Optimised Deep k-Nearest Neighbour's Based Diabetic Retinopathy Diagnosis(ODeep-NN) Using Retinal Images

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Abstract

Diabetes mellitus has been regarded as one of the prime health issues in present days, which can often lead to diabetic retinopathy, a complication of the disease that affects the eyes, causing loss of vision. For precisely detecting the condition's existence, clinicians are required to recognise the presence of lesions in colour fundus images, making it an arduous and time-consuming task. To deal with this problem, a lot of work has been undertaken to develop deep learning-based computer-aided diagnosis systems that assist clinicians in making accurate diagnoses of the diseases in medical images. Contrariwise, the basic operations involved in deep learning models lead to the extraction of a bulky set of features, further taking a long period of training to predict the existence of the disease. For effective execution of these models, feature selection becomes an important task that aids in selecting the most appropriate features, with an aim to increase the classification accuracy. This research presents an optimised deep k-nearest neighbours'-based pipeline model in a bid to amalgamate the feature extraction capability of deep learning models with nature-inspired metaheuristic algorithms, further using k-nearest neighbour algorithm for classification. The proposed model attains an accuracy of 97.67% and 98.05% on two different datasets considered, outperforming Resnet50 and AlexNet deep learning models. Additionally, the experimental results also portray an analysis of five different nature-inspired metaheuristic algorithms, considered for feature selection on the basis of various evaluation parameters.

Keywords- Diabetic retinopathy; Deep Learning; Transfer Learning; Nature-Inspired Metaheuristic; Feature Selection;

1. Introduction

Recently, diabetes mellitus has been found to be one of the most common diseases and is considered as a major public health concern worldwide [1,2]. Diabetic retinopathy is a common condition primarily found among people with a history of diabetes. The condition is caused by the presence of high blood glucose levels which damage the blood vessels of the retina causing leakage of blood and other fluids from these vessels and, if not detected early, can lead to loss of vision in subjects suffering from diabetes [3,4]. Around 50% of the global population below the age of 70 become seriously affected by this condition thus resulting in a surge of cases of diabetic retinopathy globally [3].

It was projected by the World Health Organisation (WHO) that the worldwide pervasiveness of diabetes mellitus was approximately 8.8% in 2017 and is likely to further increase to 9.9% by the year 2045 [5, 6]. Subjects suffering from diabetes are 25 times more likely to suffer from vision loss as a result of diabetic retinopathy, which can be a significant and enduring microvascular issue, and one of the top causes of blindness in high-income countries. In U.S. only, 7.7 million people aged over forty years suffer from diabetes [2]. Diabetic retinopathy can occasionally go unnoticed until it reaches an advanced vision-threatening juncture [7].

Early diagnosis and identifying the severity level can prevent the damage caused by this condition, by taking appropriate decisions regarding the treatment. Current research propose a computer aided diabetic retinopathy diagnosis model using the concepts of traditional machine learning, transfer learning models of deep learning, and

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nature-inspired metaheuristic algorithms to incorporate feature selection in order to reduce the dimensionality of the data to encourage the prompt diagnosis of this perilous disease [8].

1.1 Deep Learning based Computer Aided Diagnosis

Today, deep learning is regarded as one of the most noteworthy spheres of research, that identifies problem-related definite features from an image, considering a diversity of images for crafting a dataset of features without relying on manual feature selection. Hence, convolutional neural network has been deemed state-of-the-art solution in a wide range of disease diagnosis systems for medical images. Consequently, the use of convolutional neural networks in developing the computer aided diagnosis systems for the early detection of diabetic retinopathy has displayed superior performance [1], which is predominantly due to the training of artificial neural networks using the large number of features extracted by the various convolutional layers.

However, the features extracted by the convolutional layers may be redundant in nature and not every feature contributes equally well to the classification performance, and training the model with these redundant features may significantly increase the training time of the model. In order to resolve this issue, this research aims to extract the features from the input images using convolutional neural network architectures, specifically-using the transfer learning models of deep learning and selecting the optimal number of features using various nature-inspired metaheuristic algorithms [8], and classifying the data using traditional k-Nearest Neighbor algorithm using the selected set of features.

1.2 Research Methodology and Structuring of the paper

The objective of the proposed research is to amalgamate the feature extraction capability of deep neural network models with the nature-inspired metaheuristic algorithms and traditional machine learning based techniques to develop a novel pipeline structure, with an aim to increase the classification accuracy and reduce the number of features selected for making the model more robust. The research methodology of the proposed research is summarized figure 1.

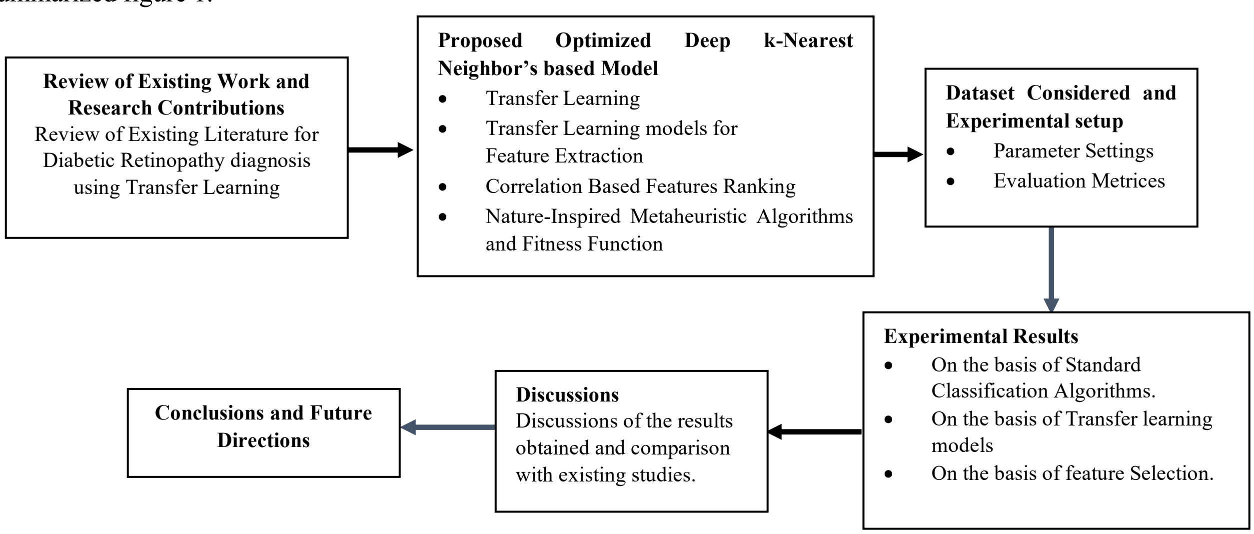

Figure 1: Research Methodology

The contribution of the presented study is threefold;

1. The study presents, a performance analyses of *AlexNet* and *Resnet50* deep learning models for the diagnosis of diabetic retinopathy.
2. The proposed research also depicts, the effect of feature selection by incorporating the use of nature-inspired metaheuristic algorithms on the classification performance for the diabetic retinopathy diagnosis.

3. The study also aims to gauge the computational time with selected optimal number of features when compared to the other deep learning models for diabetic retinopathy diagnosis.

The rest of the article is structured as follows: a brief review of the state of the art work completed for the detection of diabetic retinopathy, as presented in Section 2; Section 3 presents the proposed optimised deep k-nearest neighbour's model for the diagnosis of diabetic retinopathy; Section 4 briefly discusses the dataset considered, parameter settings and evaluation metrics considered for the experimentation; a comparative analysis of the results is presented in the Section 5; a brief discussion of the results obtained and performance of the proposed model is presented in Section 6; finally, Section 7 concludes with several future endeavors of the proposed work.

2. Literature Review

In the past few years, many researchers have explored the domain of deep learning for the diagnosis of diabetic retinopathy. Shankar K. et al. [3] proposed a deep learning based system that automatically detects and classifies the fundus diabetic retinopathy images. The process begins with the removal of unimportant noise from the edges of the images. For further extraction of useful regions from the images, a histogram-based segmentation technique was employed. Afterwards, classification of the fundus images was done by using- a synergic deep learning model on the Messidor diabetic retinopathy dataset. From the experimentation, it was observed that the proposed strategy showed admirable results with the highest classification accuracy of 99.28 %, with sensitivity and specificity values 98.54 % and 99.38% respectively.

Pires R. et al. [2] explored data-driven methodologies that mine influential abstract representations from retinal images. The authors progressively developed the solution based on convolutional neural networks: adding data augmentation; multi-resolution training; robust feature-extraction augmentation; a patient-basis analysis, and proceeded to test the efficacy of each enhancement. The results for the proposed method were gauged on Messidor-2 and DR2 datasets achieving an area under the ROC curve of 98.2% under a strict cross-dataset protocol designed to test the ability to generalise training on the Kaggle dataset and testing using the Messidor-2 dataset. Furthermore, with a 5 × 2-fold cross-validation, similar results are achieved, reducing the classification error by over 44% in comparison with other studies published.

A model was presented by Gayathri S. et al. [4] with six convolutional and two fully connected layers for feature extraction for the classification of the retinal fundus images. For the classification, support vector machine, adaboost, naive bayes, random forest, and J48 algorithms were used on IDRiD. MESSIDOR, and KAGGLE datasets. The proposed technique with J48 classifier outperformed the other algorithms taken for comparison achieving an average classification accuracy of 99.89% and 99.59% for binary and multiclass classification respectively. Moreover, the J48 classifier achieves an average Kappa-score of 0.994 for both binary and multi-class classification.

An effort was made by Dwivedi S. A. et al. [9] that included the different deep transfer learning architectures namely MobilenetV2, DenseNet121, InceptionV3, ResNet50, VGG for the detection of the diabetic retinopathy from the APTOS 2019 and HRF Image dataset. Additionally, f1 Score, Area Under Curve, Cohen's Kappa Score were used as the result metrics. The results indicated that 8-Layer CNN, DenseNet121, and Inception V3 performed almost the same in terms of accuracy with MobileNetV2 outperforming the other models.

A system for detecting the different stages of diabetic retinopathy was presented by Dai L. et al. [10] as DeepDR, which is trained with over 466,247 fundus images. Evaluation is performed on a local dataset with 200,136 fundus images from 52,004 patients and three external datasets with a total of 209,322 images. The classification of diabetic retinopathy as mild, moderate, severe and proliferative attains area under the curves values of 0.943, 0.955, 0.960 and 0.972, correspondingly.

Jena P. K. et al. [11] proposed an asymmetric deep learning feature-based technique for diabetic retinopathy detection. The asymmetric deep learning features are extracted using U-Net for segmentation of the optic disc and blood vessels, and a convolutional neural network and support vector machine is considered for lesion classification belonging to diabetic retinopathy. APTOS and MESSIDOR datasets were considered to test the proposed method.

Further, retinal image segmentation aided in improving the accuracy of the classification of diabetic retinopathy. The results indicate that the accuracy for non-diabetic retinopathy detection is 98.6% and 91.9% respectively for the both the datasets and for exudate detection the accuracy values are 96.9% and 98.3%, respectively.

Saranya, P. et al. [12] proposed a model for diagnosing the early stages of diabetic retinopathy based upon red lesions in retinal images. The images are subjected to pre-processing to remove noise and are further subjected to semantic segmentation of red lesions using UNet. The segmented images were fed to convolutional neural networks for classification. Four different datasets IDRiD, DIARETDB1, MESSIDOR, and STARE, were used for experimentation, and performance was gauged on the basis of parameters like specificity, sensitivity, and accuracy. On working with the IDRiD dataset, the specificity and sensitivity were observed as 99% and 89%, respectively, with an accuracy of 95.65%. Furthermore, for MESSIDOR dataset the specificity, sensitivity, and accuracy values obtained for the Diabetic retinopathy severity classification were 93.8%, 92.3%, and 94%, respectively.

Tsiknakis N. et al. [13] reviewed the existing research, and presents the use of deep learning methods at various steps in the diagnosis of the diabetic retinopathy pipeline. Authors present the several aspects of the pipeline, ranging from datasets, preprocessing methods and how they increase the efficiency of the models for detection of diabetic retinopathy from fundus images. Similarly, Burcu, O. et al. [14] reviews the applications of deep learning for the diagnosis of diabetic retinopathy by taking into account forty-three articles published from 2016 to 2021. The authors summarised the research in terms of twenty-nine pre-trained convolutional neural network models, thirteen diabetic retinopathy data sets and some of the performance metrics.

Badgujar, R. D. [15] presented a computer aided system for classification of retinal fundus images using a novel nature inspired spider monkey optimization for parameter tuning of gradient boosting machines classifier. The image enhancement has been performed with histogram equalization and contourlet transform. We have employed Kirsch's matrices for blood vessel detection. The GLCM based feature vector extraction has been employed for textural features. Experiments were performed on the STARE database for validation of proposed technique. Benchmarking analysis of nature inspired hybrid SMO-GBM classifier indicated the outperformance with other methods attaining the mean accuracy of classification more than 97.5%.

Mrad, Y. et al. [16] present an automated method for glaucoma screening dedicated for Smartphone Captured Fundus Images (SCFIs). The idea consists of detecting glaucoma based on the vessel displacement inside the Optic Disk (OD). The objective of the research includes segmenting retinal vessels inside the OD, locating centroid points that adequately model the vessel distribution, identifying features that relevantly reflect the vessel displacement, and providing the feature set to a classifier in order to detect the glaucoma. The first evaluation of proposed method was performed using DRISHTI-DB and DRIONS-DB databases, where 99% and 95% accuracy, are respectively achieved. Thereafter, the method was evaluated using two fundus image databases respectively captured through a smartphone and retinograph for the same persons and achieves 100% accuracy using both databases.

Some of the other studies considering the use of transfer learning models for the diagnosis of diabetic retinopathy in retinal images have been summarised as: Wu Y. et al. [17] considered VGG-19, InceptionV3, Resnet50 models for implementation on 35,126 images obtained from kaggle and found that the InceptionV3 model outperforms the other models in terms of accuracy. Khalifa N. E. M. et al. [18] considered AlexNet, ResNet18, SqueezeNet, GoogleNet, VGG-16, and VGG-19 models for the performance analysis on APTOS 2019 dataset with 3662 images and observed that AlexNet model obtains highest accuracy of 97.9%.

Gangwar A. K. et.al. [19] implemented Inception and ResNet-v2 models on Messidor-1 and APTOS 2019 datasets containing 1200 and 3662 respectively and observed that hybrid model obtains 72.33% and 82.18% accuracy on Messidor-1 and APTOS datasets respectively. Patel R. et al. [20] considered MobileNetv2 model and performed experiment on 3662 images obtained from kaggle and obtained an accuracy of 91%. Al-Smadi M. et al. in [21] considered ResNet-50, InceptionResNet-V2 EfficientNet-B4, Xception, DenseNet-169, Inception-V3 with global average pooling and ensemble (DenseNet-169, Inception-V3, Xception) for experimentation on APTOS 2019 dataset and it observed that ensemble model obtained highest accuracy of 82.4%.

Salvi R. S. et al. [22] implemented VGG-16, Resnet50 V2, and EfficientNet B0 models on APTOS 2019 Blindness Detection dataset with 1000 images and obtained 95% accuracy with VGG-16 and 93% accuracy with ResNet50 V2 models. Sanjana S. et al. [23] used two public datasets containing 1115 retinal fundus images and implemented Xception, InceptionResNetV2, MobileNetV2, DenseNet121, and NASNetMobile and found to achieve the highest validation accuracy of 86.25%, 96.25%, 93.75%, 81.25%, and 80.00% respectively.

3. Proposed Optimized Deep k-Nearest Neighbor's based Model

Recently, a lot of curiosity has arisen in performing image classification by implementing deep learning [24]. To cope with disease diagnosis in medical images, deep learning has come up as a subcategory of artificial intelligence(AI), AI makes its evaluations by deploying the artificial neural networks amid numerous input and output layers, but due

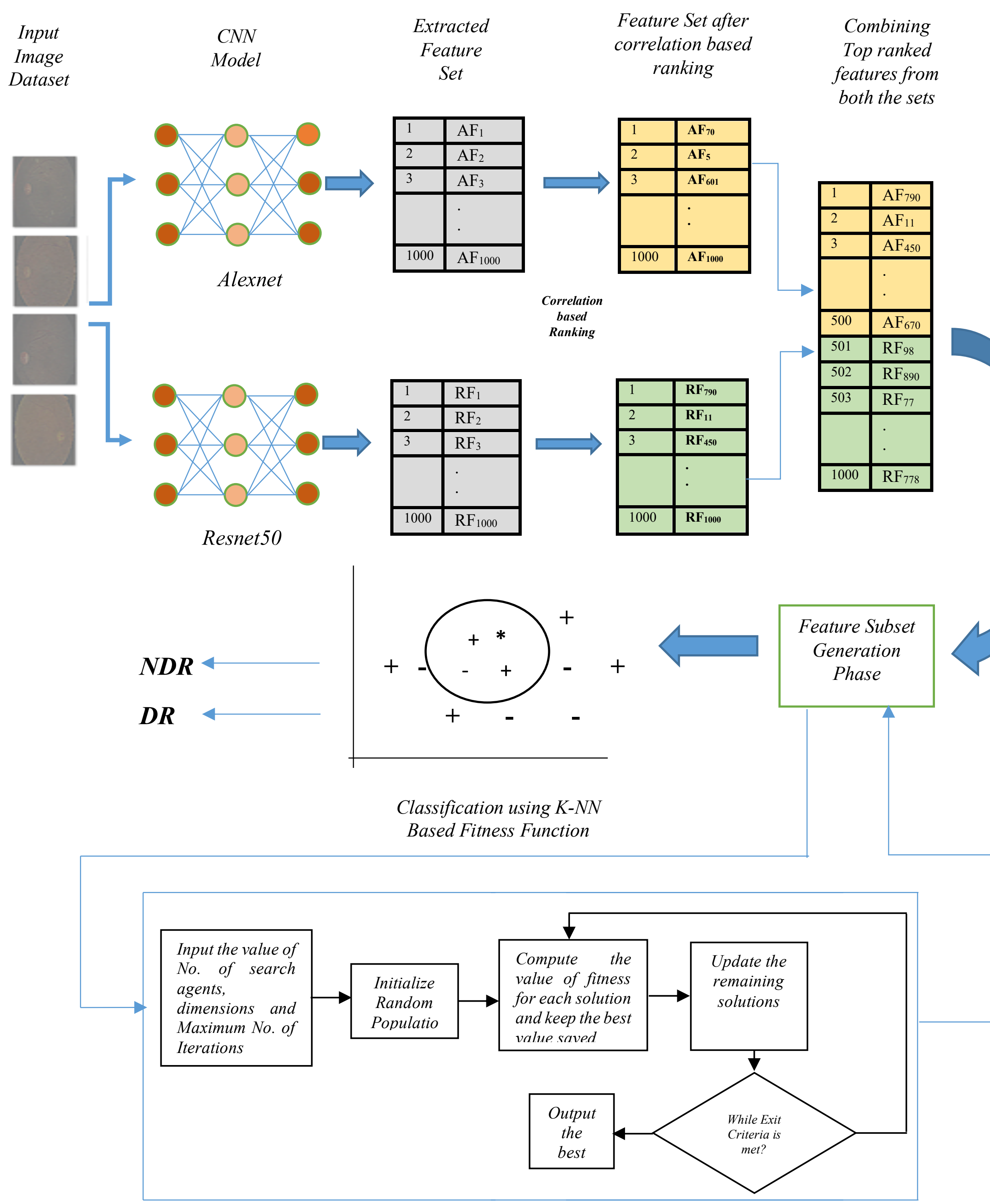

Figure 2: Proposed Optimised Deep k-Nearest Neighbors'-based Model *(AF- AlexNet Features and RF- Resnet50 Features)*

to the large number of computations it requires a lengthy training period. The proposed model amalgamates the feature extraction capability of deep neural networks with nature-inspired metaheuristic algorithms, and the traditional k-nearest neighbor algorithm, to classify the images in a significantly reduced time frame and to make the model robust. The presented model can be seen in the Figure 2 and the various strategies and concepts employed to make an integrated proposed model are summarised in below subsections:

3.1. Transfer Learning

Deep learning makes use of large datasets to train a convolutional neural network for performing a specific task. One of the utmost important factors for the efficacious training of the convolutional neural networks is the existence of the data for the initial training. Meanwhile, convolutional neural networks can learn to mine noteworthy features of the image. The aptness of the model for transfer learning can be judged by the competence of the convolutional neural network to recognise and mine the most outstanding image features [25].

Subsequently, convolutional neural networks are further deployed to process a different set of images of varying-nature and to perform feature extraction with the knowledge gained during the initial training. To exploit the capability of pre-trained convolutional neural networks; -the first strategy is regarded as feature extraction via transfer learning in which the pre-trained model holds its initial architecture with weights learned and hence acts as a feature extractor; the features extracted are injected into a new network that then computes the classification. This strategy is essentially used to avoid the computational overheads spawned from training a very deep network, or to hold the valuable feature extractors trained in the primary stage [25]. The second strategy makes explicit alterations to the pre-trained model, with an aim to get optimal results which may comprise of architectural and parameter tuning. In this method, only definite information extracted from the earlier task is retained, while fresh trainable parameters are injected into the network, this needs training on a comparatively large dataset to become expedient [25].

To implement transfer learning in medical domain, convolutional neural network models are considered that outperformed in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [26], which evaluates the performance of an algorithm by carrying out object detection and image classification at bulky level [25]. Transfer learning aims to transfer knowledge from one task to another, that are, to some extent correlated [27]. The knowledge extracted by a convolutional neural network from given data is relocated to solve a different but correlated task, encompassing new data, usually with a smaller size.

3.2. Transfer Learning models for Feature Extraction

This research aspires to perform feature extraction using *AlexNet* [28] and *ResNet50* [29] deep transfer learning models. *AlexNet* is an eight layered convolutional neural network model and is the winner of the ImageNet Large Scale Visual Recognition Challenge 2012 [28]. The architecture of the *AlexNet* model encompasses a, 11×11 window of convolution present on the first layer, with 227×227 input size before this layer. The convolution window is reduced to 5×5 and then to 3×3 in the second layer, while adding 2-step stride and max pooling layers. After the convolution layer there is an output layer of 4096. Continuing further, a layer regarded as “FC8” comes next from where the first set of 1000 feature vectors are obtained for experimentation in this research. This model uses RELU as an activation function as an alternative of Sigmoid.

The *ResNet* [29] model which contains several blocks in each layer was developed by Microsoft Research Team who won the 2015 “ImageNet Large Scale Visual Recognition Challenge (ILSVRC)”. Before *ResNet*, the earlier models with deeper architectures were difficult to train due to the vanishing gradient problem; as the backpropagation of the gradient to the previous layers, recurrent multiplications make the gradient infinitively small. By introducing a skip connection to fit the input from the previous layer to the next without any modification of the input, *ResNet* may have a 152 layered deep network [30, 31].

For the implementation of *ResNet* the two shortcut modules include an identity block having no convolution layer at shortcut. The other is a convolution block with convolution layer at shortcut. In both of the blocks, 1×1 convolution layers are incorporated to the start and end of the network, the method is known as bottleneck design, decreasing the number of parameters not reducing the performance [32]. From the layer "fc1000" of this model, 1000 features have been extracted for our experimentation.

3.3. Correlation Based Features Ranking

The feature sets are obtained from the two different processes of convolutional neural networks, which are FC8 layer of the *AlexNet* model and FC1000 layer of the *Resnet50* as shown in eqn. 3.1 and eqn. 3.2. The obtained

$$AlexFeatures_{1000}(Imgs) = \{AF_1, AF_2, AF_3, \dots \dots \dots \dots \dots \dots AF_{1000}\} \dots \dots \dots \dots \dots \dots \dots (3.1)$$
$$ResFeatures_{1000}(Imgs) = \{RF_1, RF_2, RF_3, \dots \dots \dots \dots \dots \dots RF_{1000}\} \dots \dots \dots \dots \dots \dots \dots (3.2)$$

Where *Imgs* is the number of input images given to the functions $AlexFeatures_i$ and $ResFeatures_i$ for extracting the features from the AlexNet and Resnet50 models and *i* is the number of features extracted. AF_k and RF_k are the features extracted from Alexnet and Resnet50 models for $k \leq 1000$. The obtained features sets $AlexFeatures_{1000}(Imgs)$ and $ResFeatures_{1000}(Imgs)$ respectively, were ranked using Correlation based feature selection algorithm as shown in eqn. 3.3 and eqn. 3.4 and two different sets of features $Correl(AlexFeatures_{1000}(Imgs))$ and $Correl(ResFeatures_{1000}(Imgs))$ were formed, in which features were ranked according to the dominance of the feature in the classification process.

$$Correl(AlexFeatures_{1000}(Imgs)) = \{AF_{90}, AF_{210}, AF_{390}, \dots \dots \dots AF_{780}\} \dots \dots \dots \dots \dots \dots (3.3)$$
$$Correl(ResFeatures_{1000}(Imgs)) = \{RF_{790}, RF_{810}, RF_{390}, \dots \dots \dots RF_{990}\} \dots \dots \dots \dots \dots \dots (3.4)$$

The top ranked features obtained according to the eqn. 3.3 and eqn. 3.4 were merged with an aim to have a better set of features obtained from both the models which are highly dominant, to get better classification accuracy as shown in eqn. 3.5 and eqn. 3.6 in a set of size 1000 and 600 each with the name *FS1* and *FS2* respectively.

$$FS1 = Correl(AlexFeatures_{500}(Imgs))\ U\ Correl(ResFeatures_{500}(Imgs)) \dots \dots \dots \dots \dots (3.5)$$
$$FS2 = Correl(AlexFeatures_{300}(Imgs))\ U\ Correl(ResFeatures_{300}(Imgs)) \dots \dots \dots \dots \dots (3.6)$$

In correlation-based feature selection, features that are having low linear relationships with other features and high linear relationships with the labels aids to perform better in terms of classification accuracy [33]. The newly created datasets still contains many redundant features that are irrelevant to the target concept. Selecting the minimum number of features while maximising the classification accuracy can be modeled as an optimisation problem. To avoid the computational overheads due to these redundant features, the authors consider the use of nature-inspired metaheuristic algorithms for selecting the most pertinent features while maximizing the classification accuracy.

3.4. Nature-Inspired Metaheuristic Algorithms and Fitness Function

In recent times, working with large datasets, choosing the most pertinent features while removing the redundant features that can aid to improve classification accuracy and reduction in the computational time, has been a crucial task. The selection of minimum number of features that can aid to improve the classification accuracy is considered to be an optimization problem. Further, to get to the bottom of this problem, metaheuristic algorithms play an important role, given that they are based on the principle of a trial and error approach for generating optimal solutions in a reasonable time frame. The algorithms have two important key processes, the first produces different solutions by globally searching the space of solutions also known as exploration, while the second focuses on search in a local region by keeping in view that a present good solution is found in this region [34, 35]. On execution, in every iteration, the metaheuristic algorithms generate a subset of solutions which is given as input to the fitness function based upon k-NN classifier [35-36] as shown in eqn. 3.7 below. Where ERrate(D) represents the rate of error in the classification process.

$$Fitness = L_1 \frac{\text{FSel}}{\text{NFtr}} + L_2 * ERrate(D) \dots \dots \dots \dots \dots \dots \dots \dots \dots (3.7)$$

Furthermore, |FSel| is the selected features subset size and | NFtr | is the number of features present, L_1 and L_2 are two constants equivalent to the significance of classification importance and feature subset size, where $L_1 \in [0, 1]$ and $L_2 = (1 - L_1)$ [35]. The k-nearest neighbor's (k-NN) aids as an evaluator of the possible solutions of the population, which is a supervised machine learning algorithm and also a non-parametric method used for classification as well as regression [34, 35, 36].

These metaheuristic algorithms consider the random solution sets of the features as initial population and subsequently improve the solutions by updating the population in every iteration, all the while comparing the solutions obtained in each iteration with the fitness values obtained when the given solution is passed through the fitness function.

4. Dataset Considered, Parameter Settings and Evaluation Metrics

For the experimentation, this study considers the Gaussian filtered retina scan images to gauge the existence of the diabetic retinopathy, available at Kaggle [37]. The dataset consisted of 3662 images with 5 classes as shown in the Figure 3, containing 1805 images with no diabetic retinopathy, 370 images with Mild non proliferative retinopathy, 999 images with Moderate non proliferative retinopathy, 193 images with Severe non proliferative retinopathy and 295 images with Proliferative diabetic retinopathy.

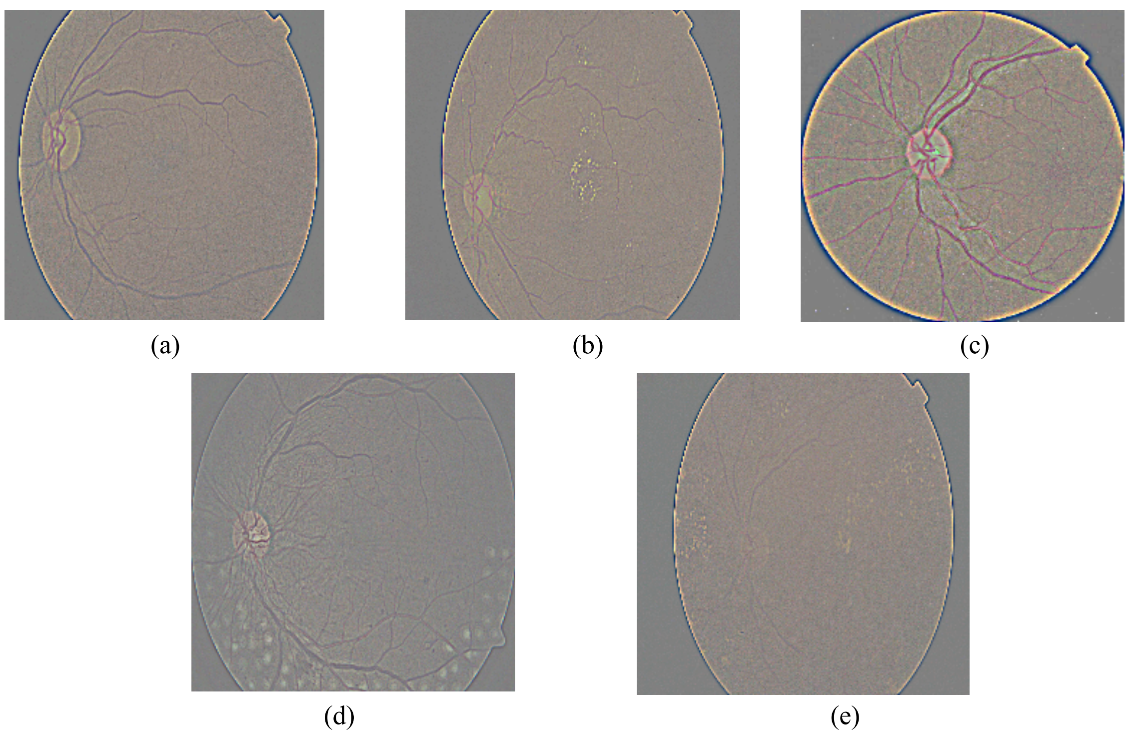

Figure 3: Image classes considered (a) Mild (b) Moderate (c) No Diabetic Retinopathy (d) Proliferate Diabetic Retinopathy (e) Severe

For the experimentation purpose and to avoid the imbalance of dataset, the dataset has been partitioned into 2 classes viz. the first is no diabetic retinopathy and the second is diabetic retinopathy containing the remaining four classes merged into a single class.

4.1. Parameter Settings

The experimentation was performed on Matlab environment with processor configuration of Intel(R) Core(TM) i5-8250U CPU @ 1.60GHz 1.80 GHz , and 4GB Ram. The parameters settings for transfer learning models is shown in the Table 1. For the performance comparison of nature-inspired metaheuristic algorithms, the various parameters considered to deal with the stochastic nature of the algorithms are shown in Table 2 and also all the results obtained have been averaged on 5 different independent runs

Table 1: Various Parameter Settings for Transfer Learning models

Parameters	AlexNet	Resnet50
Optimization	Stochastic Gradient Descent (SGD)	Stochastic Gradient Descent (SGD)
Image Size	227 × 227	224 × 224
Momentum	0.9	0.9
Learning	1.00E-05	1.00E-05
Mini Batch	64	64

Table 2: Various parameter Settings for Nature Inspired Algorithms Considered

Algorithm	Parameter	Value
Basic Parameters for running the simulations	No. of Runs	5
	Number of Iterations	120
	Population Size(No. of Search Agents)	20
	lb(Lower Bound) and ub(Upper Bound)	0 and 1
	Dimensions	Total features in dataset
	S_2 and S_1 (for fitness function)	0.99 and 0.01
Genetic Algorithms(GA)	Crossover Ratio in GA	0.9
	Selection Mechanism in GA	Roulette wheel selection
	Mutation Probability	0.005
Biogeography based optimization(BBO)	Habitat Modification Probability	1
	Maximum immigration and emigration	1
	Mutation Probability	0.005
	Immigration Probability bounds per gene	[0,1]
Particle Swarm Optimization(PSO)	Cognitive Constant(C_1)	1
	Social Constant(C_2)	1
	Inertia Constant(w)	0.3
GWO	Value of A in GWO	2 to 0
Salp Swarm Optimization	Value of C3 in Salp Swarm	0.5

4.2. Evaluation Metrics

To quantify the performance of algorithms various performance metrics have been considered. To compare the performance of two transfer learning models viz. *AlexNet* and *Resnet50* the following performance metrics are considered:

a) **Training accuracy-** Refers to the percentage of correctly classified instances from the training data using a particular solution or individual. It indicates how well the solution performs on the training set. The higher the training accuracy, the better the solution is at fitting the training data.

b) **Training loss-** Represents the measure of how well a solution performs on the training data or tells the error of the model on training set.

c) **Validation accuracy-** Refers to the performance metric used to evaluate the quality of a solution or individual on a separate validation dataset. This helps to gauge the model's ability to generalise and make accurate predictions beyond the training data.

d) **Validation loss-** Represents the loss or error calculated on a separate validation dataset during model training. It is used to evaluate the performance of a trained model on data that is distinct from both the training data and the final test data. Validation loss helps assess how well the model generalises unseen data.

To compare the performance of various nature-inspired algorithms for the proposed model, the various metrics considered are given below:

a) **Average Classification Accuracy**- This can be described as the proportion of samples taken for testing correctly classified by the algorithm. It generally evaluates the ability of a classifier in classifying the data in N runs, where Acc_t is the accuracy obtained in the t^{th} run.

$$Avg\_Acc = \frac{1}{N}\sum_{t=1}^{N} Acc_t$$

b) **Average fitness** - This metric gives the average of the various fitness values achieved by a probabilistic algorithm in N runs, where Fit_t is the fitness obtained in t^{th} run.

$$Avg\_fit = \frac{1}{N}\sum_{t=1}^{N} Fit_t$$

c) **Worst fitness**- This criterion gives the maximum of the N fitness values achieved by a probabilistic algorithm in N runs, where Fit_t is the fitness obtained in t^{th} run.

$$Worst\_fit = \max(Fit_1 : Fit_{\mathrm{N}})$$

d) **Best fitness**- This measure gives the minimum of the N fitness values achieved by a probabilistic algorithm in N runs, where Fit_t is the fitness obtained in t^{th} run.

$$Best\_fit = \min(Fit_1 : Fit_{\mathrm{N}})$$

e) **Standard Deviation**- This metric is defined as the divergence of the finest achieved solutions found after running a stochastic optimizer for N runs.

$$St\_dev = \sqrt{\frac{\sum_{t=1}^{N}(Fit_t - \overline{Fit})^2}{N-1}}$$

f) **Average Number of Features Selected**- This criterion is defined as the average number of features selected during all the runs, where FS_t is the number of features selected in t^{th} run.

$$Avg\_FS = \frac{1}{N}\sum_{k=1}^{N} \mathrm{SizeFS}_t$$

g) **F-Measure-** F-measure is also known as F-score; It is an assessment of classifier's accuracy, which integrates both the precision as well as the recall as a harmonic mean.

$$F\_Measure = \frac{2.\mathrm{Precision.Recall}}{(Precision + Recall)}$$

5. *Results*

In this section, a threefold summarisation of the results has been illustrated; firstly, the comparative analysis of the results is done on the basis of various parameters for performance comparison between the standard machine learning algorithms and among the *AlexNet* and *Resnet50* transfer learning models; secondly, the results are analysed based on various nature-inspired metaheuristic algorithms viz. *Genetic Algorithm(GA)*[38], *Particle swarm optimization (PSO)*[39] and *Biogeography-based optimization(BBO)*[40], *Grey Wolf Optimization (GWO)* [41] and *Salp Swarm Optimization (SSA)* [42] considered for getting into the bottom of feature selection problem [43] in the proposed model; and lastly, the results are compared on the basis of various datasets created using correlation-based features selection method.

Table 3: Comparative analysis of the results obtained by using various algorithms on $AlexFeatures_{1000}(Imgs)$ dataset.

Algorithm	*Accuracy*	*Precision*	*Recall*	*F-measure*
Random forest	0.907	0.936	0.878	0.878
Naïve Bayes	0.871	0.887	0.856	0.856
KNN	0.943	0.925	0.967	0.967
SVM	0.940	0.943	0.940	0.940
Adaboost	0.930	0.925	0.930	0.937

Table 4: Comparative analysis of the results obtained by using various algorithms on $ResFeatures_{1000}(Imgs)$ dataset.

Algorithms	*Accuracy*	*Precision*	*Recall*	*F-measure*
Random forest	0.940	0.960	0.921	0.921
Naïve Bayes	0.935	0.973	0.897	0.897
KNN	0.960	0.947	0.976	0.976
SVM	0.961	0.964	0.959	0.959
Adaboost	0.947	0.925	0.976	0.976

It can be easily gauged from the Table 3 and Table 4 that when dataset extracted from *Alexnet* and *Resnet50* was used for performing classification, the standard machine learning algorithms *Random Forest, Naïve Bayes, k-Nearest Neighbor(K-NN), Support Vector Machine(SVM) and Adaboost* show different performance in terms of various parameters; the performance of the *K-NN* and *SVM* algorithms is on the higher side. For data extracted from *AlexNet* the *K-NN* algorithm performs slightly better in terms of accuracy and for the *Resnet50* model the svm algorithm performs fairly well.

Pondering further, Figure 4 gives the basic confusion matrix for the binary classification problem from which the values of True Positive, False Positive, True Negative, and False Negative are judged, whereas Figure 5 clearly depicts the confusion matrices of both models. Performance metrics are calculated from the confusion matrix obtained

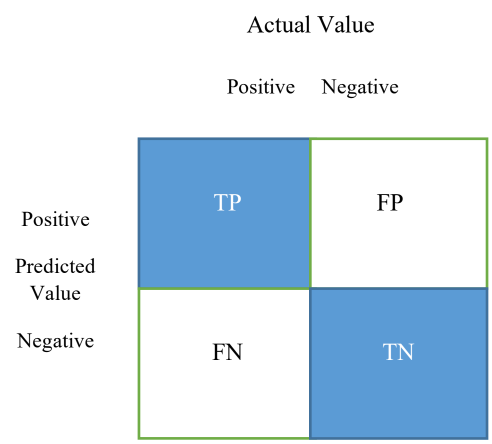

Figure 4: Confusion Matrix for Binary Classification

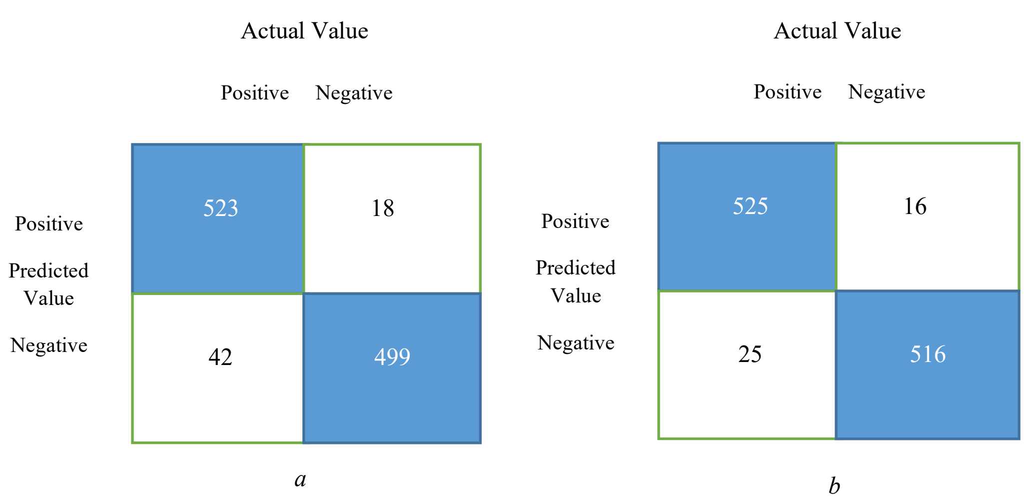

Figure 5: Confusion Matrix Obtained for (a) $AlexFeatures_{1000}(Imgs)$ (b) $ResFeatures_{1000}(Imgs)$

Table 5: Results obtained from Confusion Matrix of both the models

Parameter	***Foremula***	***AlexNet***	***Resnet50***
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$	0.9445	0.9621
Sensitivity	$\frac{TP}{TP+FN}$	0.9224	0.9538
Specificity	$\frac{TN}{TN+FP}$	0.9667	0.9704
Precision	$\frac{TP}{TP+FP}$	0.9652	0.9699
F-Measure	$\frac{2TP}{2TP+FP+FN}$	0.9433	0.9618

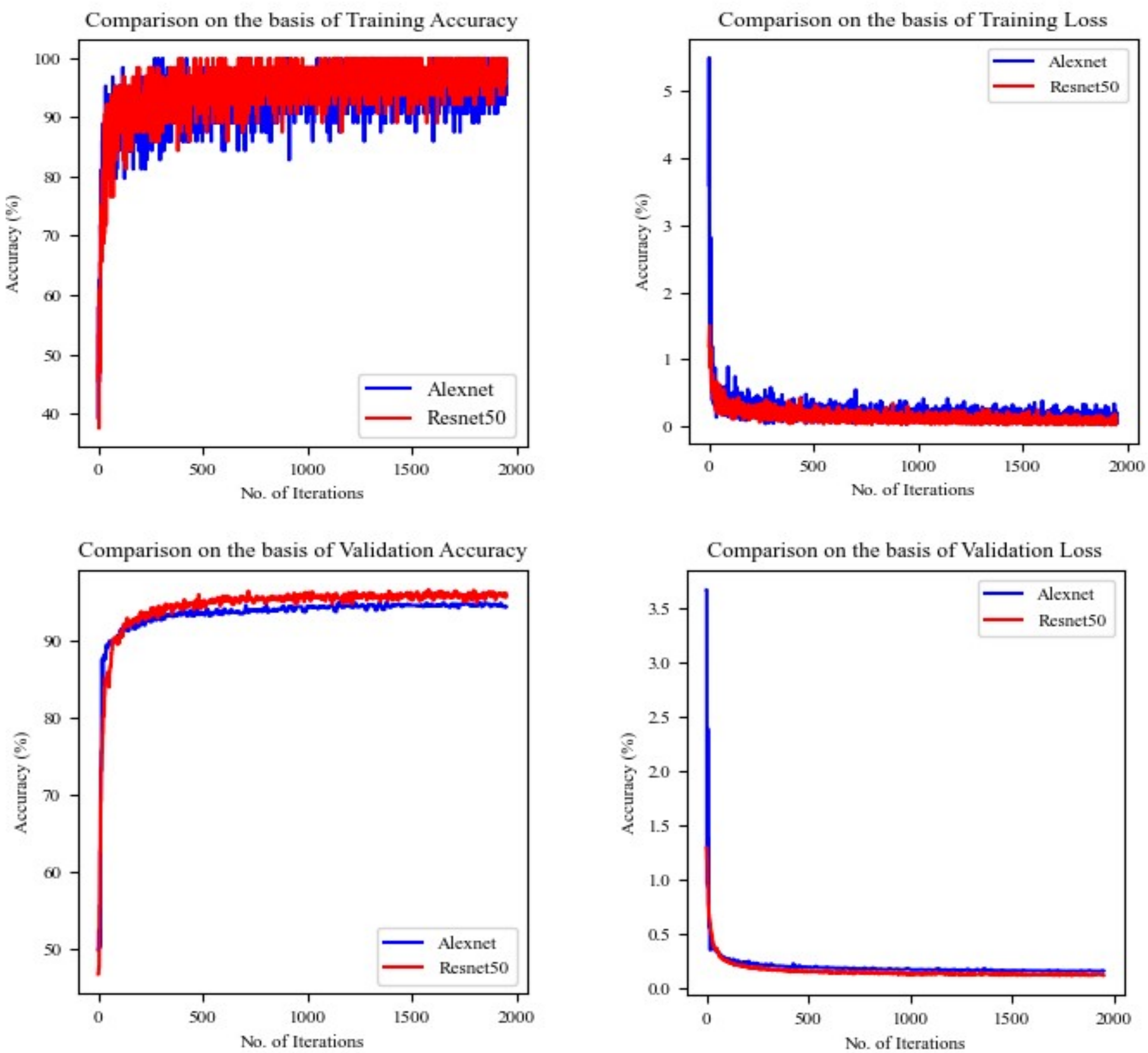

Figure 6: Performance Comparison of *AlexNet* and *ResNet50* Models on the basis of various parameters

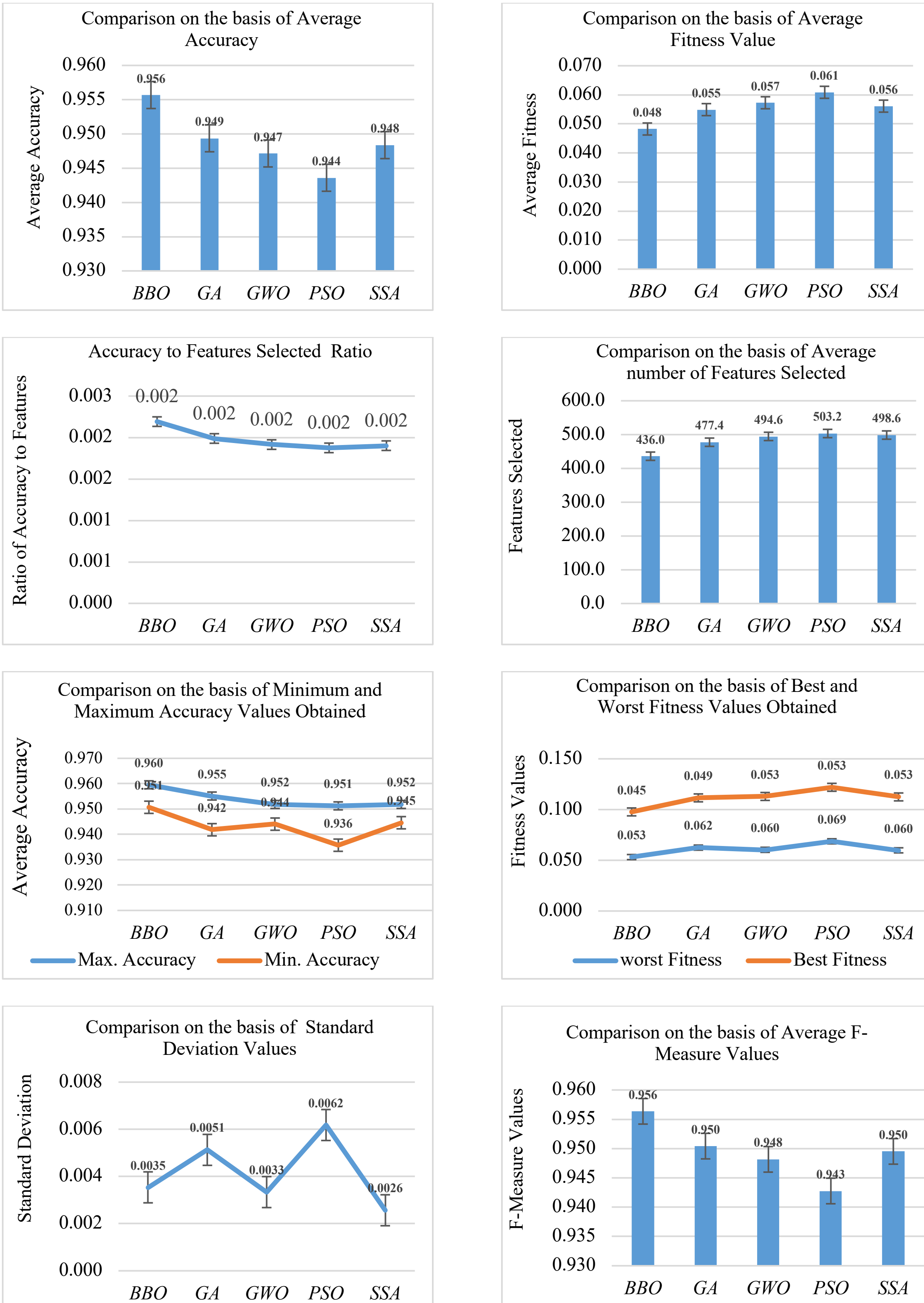

Figure 7: Performance Comparison of various nature inspired algorithms on $AlexFeatures_{1000}$ dataset.

Figure 8: Performance Comparison of various nature inspired algorithms on $ResFeatures_{1000}$ dataset.

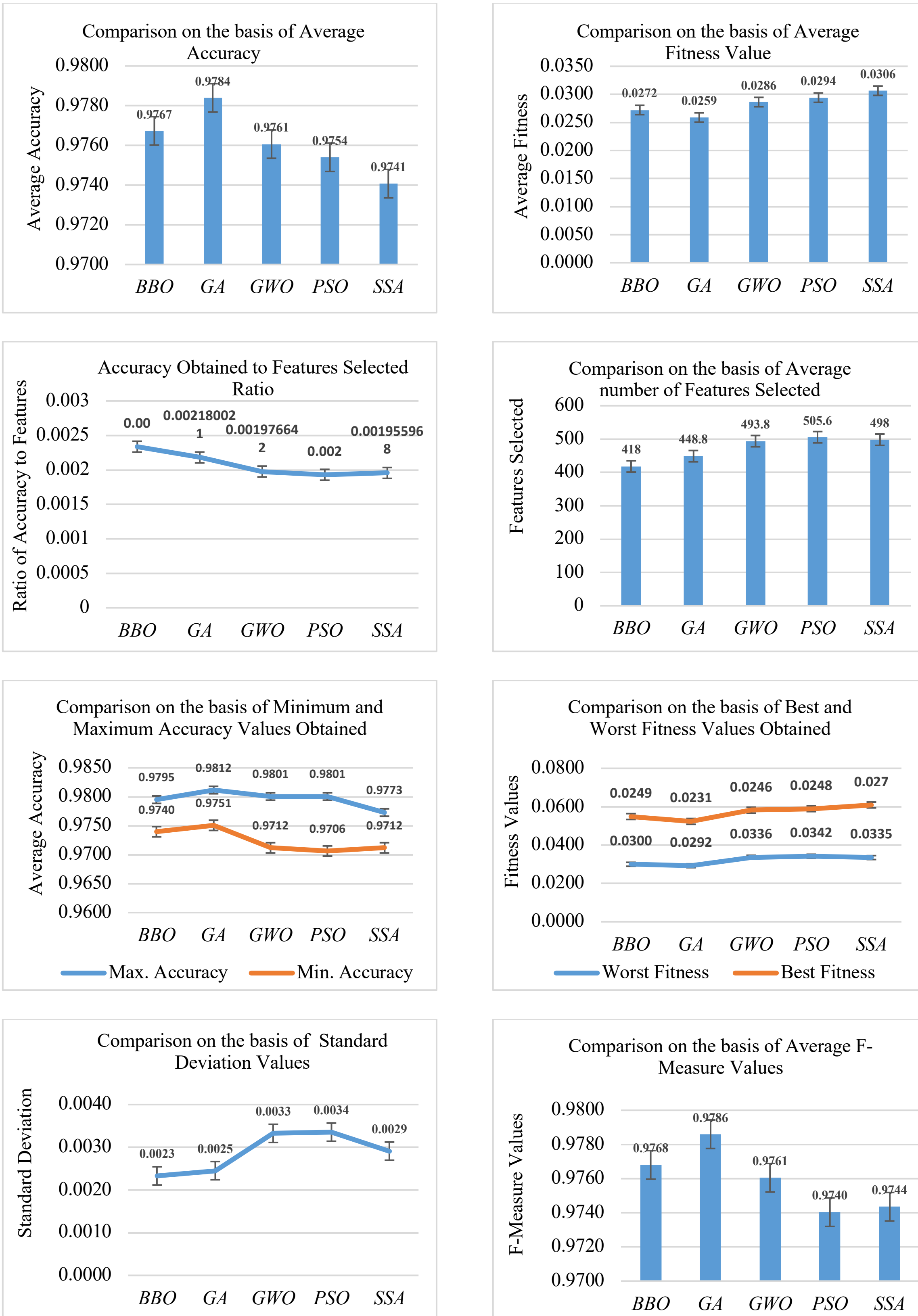

Figure 9: Performance Comparison of various nature inspired algorithms on FS1 dataset.

Figure 10: Performance Comparison of various nature inspired on FS2 dataset.

in the experimental results. These metrics are Sensitivity, Specificity, F-measure, Precision, and Accuracy. True Positive, False Positive, True Negative, and False Negative values are used to calculate the metrics and results are summarised in the Table 5 which clearly indicates that the *Resnet50* model performs much better as compared to the *AlexNet* model in terms of various performance metrics. Whereas, in-depth comparison of the performance of the algorithms can be seen in Figure 6 which compares the performance of the *AlexNet* and *Resnet50* transfer learning models based upon training accuracy, training loss, validation accuracy and validation loss. The results clearly show that the *Resnet50* model performs better in terms of various parameters considered. The validation and training accuracy value of the *Resnet50* model is better than as compared with the *AlexNet* model with validation and training loss on the lower side, but the training time of *Resnet50* model is on the higher side as compared with the *AlexNet* model. The *Resnet50* model works on the principle of skip connections that aids in building much deeper architecture without affecting the performance which is the reason for achieving higher accuracy as compared to the *AlexNet* model. Figure 7 summarises the results obtained from the features extracted from the "FC8" layer of the *AlexNet* model that is $AlexFeatures_{1000}$ dataset. The results clearly indicate that the performance of the BBO algorithm is better than the remaining algorithms taken for comparison, however the performance of SSA algorithm is better for the standard deviation parameter.

Figure 8 summarises the results obtained for $ResFeatures_{1000}$ dataset. The results show same behavior, the performance of the *BBO* algorithm is better than the remaining algorithms taken for comparison in terms of features selected, however the performance of *SSA* algorithm is slightly better for the average accuracy parameter. Moving further, Figure 9 presents the results obtained for correlated dataset *FS1* after applying correlation-based ranking on the feature set obtained from the $AlexFeatures_{1000}$and $ResFeatures_{1000}$ datasets. The *GA* algorithm outperforms the other algorithms in terms of average classification accuracy while *BBO* performs well for average number of features selected. Similarly, Figure 10 presents the results obtained for correlated dataset *FS2* dataset. The *BBO* algorithm outperforms the other algorithms in terms of average classification accuracy and number of features selected.

Table 6: Average Number of Features Selected and Reduction Percentage on all the datasets

	$AlexFeatures_{1000}$ *(1000)*		$ResFeatures_{1000}$ *(1000)*		*FS1(Correlated Feature Set) (1000)*		*FS2(Correlated Feature Set) (600)*	
	Features Selected	*Reduction Percentage*	*Features Selected*	*Reduction Percentage*	*Features Selected*	*Reduction Percentage*	*Features Selected*	*Reduction Percentage*
BBO	436	56.40%	447.2	55.28%	418	**58.20%**	257.4	**57.10%**
GA	477.4	52.26%	475.4	52.46%	448.8	55.12%	276.8	53.87%
GWO	494.6	50.54%	493.4	50.66%	493.8	50.62%	303	49.50%
PSO	503.2	49.68%	499.4	50.06%	505.6	49.44%	290.4	51.60%
SSA	498.6	50.14%	494.4	50.56%	498	50.20%	297.8	50.37%

Table 7: Average Fitness Values obtained on all the datasets

	$AlexFeatures_{1000}$ *(1000)*	$ResFeatures_{1000}$ *(1000)*	*FS1(Correlated Feature Set) (1000)*	*FS2(Correlated Feature Set) (600)*
BBO	0.0482	0.0476	0.0272	**0.0236**
GA	0.0549	0.0490	**0.0259**	0.0264
GWO	0.0573	0.0505	0.0286	0.0303
PSO	0.0609	0.0512	0.0294	0.0290
SSA	0.0561	0.0475	0.0306	0.0299

The results are also analysed on the basis of various parameters when performance of the algorithms is compared by considering the various datasets. The Table 6 clearly demonstrates, that average reduction in the number of features is high on the correlated dataset *FS1* by using *BBO* algorithm, similarly average fitness value obtained is better in the newly formed datasets by BBO and GA algorithms as shown in Table 7. The same pattern was seen in the average F-Measure values as shown in the Table 8. Furthermore, when the datasets are created by taking the union of the top best 500 and top best 300 features the accuracy of the classification increases by 2% with reduced feature set size, as shown in the Table 9.

Table 8: Average F-Measure obtained on all the datasets

	$AlexFeatures_{1000}$ *(1000)*	$ResFeatures_{1000}$ *(1000)*	*FS1(Correlated Feature Set) (1000)*	*FS2(Correlated Feature Set) (600)*
BBO	0.956	0.957	0.977	**0.980**
GA	0.950	0.956	**0.979**	0.978
GWO	0.948	0.954	0.976	0.975
PSO	0.943	0.953	0.974	0.975
SSA	0.950	0.958	0.974	0.975

Table 9: Average Classification Accuracy obtained on all the datasets

	$AlexFeatures_{1000}$ *(1000)*	$ResFeatures_{1000}$ *(1000)*	*FS1(Correlated Feature Set) (1000)*	*FS2(Correlated Feature Set) (600)*
BBO	0.9557	0.9565	**0.9767**	**0.9805**
GA	0.9494	0.9553	0.9784	0.9780
GWO	0.9471	0.9540	0.9761	0.9745
PSO	0.9436	0.9534	0.9754	0.9756
SSA	0.9484	0.9570	0.9741	0.9748

It can be clearly gauged from the results obtained that the ranking of features using correlation-based feature selection algorithm and implementing nature-inspired algorithms, has a huge impact on the performance of the proposed model. The higher performance is obtained by both the *BBO* and *GA* algorithms in most of the computations, which is due to the evolutionary operators being used by both algorithms which aids better performance by incorporating a good balance between exploration and exploitation. Similarly, *BBO* shows even better performance than the *GA* because it makes use of the elitism which aids the algorithm to consider only better solutions in the next generation and rejecting the unfit individuals to be considered for the next generation.

6. Discussions

In this study, deep transfer learning models and nature inspired metaheuristic algorithms are used together for classification of diabetic retinopathy. Initially the performance of *AlexNet* and *Resnet50* models was compared, and results indicate the outperformance of the *Resnet50* model in terms of various parameters but the average computational time taken by both models is on the higher side. This study aimed to develop a novel pipeline model for the diagnosis of diabetic retinopathy using transfer learning models and traditional nature-inspired metaheuristic learning algorithms with k-nearest neighbor algorithm for classification. The proposed model also made use of correlation-based feature selection algorithm for ranking the features before they are given as input to metaheuristic algorithms for finding the optimal solution. The results clearly indicate the outperformance of the proposed models on all the datasets as shown in Figure 11; dataset obtained from the $Alexnet$ model that is $AlexFeatures_{1000}$, dataset obtained from *Resnet50* model that is $ResFeatures_{1000}$, dataset obtained by implementing correlation-based feature selection on $AlexFeatures_{1000}$ and $ResFeatures_{1000}$ that is $FS1$ and $FS2$. The results clearly indicate that the metaheuristic algorithms result in better accuracy as compared with the results obtained from the deep learning models. Further, the results obtained by nature-inspired metaheuristic algorithms and the performance of the best algorithm

BBO is compared with the performance of *AlexNet* and *Resnet50* transfer learning models in Figure 10, which clearly indicates the superior performance of the proposed model. Additionally, the proposed model shows a dramatic

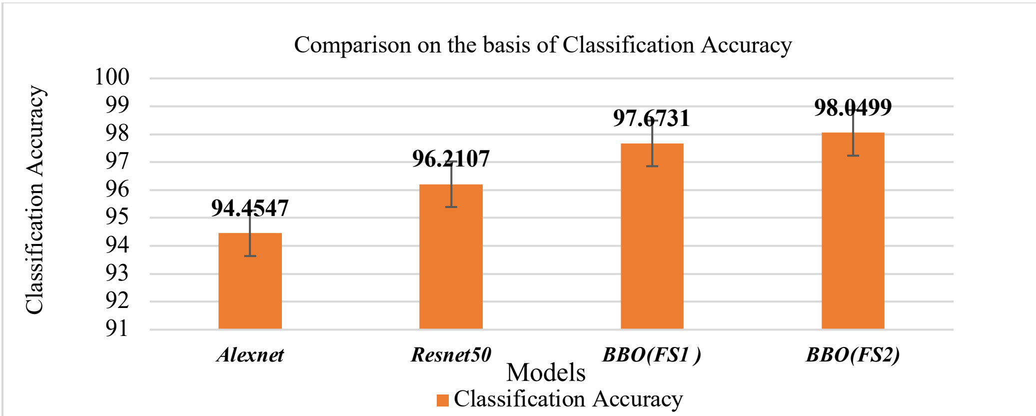

Figure 11: Comparison on the basis of Average Classification accuracy of proposed model and transfer learning models.

reduction in the computational process, the *Resnet50* and *AlexNet* models take 3535 minutes and 1182 minutes, respectively, to complete the training process and get the classification accuracy however the proposed model with *BBO* algorithm on *FS1* and *FS2* completes the computational process in 18 minutes and 11 minutes respectively.

Table 10: Comparison with existing state of the art research works

Reference	Year	Transfer learning models	Dataset/Size/ Partition	Highest Accuracy out of all models
Wu Y. et al. [17]	2019	VGG-19, InceptionV3, Resnet50	Kaggle/ 35,126/NS	InceptionV3- 61%
Khalifa N. E. M. et al. [18]	2019	AlexNet, Res-Net18, SqueezeNet, GoogleNet, VGG-16, and VGG-19.	APTOS 2019/3662/NS	AlexNet- 97.9%
Thota N. B. et al. [44]	2020	VGG-16	Kaggle/ 35,126/NS	74%
Gangwar A. K. et al. [19]	2020	Inception-ResNet-v2	Messidor-1 and APTOS 2019/1200 and 3662/75:25	Hybrid model/72.33% and 82.18% on Messidor-1 and APTOS dataset
Patel R. et al. [20]	2020	MobileNetv2	Kaggle/ 3662/80:20	91%
Ramchandre S. et al. [45]	2020	SEResNeXt32x4d and EfficientNetb3	Kaggle/3662/NS	EfficientNetb3/91.44 2%
Al-Smadi M. et al. [21]	2021	ResNet-50+GAP, InceptionResNet-V2+GAP EfficientNet-B4+GAP, Xception+GAP DenseNet-169+GAP, Inception-V3+GAP Ensemble (DenseNet-169, Inception-V3, Xception)	APTOS 2019/ 3562/NS	Ensemble (DenseNet-169, Inception-V3, Xception) 82.4%
Salvi R. S. et al. [22]	2021	VGG-16, Resnet50 V2, and EfficientNet B0 models.	APTOS 2019 Blindness Detection/1000/80:20	VGG 16(95%.), ResNet50 V2(93%.)
Sanjana S. et al. [23]	2021	Xception, InceptionResNetV2, MobileNetV2, DenseNet121, and NASNetMobile	Two public datasets which contain 1115 retinal fundus images /NS	InceptionResNetV2 (96.25%)
Islam K. T. et al. [46]	2019	AlexNet,GoogLeNet, DenseNet-201, etc	OCT/109309/NS	DenseNet-201 (0.98%)
Dong B. et al. [47]	2022	Multi-branch convolutional neural network	OCTA images of the eyes of 288 diabetic patients and 97 healthy people	Proposed Model-96.11%
Proposed Model	2023	ODeep-NN(BBO, GA, PSO, SSA, GWO)	Gaussian filtered retina scan images /3662/5-Fold Cross Validation	BBO 98.01% with lesser number of features.

The most effective features were selected with the help of metaheuristic algorithms. In order to confirm the accuracy of the results obtained, the reliability of the approach was proposed using k-fold cross validation methods. The benefit of the proposed research comprises presenting the outcome of feature selection while reducing the computational time. Whereas the drawback of the study is that it is not necessary that all the transfer learning models attains success with the proposed approach. This can be further depicted by considering other transfer learning models that can guarantee better performance.

Moreover, results are also compared with some of the previous studies conducted using deep learning models to assist the early detection of diabetic retinopathy. The outperformance of the proposed model can be clearly seen from Table 10 against most of the other models considered for comparison.

7. Conclusions and Future Works

One of the major health issues arising in the modern day is diabetes mellitus, which affects the lives of many worldwide and can often cause a serious condition known as diabetic retinopathy, which can lead to loss of vision. Timely diagnosis of diabetic retinopathy can reduce the permanent effects of the condition. Deep learning-based techniques are being widely explored for disease diagnosis in the medical sector. This study explored the potential of feature extraction capability of deep neural networks and its integration with standard nature-inspired metaheuristic algorithms for the feature selection, and traditional machine learning algorithm k-nearest neighbours for classification. The results clearly indicate that the proposed model achieves better predictive accuracy when compared with standard deep transfer learning models *AlexNet* and *Resnet50*, while selecting the minimum number of features. Moreover, the training period of a deep learning model when attempting to obtain the accuracy value is observed to be far longer than when compared with the proposed model. For performance evaluation, five different nature-inspired metaheuristic algorithms were used and it was observed that the biogeography-based optimisation algorithm outperforms almost all the other metaheuristic algorithms and also aids in making the model more robust. The future endeavor of the study can lead in many different directions. The application of the proposed technique can be considered for the detection of other diseases in medical images like breast cancer and brain tumor etc. furthermore, feature selection can be applied in any domain of computer vision to reduce the dimensionality of the data extracted by deep learning models. Precisely, for the feature extraction phase other transfer learning models must be considered for feature extraction and performance must be evaluated on the basis of the same. In the near future, an enhanced version of another nature-inspired metaheuristic algorithm must be proposed to achieve better classification accuracy. Lastly, to answer the black box nature of the proposed model, explainable AI must be incorporated for validating the number and type of features selected and the accuracy attained.

Authors' contributions

R.H. applied the algorithms and computed the results from the proposed model. S.K.S. performed the graphical analysis of the results. Both R.H. and S.K.S. worked on the development of the first draft of the manuscript. U.A. did the meticulous proofreading of the manuscript and suggested section wise improvements in the manuscript. All authors read and approved the final manuscript.

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Data availability

Dataset used in this article was obtained from the Kaggle (https://www.kaggle.com/sovitrath/diabetic-retinopathy-224x224-gaussian-filtered).

Declarations

Conflict of interest

The authors declare that there is no conflict of interest.

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