Deep-CNN with Bacterial Foraging Optimization Based Cascaded Hybrid Structure for Diabetic Foot Ulcer Screening

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Abstract: Diabetic Foot Ulcer (DFU) poses a challenge for healing as a result of inadequate blood circulation and susceptibility to infections. Untreated DFU can result in serious complications, such as the necessity for lower limb amputation, which has a substantial impact on one's quality of life. Although several systems have been created to recognize or categorize DFU using different technologies, only a few have integrated Machine Learning (ML), Deep Learning (DL), and optimization techniques. This study presents a novel method that utilizes sophisticated algorithms to precisely detect Diabetic Foot Ulcers (DFU) from photographs. The study is organized into distinct phases: generating a dataset, extracting features from DFU photos using pre-trained Convolutional Neural Networks (CNN), identifying the most effective features through an optimization technique, and categorizing the images using standard Machine Learning algorithms. The dataset is divided into photos that are DFU-positive and images that are DFU-negative. The Bacterial Foraging Optimization (BFO) approach is used to choose crucial features following their extraction from the CNN. Subsequently, seven machine learning techniques are employed to accurately classify the photos. The effectiveness of this strategy has been evaluated through the collection and analysis of experimental data. The proposed method achieved a remarkable 100% accuracy in classifying DFU images by utilizing a combination of EfficientNetB0, Logistic Regression Classifier, and BFO algorithms. The research also contrasts this novel methodology with prior methodologies, showcasing its potential for practical DFU identification in real-world scenarios.

1 INTRODUCTION

High blood sugar levels are indicative of diabetes mellitus (DM), which is caused by inadequate insulin or inadequate glucose utilization. This results in complications, including diabetic foot ulcers (DFU) and amputations, as well as heart, kidney, eye, and foot diseases(Association, 2009), (Cho et al., 2015), (Khandakar et al., 2022b), (Munadi et al., 2022). The global number of adults with diabetes increased by 10.5% from 2000 to 2021, from 151 million in 2000 to over 537 million in 2021. It is anticipated that 630 million individuals will have diabetes by 2035, with 80% of them residing in underdeveloped countries (IDF,), (Thotad et al., 2023). DFU is a severe complication of diabetes that frequently results in amputation and substantial morbidity. DFU will develop in approximately 34% of individuals with diabetes at some point (Association, 2009), (Saeedi et al., 2019), (Armstrong et al., 2017). Redness, calluses, and blisters are symptoms of DFU, which are caused by skin and tissue injury as a result of poor blood flow and infections. DFU can lead to amputation and even mortality if left untreated (Ghanassia et al., 2008), (Kendrick et al., 2022), (Ahsan et al., 2023). Research indicates that 10-25% of individuals with diabetes will develop DFU, with a significant number of cases resulting in hospitalization and amputation (Jeffcoate and Harding, 2003), (Cavanagh et al., 2005), (Abdissa et al., 2020), (Almobarak et al., 2017). Diabetes-related foot issues are a significant cause of hospitalization and amputations in highly developed countries such as the United States and Qatar (Singh and Chawla, 2006), (Ponirakis et al., 2020), (Ananian et al., 2018).

On the other hand, Anxiety and depression are also significant mental health consequences of DFU.

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The treatment is a multidisciplinary approach that emphasizes the control of diabetes and the passage of blood to the feet, which includes imaging and blood tests (Ahmad et al., 2018). The diagnostic process can be impeded by human errors and a lack of specialists, but more accurate and early DFU detection could prevent serious complications (Khandakar et al., 2022a). This underscores the necessity of automatic DFU identification and categorization systems. In the sharp opposite, Artificial Intelligence (AI) is essential for the early detection of diseases, particularly in the context of primary care and patient health surveillance. Numerous automated systems have been developed to identify and monitor diabetic foot ulcers (DFU) through the use of Deep Learning (DL) and Machine Learning (ML). A traditional ML method was employed in a study (Khandakar et al., 2021) to identify diabetic feet in thermogram images. It presented a comparison between Convolutional Neural Networks (CNNs) and machine learning techniques. MobilenetV2 achieved an F1-score of 95% for two-foot thermogram images, while the AdaBoost Classifier, which employed 10 features, achieved a score of 97%. The EfficientNet model was proposed in a separate study (Thotad et al., 2023) for the early detection of DFUs. The model achieved an accuracy of 98.97%, an F1-score of 98%, a recall of 98%, and a precision of 99%. A new training method for the FCN32 VGG network was introduced in paper (Kendrick et al., 2022) to enhance DFU wound segmentation, resulting in a Dice score of 0.7446. Two models for categorizing foot thermograms were evaluated in an additional study (Filipe et al., 2022). The initial model classified images into four categories. The second model initially classified the foot as either healthy or DFU, and subsequently classified DFUs into three severity levels. Model 2 demonstrated a superior accuracy of 93.2% in the classification of healthy and first-class diabetic feet.

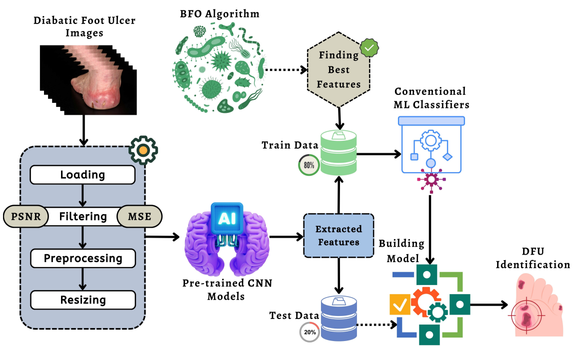

Figure 1: Architecture of the proposed system.

Table 1: Sample foot ulcer images for this research.

Sample Images	**Class Name**	**Class No.**	**No. Sample Images**
	Normal Feet	0	493
	Abnormal Feet	1	493

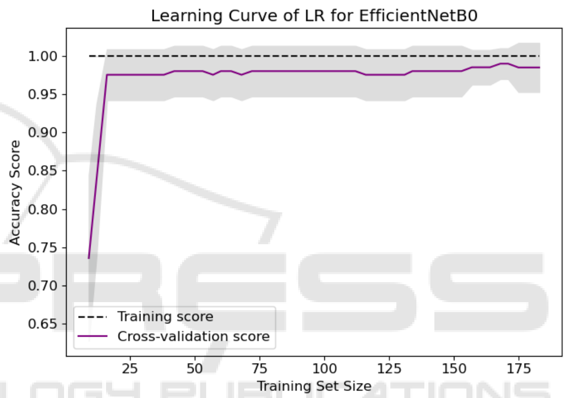

Figure 2: Learning curve of ResNet50-BFO-LR approach for different classifiers.

Besides, current automated DFU detection methods, public datasets, object identification systems, and deep learning methods were examined in an article (Yap et al., 2021). Another paper (Scebba et al., 2022) suggested a Detect-and-Segment (DS) method that employs deep neural networks to identify DFUs, distinguish them from the adjacent tissue, and generate a wound segmentation map. The Matthews' correlation coefficient (MCC) was enhanced from 0.29 to 0.85 by this method. The objective of a study (Das et al., 2022) was to develop a CNN-based classification framework that surpassed existing results. The framework was able to achieve 97.4% accuracy by optimizing the model architecture and parameters. An additional innovative system for DFU categorization was proposed (Munadi et al., 2022). This system effectively separated DFU thermal images into positive and negative categories with 100% accuracy. The system was based on thermal imaging and deep neural networks. AlexNet, VGG16/19, GoogLeNet, ResNet50.101, MobileNet, SqueezeNet,

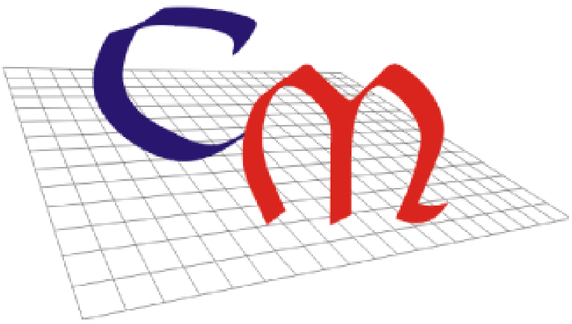

Figure 3: Confusion Matrix With the EfficientNetB0-BFO-LR network.

and DenseNet are among the CNN-based frameworks that Research (Ahsan et al., 2023) suggested for the classification of ischemia and infection. The ResNet50 model demonstrated the maximum level of accuracy, with a 99.49% accuracy rate for ischemia and an 84.76% accuracy rate for infection. Another study (Kendrick et al., 2022) clustered the severity risk of DFUs using the k-means clustering algorithm and a labeled diabetic thermogram dataset using an unsupervised method. The severity classification was most effectively performed by the VGG19 CNN model, which achieved an accuracy of 95.08%, precision of 95.08%, sensitivity of 95.09%, F1-score of 95.08%, and specificity of 97.2%.

However, the current methods have some flaws, such as misrepresenting classes and making it hard to find risky areas when both feet are affected. Certain models only label feet as diabetic or healthy, without checking to see how many problems they have (Filipe et al., 2022). The study aims to get around these problems by using CNN frameworks that have already been trained for feature extraction, Bacterial Foraging Optimization for feature selection, and ML models for DFU classification.

The article is classified into 4 interconnected parts: Section 2 provides the materials and method. Section 3 illustrates the associated results adopted from the proposed methodology. Finally, section 4 represents the conclusion of this paper.

2 MATERIALS AND METHOD

This section describes the dataset distribution and the methods used to choose, train, and test the models for the suggested cascaded network.

2.1 Dataset

We obtained ulcer-infected photos from both a publicly available dataset (Laith, 2021; Alzubaidi et al., 2020) and a local general hospital. Subsequently, a proficient dermatologist scrutinized these photographs to ascertain the existence of anomalous foot in them. The dermatologist evaluated the images using a scale ranging from 0 to 1, with 1 representing a significant level of abnormality in the foot. For our investigation, we exclusively included photos that received a score of either 1 or 0. In order to validate the appropriateness of these photos for training machine learning models, we assessed their quality using the reference image quality evaluation approach devised by Yagi et al., which takes into account factors such as sharpness and noise. This dataset has 1050 photos depicting deformed feet and 1026 images depicting normal feet. Tab. 1 displays a selection of photos taken from the dataset.

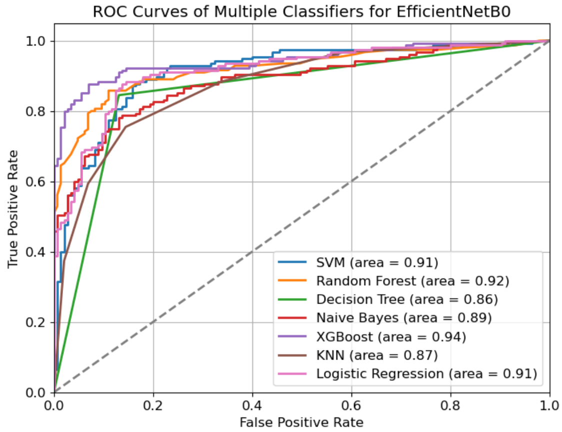

Figure 4: ROC curves of EfficientNetB0-BFO approach for different classifiers.

2.2 Proposed Architecture and Working Principles

This section will present various image preprocessing techniques. Prior to classifying diabetic foot ulcers, it is important to pre-process the images in the dataset to ensure dependable results due to the presence of diverse forms of noise in the images. Image filtering techniques are employed to eliminate undesired aspects, whilst augmentation approaches are utilized to tackle the problem of a restricted dataset. Figure 1 illustrates the structure of the suggested system, while Algo. 1 provides a detailed explanation of the proposed method, outlining each step. The proposed method commences with the pre-processing of the input image, a vital step to guarantee the seamless operation of the system. The pre-processing stage entails evaluating the image's quality. In order to examine the quality of the image, we have created a tool called the Image Quality Assessment Tool (IQAT).

Table 2: Performance of Various CNN Based Feature Extractors with Different Classifiers.

CNN Based Feature Extractor	Classifiers	Accuracy (A)	Precision (P)	Recall (R)	F1-Score (F1)
DenseNet121 + BFO	SVC	0.9706	0.9706	0.9706	0.9706
	RF	0.9853	0.9860	0.9850	0.9853
	DT	0.9559	0.9586	0.9552	0.9558
	NB	0.9363	0.9368	0.9360	0.9362
	XGB	0.9755	0.9762	0.9752	0.9755
	KN	0.9657	0.9685	0.9650	0.9656
	LR	0.9853	0.9860	0.9850	0.9853
EfficientNetB0 + BFO	SVC	1.0000	1.0000	1.0000	1.0000
	RF	0.9951	0.9950	0.9952	0.9951
	DT	0.9853	0.9854	0.9856	0.9853
	NB	0.9510	0.9513	0.9513	0.9510
	XGB	1.0000	1.0000	1.0000	1.0000
	KN	0.9951	0.9952	0.9950	0.9951
	LR	1.0000	1.0000	1.0000	1.0000
InceptionV3 + BFO	SVC	0.9559	0.9586	0.9552	0.9558
	RF	0.9608	0.9643	0.9600	0.9606
	DT	0.9265	0.9289	0.9258	0.9263
	NB	0.7745	0.7940	0.7719	0.7695
	XGB	0.9804	0.9815	0.9800	0.9804
	KN	0.9118	0.9164	0.9108	0.9113
	LR	0.9559	0.9602	0.9550	0.9557
MobileNetV2 + BFO	SVC	0.9706	0.9706	0.9706	0.9706
	RF	0.9853	0.9852	0.9854	0.9853
	DT	0.9167	0.9172	0.9163	0.9166
	NB	0.9265	0.9271	0.9269	0.9265
	XGB	0.9755	0.9756	0.9754	0.9755
	KN	0.9363	0.9368	0.9360	0.9362
	LR	0.9755	0.9762	0.9752	0.9755
ResNet50 + BFO	SVC	1.0000	1.0000	1.0000	1.0000
	RF	1.0000	1.0000	1.0000	1.0000
	DT	0.9902	0.9906	0.9900	0.9902
	NB	0.9804	0.9804	0.9806	0.9804
	XGB	0.9902	0.9906	0.9900	0.9902
	KN	0.9951	0.9952	0.9950	0.9951
	LR	1.0000	1.0000	1.0000	1.0000
VGG16 + BFO	SVC	1.0000	1.0000	1.0000	1.0000
	RF	0.9902	0.9902	0.9902	0.9902
	DT	0.9755	0.9754	0.9756	0.9755
	NB	0.9853	0.9852	0.9854	0.9853
	XGB	0.9853	0.9854	0.9852	0.9853
	KN	0.9657	0.9685	0.9650	0.9656
	LR	1.0000	1.0000	1.0000	1.0000
VGG19 + BFO	SVC	0.9902	0.9902	0.9902	0.9902
	RF	0.9902	0.9902	0.9902	0.9902
	DT	0.9804	0.9804	0.9804	0.9804
	NB	0.9804	0.9804	0.9804	0.9804
	XGB	0.9902	0.9902	0.9902	0.9902
	KN	0.9804	0.9804	0.9804	0.9804
	LR	0.9902	0.9902	0.9902	0.9902
Xception + BFO	SVC	0.9363	0.9403	0.9354	0.9360
	RF	0.9804	0.9813	0.9800	0.9804
	DT	0.9314	0.9333	0.9308	0.9312
	NB	0.7745	0.7875	0.7765	0.7727
	XGB	0.9657	0.9672	0.9652	0.9656
	KN	0.9461	0.9487	0.9454	0.9459
	LR	0.9510	0.9544	0.9502	0.9508

Table 3: Performance Metrics and Complexities for Various Techniques.

Techniques	A	P	R	F1	Time Complexity	Space Complexity
DenseNet121 + BFO+ RF	0.9853	0.9860	0.9850	0.9853	2.15 s ± 87.7 ms	PM: 486.81 MiB, INC: 56.38.45 MiB
EfficientNetB0 + BFO+ LR	1.0000	1.0000	1.0000	1.0000	39.3 ms ± 3.16 ms	PM: 691.94 MiB, INC: 62.14 MiB
InceptionV3 + BFO+ XGB	0.9804	0.9815	0.9800	0.9804	1.54 s ± 35.4 ms	PM: 700.20 MiB, INC: 62.44 MiB
MobileNetV2 + RF	0.9853	0.0952	0.9854	0.9853	629 ms ± 6.46 ms	PM: 711.17 MiB, INC: 62.88 MiB
ResNet50 + BFO+ SVC	1.0000	1.0000	1.0000	1.0000	126 ms ± 1.73 ms	PM: 1466.89 MiB, INC: 876.52 MiB
VGG16 + BFO+ LR	1.0000	1.0000	1.0000	1.0000	277 ms ± 19.6 ms	PM: 851.52 MiB, INC: 61.44 MiB
VGG19 + BFO+ LR	0.9902	0.9902	0.9902	0.9902	283 ms ± 10.3 ms	PM: 945.81 MiB, INC: 62.97 MiB
Xception + BFO+ RF	0.9804	0.9813	0.9800	0.9804	681 ms ± 21.5 ms	PM: 738.36 MiB, INC: 63.45 MiB

The IQAT evaluated the image's quality based on its sharpness and noise levels. In our research we have considered the six conventional image filtering techniques: Average Filter, Gaussian Filter, Median Filter, Bilateral Filter, Min Filter, and Max Filter. In Algo. 1, a linear regression model was utilized to determine the quality of the image. Regression analysis employing mean square errors was used to precalculate the coefficients of quality predictors. Lower image quality was indicated by a higher Q_i value. The picture was used for additional analysis if Q_i was less than the threshold Q_{th}, which was set at 10 for our study. The image was reduced to comply with the AI model input size and moved to sRGB space to balance color values after IQAT approved its quality. The practical usage of the proposed system depends on these preprocessing procedures, particularly quality checking (Hossain et al., 2018). After the post-preprocessing, a CNN model that has already been trained—ResNet50 in particular—is used to treat the image based on its applicability and performance. The most pertinent traits are then chosen for classification using the BFO approach. Using the SVC model as the classifier, the final prediction divides the image into two categories: Normal Foot and Abnormal Foot. The procedure for choosing the feature extractor and classifier models for the suggested approach is described in depth in the following section.

2.3 Model Selection and Pipeline Building

In this study, we extracted features from images using eight pre-trained CNN approaches. To extract the features, a CNN model that has already been trained is given images from the dataset. For this, we employed models from ResNet50, EfficientNetB1, MobileNetV2, Xception, InceptionV3, VGG16, and VGG19. We employed Bacterial Foraging Optimization (BFO) to select the optimal features. Upon obtaining the features, we classified the images using seven standard machine learning methods. Next, the suggested system determines the relative importance of each class in the total assessment.

We investigated seven machine-learning models for classification: SVC, DT, RF, NB, XGB, KNN, and LR. The CNN model was employed as the feature extractor, and conventional machine learning models as the classification model in the suggested cascaded network. Thus, in this study, we combined five feature extractor models with seven classifier models to create 35 distinct networks.

3 EXPERIMENTAL RESULTS ANALYSIS

This subsection presents the findings of the current study that combined the seven ML-based approaches with CNN pre-trained frameworks. All of the code for the suggested work was executed on the Google Colab, which has 53GB of random-access memory (RAM) and a dedicated Graphics Processing Unit (GPU). For this study, the "pro" tier of the subscription service was used. Using the pre-trained models, the study retrieved important elements from the given image. After that, ML-based models were utilized to evaluate the obtained data in the model evaluation processes. 80 percent of the dataset was set aside for training and 20 percent for testing in order to train and assess the proposed model.

Data: $InputImage_{RGB}$
Result: $Result$
Initialize: $Params \leftarrow \{P_1, P_2, \ldots, P_n\}$;
while $InputImage_{RGB} \neq NIL$ **do**
  $ProcessedImage_{sRGB} \leftarrow IQAT(InputImage_{RGB})$;
  $ResizedImage \leftarrow$ Resize to 224×224;
  $FeatureExtractor \leftarrow$ Load ResNet50 with $Params$;
  $ExtractedFeatures \leftarrow$ Extract features from $ResizedImage$;
  $BFOProcessor \leftarrow$ Load BFO with $Params$;
  $SelectedFeatures \leftarrow$ Select features from $ExtractedFeatures$;
  $ClassifierModel \leftarrow$ Load SVC with $ClassParams$;
  $Prediction \leftarrow$ Predict using $SelectedFeatures$;
  if $Prediction > 0.5$ **then**
    $Result \leftarrow$ Abnormal Foot;
  else
    $Result \leftarrow$ Normal Foot;
  end
end
Output: $Result$;
Procedure `IQAT`($InputImage_{RGB}$)**:**
  Initialize: $\alpha, \beta, \gamma, Threshold$;
  Load parameters α, β, γ;
  $QualityIndex = \alpha + \beta \times Sharpness + \gamma \times Noise$;
  Estimate $Sharpness$ and $Noise$;
  if $QualityIndex < Threshold$ **then**
    if $LinearColor \leq 0.0031$ **then**
      $ProcessedImage_{sRGB} = 12.92 \times LinearColor$;
    else
      $ProcessedImage_{sRGB} = 1.0552 \times LinearColor^{\frac{1}{2.4}}$;
    end
  end
  Return $ProcessedImage_{sRGB}$;
Procedure `BFO`($ExtractedFeatures$)**:**
  Initialize: $filterVar \leftarrow 2F - 1$, Where $F = 1, 2, \ldots, filterVar$;
  $InputImage \leftarrow$ Input image;
  $FeatureVector \leftarrow$ Feature vector;
  Start:;
  $BestFilter \leftarrow$ Apply filter to $InputImage$;
  $FilteredQuality \leftarrow$ Filtered image;
  $ArrayConversion \leftarrow$ Convert image to array;
  for *each* $ArrayConversion$ **do**
    Extract feature vector $ResultFeature\{V_0, V_1, \ldots, V_{14}\}$;
    $FeatureVector \leftarrow ResultFeature$;
  end
  Return $FeatureVector$;

Algorithm 1: Proposed algorithm to build the pipeline.

Tab. 2 shows the experimental result analysis with the pre-trained CNN Models and conventional machine learning (ML) classifiers. In our experiment, we have utilized eight (08) pre-trained CNN models to extract the feature vectors. Initially, we have enumerated the models with performance evaluation matrices such as accuracy, precision, recall, and F1-score. At the beginning, we have evaluated the model with extracted features and then we have applied the BFO algorithm to find the best features. Then we applied the ML seven (07) classifiers to assess the result. The experimental result shown in Fig. 2 that we have found the highest accuracy of 100% with the pre-trained models like EfficientNetB0, ResNet50, and VGG16. From this table, we can easily track out that some models provided the best result with the Support Vector Classifiers (SVC) and some of the models extracted the highest accuracy with the Logistic Regression (LR) classifier.

To check the efficacy of these models, we didn't rely on the performance evaluation matrices alone; thus, we have applied time complexity and space complexity like Peak Memory (PM) and Increment (INC) to the highest-performing network as depicted in Tab. 3. This table clearly shows that the EfficientNetB0 with the BFO algorithm and LR classifier performed better as per the table. From this table, we tracked out that EfficientNetB0-BFO-LR network consumed the complexity of 681 ms ± 21.5 ms and space complexity of 738.36 MiB and INC: 63.45 MiB that is the lower than ResNet50, VGG16 and VGG19 models. Fig. 2 shows the learning curve of this network which is very promising for ulcer identification. On the other hand, Fig. 3 shows the confusion matrix of the EfficientNetB0-BFO-LR network and Fig. 4 illustrates the roc-curve of the seven classifiers from the EfficientNetB0-BFO network.

4 SUMMARY

This section presents a comparison between the existing work and the proposed framework, as seen in Tab. 1 and Tab. 2. Prior studies (Thotad et al., 2023), (Ahsan et al., 2023), (Das et al., 2022),(Alzubaidi et al., 2022) and (Filipe et al., 2022), (Haque et al., 2022), (Khandakar et al., 2022b) only employed deep learning approaches and machine learning models to classify diabetic foot ulcers (DFU). The study employed both machine learning (ML) and deep learning (DL) approaches (Khandakar et al., 2022a), (Munadi et al., 2022), (Khandakar et al., 2022b). In the context of CNN and ML models, previous studies (Yap et al., 2021), (Das et al., 2022), (da C. Oliveira et al., 2021) primarily depended on various pre-trained models or ML methodologies. Only a limited number of previous studies, specifically (Haque et al., 2022), (Xie et al., 2022) have employed feature optimization methods. The study (Filipe et al., 2022) using planter thermogram and thermogram picture database to achieve accuracy rates of 95.08%, 100%, and 93.2% in diagnosing problems related to DFU. The research (Das et al., 2022) utilized a dataset of 292 pictures of foot ulcers and achieved a classification accuracy of 97.4% in identifying diabetic foot ulcers (DFU). In the study conducted by (Ahsan et al., 2023), the classification of DFU based on ischemia and infection was performed using the DFU dataset from 2020. The achieved accuracy rates were 99.49% for ischemia classification and 84.76% for infection classification. Study [36] achieved an accuracy of 01.01% in early DFU identification using solely a public dataset. However, in study (Alzubaidi et al., 2022), both public and private datasets of DFU were used, resulting in an accuracy of 94.8% and 97.3% respectively. The authors of (Haque et al., 2022) utilized DFU images of electromyography and ground reaction forces to achieve accuracy rates of 96.18% and 98.68%. On the other hand, the suggested method employed eight pre-trained models of Convolutional Neural Network (CNN) architecture and seven traditional Machine Learning (ML) techniques, along with a Bacterial Foraging Optimization (BFO) model, to classify photos of Diabetic Foot Ulcers (DFU). The proposed strategy heavily relies on the utilization of filtering and enhancing techniques for photographs. The dataset was subjected to feature optimization using the BFO technique to extract the most important features. Subsequently, the data was sent to the ML classifiers for classification. The proposed framework, employing the EfficientNetB1+BFO+LR network, has achieved a remarkable accuracy of 100%. This advancement would greatly enhance the current state-of-the-art in categorizing DFU field.

5 CONCLUSIONS

One of the key challenges today is preventing and managing fatal illnesses like diabetic foot ulcers (DFU). This study looks at using advanced techniques like machine learning (ML), deep learning (DL), and feature optimization to classify DFU images. We started by using features from pre-trained CNN models. The BFO method was used to select these features. Initial tests with standard ML algorithms and pre-trained CNN models achieved 100% accuracy. By combining EfficientNetB0, logistic regression (LR), and BFO, we also reached 100% accuracy.

However, the model has some limitations. It hasn't been tested in real-time for DFU classification, and the BFO method was used for basic analysis. Future research will focus on applying this method to deeper CNN layers, making it suitable for smart devices and IoT. Further studies will also include data from more databases to improve the real-world application of the DFU classification method

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