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A novel skin cancer Detection based transfer learning with optimization algorithm using Dermatology Dataset

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Abstract

Detecting skin cancer at the preliminary stage is a challenging issue, and is of high significance for the affected patients. Here, Fractional Gazelle Optimization Algorithm_Convolutional Neural Network based Transfer Learning with Visual Geometric Group-16 (FGOA_CNN based TL with VGG-16) is introduced for primary prediction of skin cancer. Initially, input skin data is acquired from the database and it is fed to the data preprocessing. Here, data preprocessing is done by missing value imputation and linear normalization. Once data is preprocessed, the feature selection is done by the proposed FGOA. Here, the proposed FGOA is an integration of Fractional Calculus (FC) and Gazelle Optimization Algorithm (GOA). After that, skin cancer detection is carried out using CNN-based TL with VGG-16, which is trained by the proposed FGOA and it is an integration of FC and GOA. Moreover, the efficiency of the proposed FGOA_ CNN-based TL with VGG-16 is examined based on five various metrics, like accuracy, Positive Predictive Value (PPV), True Positive Rate (TPR), True Negative Rate (TNR), and Negative Predictive Value (NPV) and the outcome of experimentation reveals that the devised work is highly superior and has attained maximal values of metrics is 92.65%, 90.35%, 91.48%, 93.56%, 90.77% respectively.

Keywords: Fractional Gazelle Optimization Algorithm, Fractional Calculus, Gazelle Optimization Algorithm, Convolution Neural Network, Transfer Learning

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1. Introduction

Skin is one of the greatest organs in the human body, so it isn't unexpected that skin malignant growth has the most noteworthy rate among human compared with other disease types [14][15]. Skin cancer is of two kinds, which are Melanoma and non-melanoma. Here, early-stage detection of cancer is very significant when compared to other types of cancers. Melanoma is the severe kind of skin cancer. which is produced in sunlight-exposed body parts [16]. A biopsy is an important technique to find skin cancer and it examines the samples from the skin to determine whether it is cancerous or not [16] [3]. Among the normal spreading diseases around the world is skin cancer, skin cancer can compromise human lives and causes serious risk. Skin cancer influences the skin cells in any region of the skin body. Depend on the abnormal growth of skin cells, skin cancer is classified into three common types named as basal cell carcinoma, squamous cell carcinoma, and melanoma. These are other less dangerous types of cancer [17] [18]. Moreover, due to the deficiency of medical resources, patients avoiding periodic checkups, far centers, lack of doctors, and huge money for detection and the treatments, which can change the intensity of skin disease to a more extreme case and help the spread. The early diagnosis, examination, and initiating precautions can diminish the severe complications and speed of skin cancer and lower the physical effects[18] [2].

For proper treatment of melanoma, there is a need for early detection, where the melanoma is recognized at a primary stage, and its rate for a 5 years is about the 92%. Visual assessment of the benign and malign lesions of the skin is a main issue in a detection of melanoma. Here, the identification of melanoma is complex even for experienced professionals and the determination of lesions visually is a difficult process.Dermoscopy is a common type of detection technique used for identifying skin diseases in recent years [8]. The skin lesion can be detected using detection tools like Dermoscopy that creates a image of dermoscopy. Relying on expert opinions only to analyze the skin lesions cannot be dependable in most cases where the requirement for dermoscopy images is extremely important. Moreover, dermoscopy images can be affected by a variety of restrictions, which makes understanding difficult, requiring extremely trained expert, and composite images, and the quality of images depends on the device utilized to take of an image affecting the exterior of a lesion. Moreover, captured region of the body in the dermoscopy image can influence the quality of the image in terms of position, skin type, magnification, skin thickness, color, and lighting[19] [20]. Thus, an automatic melanoma recognition tool or algorithm based on dermoscopy images is important in skin lesions identification and management rather than relying only on clinical expertise [21] [2].

Deep learning (DL) has newly presented end-to-end advantages to identify brain tumors, lung cancer, breast cancer, foot ulcer skin cancer, and esophageal cancer. Techniques of imaging like, Computed Tomography (CT), dermoscopy, Magnetic Resonance Imaging (MRI), and High-Resolution Computed Tomography (HRCT) are utilized in diagnosing cancer and capturing data on skin cancer from the affected people globally. Skin data imaging has an important power behind the image of skin lesions and expert justification for an automated Computer-Aided Diagnostics (CAD). The detection of cancer is based on the solution of Artificial Intelligence (AI), which is managed based on computing resources, dependable cloud storage to preserve, High-speed internet, and distribution of skin cancer dataset [22] [23]. These procedures can function on various platforms, computers, and an operating methods to convert into a cutting-edge medical tool. An experienced dermatologist uses various steps, from visual examination to dermoscopy continued by a biopsy[4] to detect skin cancer. In recent days, DL-based techniques are receiving more attention in medical imaging. The simple portion of image including melanoma-suffered portions are taken through Convolutional Neural Network (CNN) for training an automated recognition method. These algorithms execute segmentation of testing images depending on the tuned technique. The prediction and segmentation of melanoma are performed based on DL approaches and handcrafted feature-based approaches. These techniques can automatically formulate the complex and feature representation set acquired from an input skin image and demonstrate enhanced position and prediction power for melanoma-suffered skin regions. In addition, DL techniques can easily identify the skin moles of modifying sizes over the presence of noise, blurring, intensity, color variations, and occurrence of light [6].

The detection of skin cancer disease at the initial stage is the major intention of this approach. Initially, input skin data is fed to a data pre-processing module. The data pre-processing is done by using missing value imputation and linear normalization and the output of data processing is subjected to the feature selection, which is done by the proposed FGOA. The proposed FGOA is a combination of FC and GOA. Once features are selected, skin cancer detection is done by CNN-based TL with VGG-16, which is trained by the proposed FGOA, which is combination of FC and GOA.

2. Methods

Proposed FGOA_ CNN-based TL with VGG-16 for detection of skin cancer: Here, FGOA_ CNN-based TL with VGG-16 is devised for detection of skin cancer. Here, feature selection is done by proposed FGOA and detection of skin cancer is carried out by CNN-based TL with VGG-16, where CNN hyperparameters are initialized by TL, which is trained by the proposed FGOA, which is an integration of FC and GOA.

The proposed FGOA_ CNN-based TL with VGG-16. The results of the experiments are analyzed and discussed in part 4. At last, part 5 indicates the concluding remarks and consequent developments.

- LSI with CFS [1] was introduced for skin cancer detection and the execution time of technique was minimum and also enhanced the optimization process, but this technique was not used in real-time applications.

- In [2], the DOLHGS algorithm was developed for the prediction of skin cancer. Here, the developed approach predicted more accurately and effectively performed in skin cancer detection, but it failed to combine the more classifiers for accurate prediction.
- Multi-scale structure [3] was introduced for the detection of skin cancer and this technique had better generalization capability, but it failed to implement other deep learning networks for improving performance of detection.
- RegNetY-320 was devised in [4] for the prediction of skin cancer detection. This technique addressed the data imbalance issue, although it had low convergence capability.
- The visual examination during the clinical analysis of skin lesions is a lengthy process die to the similarity among the affected region and the surrounding skin. These pose a great challenge in skin cancer detection along with the low contrast variations.

2.1.1. Proposed FGOA_ CNN-based TL with VGG-16 for skin cancer detection

The primary goal of this paper is to design and develop an effectual model for skin cancer detection utilizing FGOA_CNN-based TL with VGG-16. At first, the input data is acquired from databases, which is forwarded to the pre-processing stage. In the data pre-processing phase, pre-processing missing values and linear normalization [12] are utilized to minimize and exclude duplicated data. Once the data is pre-processed, the feature selection is carried out using the proposed FGOA, which is designed by the formation of FC [9] and GOA [10]. After that, skin cancer detection is carried out using CNN-based TL with VGG-16 [13], which is trained based on the proposed FGOA. Here, CNN based hyperparameter is initialized by the VGG-16 by applying TL and Figure 1 depicts the structural diagram of Proposed FGOA_ CNN-based TL with VGG-16.

3 Results

The FGOA_ CNN-based TL with VGG-16's outcome for skin cancer detection is demonstrated in this part. The description of the experimental setup, dataset, performance metrics, comparative assessment, and algorithmic assessment are detailed in this part.

3.1 Experimental set-up

The proposed FGOA_ CNN-based TL with VGG-16 for the detection of skin cancer is implemented with the PYTHON tool utilizing the dermatology dataset [11].

3.2 Dataset description

The dermatology dataset [11] is utilized here for skin cancer detection. Diagnosis of various skin cancer diseases is a common problem in dermatology, and a small difference exists in clinical features of scaling and, erythema. Commonly, a biopsy is required for the detection more histopathological features as well. An additional complexity for the discrepancy detection is that a disease may demonstrate the features of a further disease at starting phase. Initially, patients are clinically evaluated with 12 features. Then, 22 histopathological features are taken for skin sample evaluation. The histopathological feature values are later determined by an examination of the microscopic sample. This database includes 34 hyperparameters, and 33 features, which are linear valued and it is ostensible.

3.3 Performance measures

Performance evaluation of devised FGOA_ CNN-based TL with VGG-16 is done by evaluation metrics such as accuracy, TPR, TNR, PPV, and NPV.

i)Accuracy

Accuracy estimates are depend on the ratio of correctly detected data of skin cancer and the whole amount of skin data and it is formulated as,

$$\Diamond = \frac{T_p + T_q}{T_p + T_q + U_p + U_q} \tag{24}$$

$\Diamond$ signifies accuracy, T_p indicates the true positive, T_q represents the true negative U_p indicates a false positive, and U_q denotes the false negative.

ii)TPR

TPR estimates the amount of positive samples that were perfectly attained out of a huge number of positive skin data samples.

$$\Omega = \frac{T_p}{T_p + U_q} \tag{25}$$

Ω represents TPR value.

iii)TNR

TNR estimates the accurate amount of the negative skin data samples detected from the entire amount of negative data samples, $\xi = \dfrac{T_q}{T_q + U_p}$ (26)

ξ signifies TNR value.

iv) PPV

The proportion of positive data outcome, which is perfectly classified as the skin cancer disease is term as PPV and is formulated using the expression,

$$\Psi = \frac{T_p}{T_p + U_p} \tag{27}$$

Ψ indicates the PPV.

v)NPV

The proportion of negative data outcome, which is truly classified as the skin cancer disease is expressed as NPV and is computed using the expression,

$$\aleph = \frac{T_q}{T_q + U_q} \tag{28}$$

$\aleph$ represents the NPV.

3.4 Comparative techniques

Various comparative techniques are used for skin cancer detection, which are LSI with CFS [1], DOLHGS [2], Multi-scale structure [3], and RegNetY-320 [4].

3.5 Algorithm analysis

For evaluating the efficiency of the proposed technique is compared to several technique such as Whale Optimization Algorithm (WOA) [24] +CNN based TL with VGG-16, Elephant Herding Optimization (EHO) [25] +CNN based TL with VGG-16, Lion Optimization Algorithm (LOA) [26]+CNN based TL with VGG-16, GOA [10]+CNN based TL with VGG-16,

3.5.1 Algorithm analysis based on varying swam size

Figure 1 indicates algorithm analysis based on varying swam size in terms of various performance measures, where a line graph is used for evaluation. Figure 1a) indicates the algorithmic analysis based on accuracy. Where swarm size is 90, the accuracy of WOA+ CNN-based TL with VGG-16 is 74.99%, EHO+ CNN-based TL with VGG-16 is 79.27%, LOA+ CNN-based TL with VGG-16 is 81.32%, GOA+ CNN based TL with VGG-16 is 85.01%, and Proposed FGOA+CNN based TL with VGG-16 is 92.64%. The TNR-based evaluation is estimated in Figure 1b). While taking swam size as 80, the TNR of 81.23% is attained for WOA+ CNN-based TL with VGG-16, 84.19% for EHO+ CNN-based TL with VGG-16, 84.32% for LOA+ CNN based TL with VGG-16, 88.24% for GOA+ CNN based TL with VGG-16, and 92.65% for Proposed FGOA+CNN based TL with VGG-16.

The evaluation of TPR is estimated in figure 1c), where TPR of algorithmic evaluation techniques such as WOA+ CNN-based TL with VGG-16 is 82.31%, EHO+ CNN-based TL with VGG-16 is 83.45%, LOA+ CNN-based TL with VGG-16 is 85.47%, GOA+ CNN based TL with VGG-16 is 87.55%, and Proposed FGOA+CNN based TL with VGG-16 is 90.23%, with swam size is 80. The estimation of NPV-based algorithmic analysis is depicted in figure 1d). When swarm size is 70, the NPV of various algorithms such as, WOA+ CNN-based TL with VGG-16, EHO+ CNN based TL with VGG-16, LOA+ CNN-based TL with VGG-16, GOA+ CNN-based TL with VGG-16, and Proposed FGOA+CNN based TL with VGG-16 is 80.87%, 82.85%, 76.59%, 76.59%, 77.27%, and 86.21% respectively. Algorithmic analysis evaluation on PPV is depicted in figure 1 e). While analyzing the swarm size is 80, the PPV of various techniques such as, WOA+ CNN-based TL with VGG-16 is 82.70%, EHO+ CNN-based TL with VGG-16 is 83.16%, LOA+ CNN-based TL with VGG-16 is 84.56%, GOA+ CNN based TL with VGG-16 is 81.85%, and Proposed FGOA+CNN based TL with VGG-16 is 88.57%.

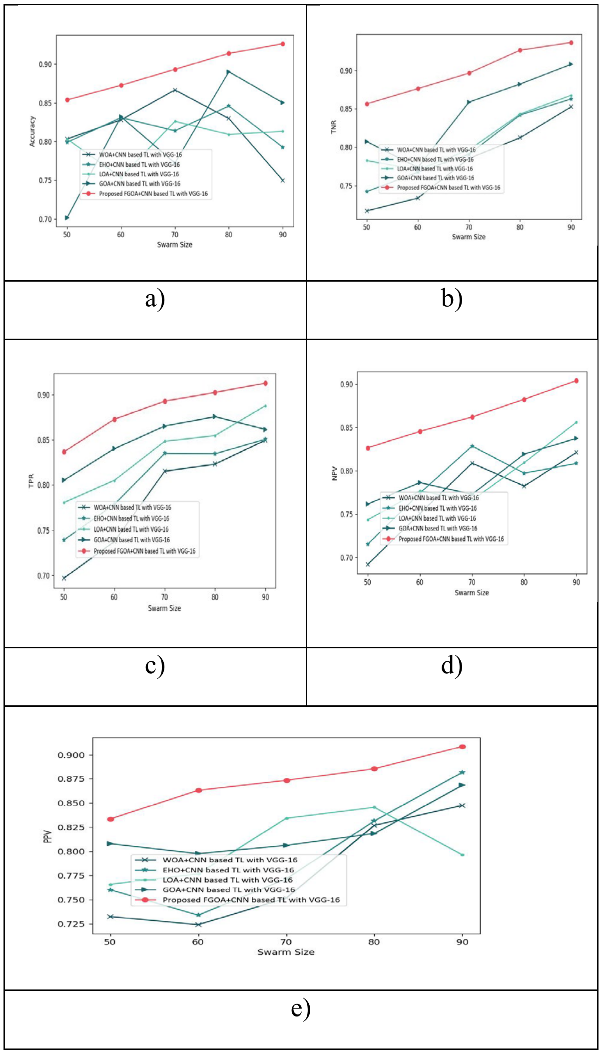


Figure 1. Algorithm analysis of the proposed FGOA_ CNN-based TL with VGG-16 on a) Accuracy, b)TNR, c)TPR, d)NPV, and e)PPV

3.6. Comparative assessment

Comparative evaluation of Proposed FGOA_ CNN-based TL with VGG-16 is processed based on the training data percentage and k-fold.

3.6.1 Evaluation Based on Varying Training Data

Figure 2 represents the line chart, which is drawn between different performance metrics with varying training data percentages. Figure 2a) represents the comparative examination of FGOA_ CNN-based TL with VGG-16 with accuracy. While examining 80% of training data, the accuracy of 91.65% is achieved for Proposed FGOA_ CNN based TL with VGG-16 and other technique's accuracy value is 81.66% for LSI with CFS, 82.03% for DOLHGS, 83.84% for Multi-scale structure, 86.64% for RegNetY-320. The performance of Proposed FGOA_ CNN-based TL with VGG-16 is 5.46% superior compared to the Multi-scale structure technique. Figure 2b) represents the evaluation of TNR in terms of varying training data. While considering training data is 90%, the TNR value of given techniques such as LSI with CFS is 85.35%, DOLHGS is 88.33%, Multi-scale structure is 84.67%, RegNetY-320 is 86.97%, and Proposed FGOA_ CNN based TL with VGG-16 is 93.13%. The performance of the proposed FGOA_ CNN-based TL with VGG-16 is 9.08% superior to the Multi-scale structure.

Figure 2c) signifies the assessment depending on TPR in terms of training data. The TPR calculated by prevailing methods, such as LSI with CFS, DOLHGS, Multi-scale structure, and RegNetY-320 is 78.52%, 77.25%, 77.36%, 82.59%, respectively and while TPR of Proposed FGOA_ CNN based TL with VGG-16 is 88.44% for considering 70% training data, which is 6.61% better compared to RegNetY-320 technique. The NPV value estimation is depicted in figure 2d). The proposed FGOA_ CNN based TL with VGG-16's NPV value is 89.66% and NPV of other technique is LSI with CFS is 84.90%, DOLHGS is 85.42%, Multi-scale structure is 85.77%, RegNetY-320 is 86.07% for taking training is 80%. The achieved NPV of the proposed technique is 4.33% better than to Multi-scale structure technique. Figure 2e) indicates the examination of PPV in terms of varying training data. While considering training data is 90%, the PPV value of existing techniques such as LSI with CFS, DOLHGS, Multi-scale structure, and RegNetY-320 is 87.88%, 88.37%, 88.68%, and 86.60% and Proposed FGOA_ CNN based TL with VGG-16 is 90.84%, which is 4.66% superior compared to RegNetY-320 technique.

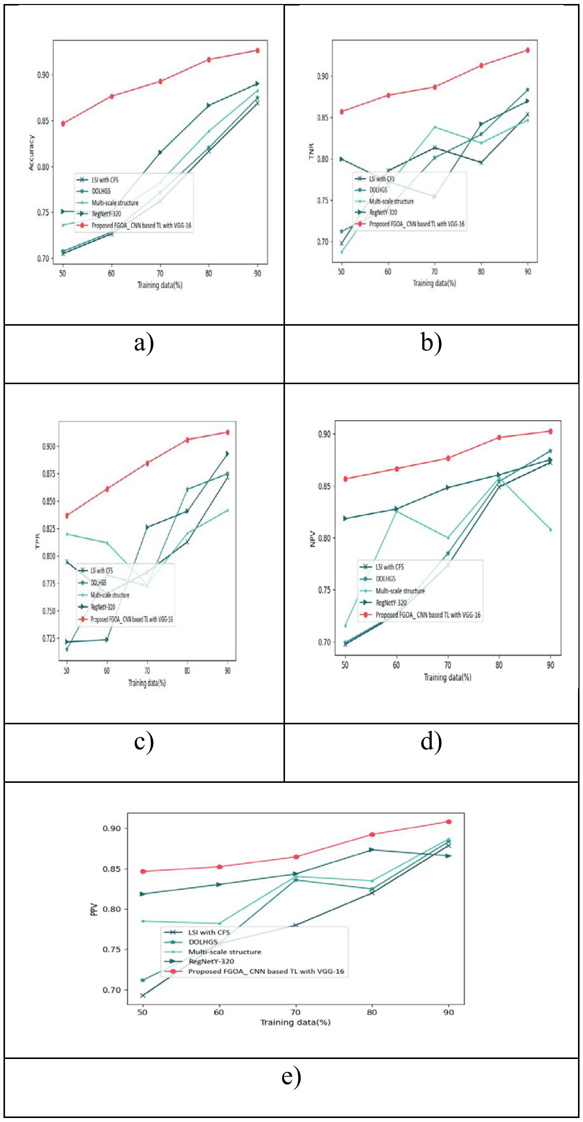
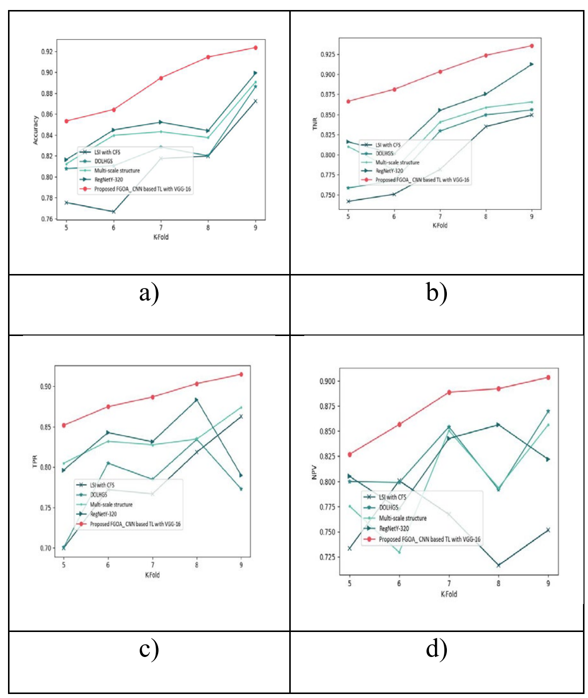


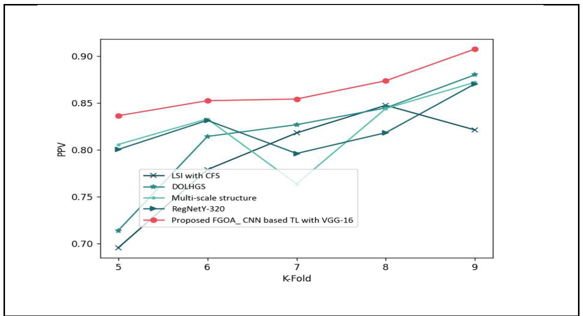
Figure 2. Comparative analysis of the proposed FGOA_ CNN-based TL with VGG-16 on a) Accuracy, b)TNR, c)TPR d)NPV and e)PPV based on training data

3.6.2 Assessment of comparison based on varying K-fold

Figure 3 represents the line chart, which is plotted between the various performance metrics with adjusting K-fold. The examination of the FGOA_ CNN-based TL with VGG-16 depend on accuracy is portrayed in figure 3a). The accuracy attained by LSI with CFS, DOLHGS, Multi-scale structure, RegNetY-320 and Proposed FGOA_ CNN-based TL with VGG-16 is 81.98%, 82.02%, 83.75%, 84.42%, and 91.47% respectively with k-fold is 8. The enhancement of performance based proposed technique is 7.70% compared to the RegNetY-320 technique. Moreover, figure 3b) represents the evaluation of the Proposed FGOA_ CNN-based TL with VGG-16 in terms of TNR value. While taking the k- fold value as 7, the TNR value of the exiting techniques is 78.17% for LSI with CFS, 82.95% for DOLHGS, 84.05% for Multi-scale structure, and 85.52% for RegNetY-320. A TNR of 90.35% is attained by Proposed FGOA_ CNN-based TL with VGG-16, which is 13.48% better compared to LSI with CFS.

Figure 3c) represents the evaluation of Proposed FGOA_ CNN-based TL with VGG-16 based on TPR. The TPR attained by LSI with CFS, DOLHGS, Multi-scale structure, RegNetY-320, proposed FGOA_ CNN based TL with VGG-16 is 81.84%, 83.43%, 83.47%, 88.31%, and 90.33% with k fold data is 8, where FGOA_ CNN based TL is 9.31% superior compared to LSI with CFS technique. Figure 3d) indicates the NPV-based estimation of the Proposed FGOA_ CNN-based TL with VGG-16. When k-fold is 9, the NPV of convention techniques such as LSI with CFS, DOLHGS, Multi-scale structure, and RegNetY-320 is 75.16%, 86.97%, 85.64%, and 82.18%, respectively and Proposed FGOA_ CNN based TL with VGG-16 attained NPV of 90.35%, which is 9.04% greater compared to RegNetY-320. The estimation of PPV is illustrated in figure 3e). While taking K fold of 8, the PPV of conventional technique is 84.75% for LSI with CFS, 84.47% for DOLHGS, 84.40% for Multi-scale structure, and 81.83% for RegNetY-320, and also 87.38% for Proposed FGOA_ CNN based TL with VGG-16, which is 3.33% greater compared to DOLHGS.





e)

Figure 3. Comparative analysis of the proposed FGOA_ CNN-based TL with VGG-16 on a) Accuracy, b)TNR, c)TPR d)NPV and e)PPV

4. Discussion

The results obtained by the Proposed FGOA_ CNN-based TL with VGG-16 technique for skin cancer detection in comparison with some conventional techniques is shown in Table 1. The proposed technique can be achieved high performance metrics values compared to existing approaches such as, accuracy is 92.65%, TPR is 91.48%, TNR is 93.56%, NPV is 90.35%, and PPV is 90.77%. Here, comparative assessment is considered based on training data of 90% and k fold data of 9. The accuracy of LSI with CFS is 88.62%, DOLHGS is 88.62%, Multi-scale structure is 89.09, and RegNetY-320 is 89.92. The TPR of LSI with CFS is 86.25%, DOLHGS is 77.27%, Multi-scale structure is 87.39%, and RegNetY-320 is 78.95%. The TNR of LSI with CFS is 84.94%, DOLHGS is 85.56%, Multi-scale structure is 86.57%, and RegNetY-320 is 91.24%. The NPV of LSI with CFS, DOLHGS, Multi-scale structure, and RegNetY-320, is 75.16%, 86.97%, 85.64%, 82.18%, and the PPV of 82.12% for LSI with CFS, 88.02% for DOLHGS, 87.21% for Multi-scale structure, and 87.05 for RegNetY-320, The proposed technique achieved maximum accuracy, TPR, and TNR because FGOA_ CNN based TL with VGG-16 algorithm the FGOA is used a feature selection technique. The utilization of TL in the proposed technique achieved superior NPV and PPV.

Table 1. Comparative discussion

Variation	Evaluation parameters	LSI with CFS	DOLHGS	Multi-scale structure	RegNet Y-320	Proposed FGOA_CNN basedTLwith VGG-16
Training set	Accuracy (%)	86.88	87.48	88.27	89.02	**92.65**
	TPR (%)	87.15	87.47	84.14	89.30	91.25
	TNR(%)	85.35	88.33	83.97	82.87	86.97
	NPV(%)	87.25	88.37	80.81	87.53	90.26
	PPV (%)	87.88	87.37	86.68	86.60	**90.84**
K-fold	Accuracy (%)	87.24	88.62	89.09	89.92	92.37
	TPR (%)	86.25	77.27	87.39	78.95	**91.48**
	TNR (%)	84.94	85.56	86.57	91.24	**93.56**
	NPV (%)	75.16	86.97	85.64	82.18	**90.35**
	PPV (%)	82.12	88.02	87.21	87.05	90.77

5 Conclusion

Early-stage detection of skin cancer, which is one of a deadliest cancer in the world, is not an easy process. Detection of skin cancer is done by DL techniques based on computer vision. Here, FGOA_CNN-based TL with VGG-16 is devised for accurate skin cancer detection. At first, input data is taken from the database, which is subjected to data preprocessing. Here, data preprocessing is done by missing value imputation and linear normalization. Once the data is preprocessed, the feature section process is carried out by the proposed FGOA. The FGOA is designed by a combination of FC and GOA. Finally, detection of skin cancer is performed and it is done by CNN-based TL with VGG-16, where the CNN is fine tuned by the proposed FGOA Evaluation of FGOA_ CNN based TL with VGG-16 shows that it attained a high value of performance measure, the maximal value accuracy is 92.65%, TPR is 91.48%, TNR is 93.56%, NPV is 90.35%, and PPV is 90.77%. In future dimensions, the skin cancer identification performance will be processed on large scale dataset and Internet of Things (IoT) enabled environment.

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