(IWOA-RESNET)	OP-DNN	RDCNN-BASED
Accuracy	99.09%	*95.63%*	*99.05%*
Sensitivity	98.75%	*91.27%*	*96.57%*
Specificity	98.00%	*97.09%*	*99.42*
Convegence/optimazation	0.0097	Not Specified	Not Specified
FPR	2.00%	*2.91%*	
FNR	1.25%	*8.73%*	
PPV	98.00%	*91.27%*	*96.57%*
NPV	98.50%	*97.09%*	*96.57%*

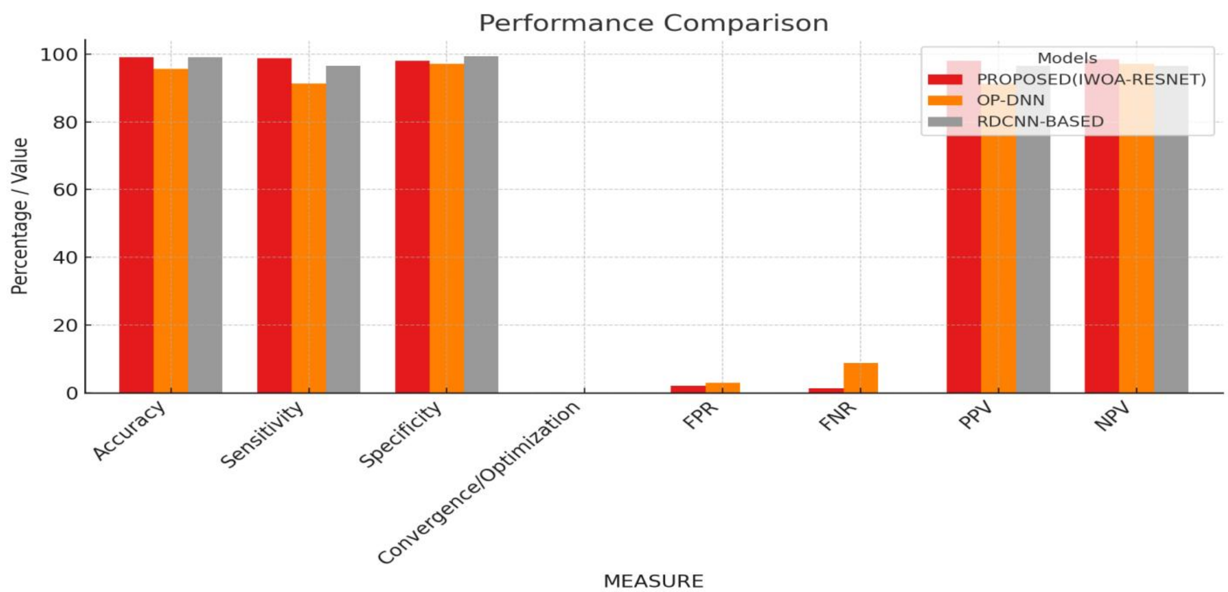

Figure 4: Accuracies of the Developed and Existing Approaches

DISCUSSION

Figure 4 demonstrates the performance of the proposed ResNet50 + IWOA model compared with the prevailing techniques OP-DNN (Jain et al., 2022) and Skin-Net deep residual network (Alsahafi et al., 2023) concerning accuracy, sensitivity, specificity, PPV, NPV, FPR, FNR, and convergence speed for multi-class skin lesion classification. From Figure 4, the sensitivity of the proposed model is high when contrasted to OP-DNN and Skin-Net techniques. The accuracy of the proposed model is **99.09%**, which is better in contrast to the prevailing systems. The recall (sensitivity) together with specificity for the proposed model is the best when contrasted to the prevailing techniques. The PPV and NPV values are also higher when contrasted to OP-DNN and Skin-Net techniques. The FPR and FNR measurements give better performance when contrasted to the prevailing techniques. The convergence speed of the proposed method is significantly faster when compared with the existing systems, with an elapsed time of 0.0097 seconds.

Therefore, from the performance graph, it is proved that the proposed ResNet50 + IWOA model with has classified the skin lesion images more effectually and accurately when contrasted to OP-DNN and Skin-Net techniques.

Among the three models assessed, the enhanced ResNet integrated with IWOA demonstrated superior performance, achieving an impressive accuracy of 99.09%,while effectively managing image variability.it outperformed the skin-Net deep residual network proposed by (Alsahafi *et al.,2023)* showcasing a well-balanced combination of speed (0.0097 seconds elapsed time)and real-time applicability. Although (Jain *et al*., 2022) OP-DNN model produced competitive results, it fell short in terms of real-time efficiency and lacked the advanced optimization capability present in the enhanced ResNet + IWOA model. Overall, the proposed approach emerges as the most robust and clinically viable solution among the evaluated methods.

CONCLUSION

The integration of ResNet with the enhanced IWOA algorithm yielded promising results, demonstrating notable improvements in convergence speed, classification accuracy, and real-time feasibility. By harnessing the synergistic effects of deep learning and metaheuristic optimization, the integrated model showcased its efficacy in accurately classifying diverse skin diseases while expediting the diagnosis process. The findings underscore the significance of leveraging advanced computational techniques for enhancing diagnostic capabilities and improving patient outcomes in dermatology.

The study contributes to the growing body of research at the intersection of artificial intelligence and healthcare, offering valuable insights into the potential of integrated approaches for medical image analysis. By combining the strengths of deep learning and optimization algorithms, the proposed model provides a robust framework for automated skin disease diagnosis, empowering healthcare professionals with advanced tools for early detection and treatment planning.

The culmination of this research sets the stage for a transformative paradigm shift in dermatological diagnosis, leveraging cutting-edge computational techniques to enhance diagnostic accuracy, efficiency, and accessibility. As the field of medical artificial intelligence continues to evolve, further advancements in deep learning, optimization algorithms, and clinical validation methodologies hold the promise of revolutionizing healthcare delivery and improving patient outcomes. By embracing innovation and collaboration, stakeholders can collectively harness the power of technology to address the complex challenges in dermatology and usher in a new era of precision medicine.

The integration of artificial intelligence into clinical practice offers unprecedented opportunities to augment human expertise, streamline workflows, and democratize access to high-quality healthcare services. By fostering interdisciplinary collaboration between computer scientists, clinicians, policymakers, and industry stakeholders, we can accelerate the translation of research findings into tangible benefits for patients and society. Together, we can embark on a journey towards a future where cutting-edge technology and compassionate care converge to create a healthier and more equitable world.

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