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Advanced domain adaptation for skin disease segmentation and classification using bootstrapping of fine-tuned deep learner

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Abstract
In medical diagnostic systems, the most challenging task is to segment and classify the varieties of skin disorders from dermoscopic images. For this purpose, Bootstrapping of Fine-tuned Segmentation and Classification Network (BF-SegClassNet) model was designed, which uses (i) cycle-Generative Adversarial Network (GAN) as domain adaptation, (ii) modified SegNet as segmentation and (iii) fine-tuned ResNet18 with Bootstrapping as classification. But, the efficiency of cycle-GAN was degraded if the source domain differs largely from the target domain. Hence, in this article, a Fuzzy Transfer Learning (FTL) model is developed based on fuzzy logic as domain adaptation. In this model, 2 different stages are performed such as training and adaptation. During the training stage, the source labeled data is used to build the Fuzzy Inference System (FIS), which extracts information from the source and transfers it to the target domain. The fuzzy sets and fuzzy rules created by an Adhoc Data-Driven Learning (ADDL) activity are included in the FIS. The created source FIS and the target data are used in the adaptation stage to adapt the fuzzy rule and the fuzzy rule base from the FIS to extract dissimilarities in the data and help bridge the contextual gap between the source and target. Thus, this FTL model is applied instead of cycleGAN to create more samples, which are further partitioned and classified by the BF-SegClassNet model efficiently. Finally, the testing outcomes exhibit that the FTL model attains a mean accuracy of 98.08% for the HAM dataset compared to the other GAN models.

Keywords Skin disease · BF-SegClassNet · Cycle-GAN · Domain adaptation · Fuzzy transfer learning · Fuzzy inference system

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1 Introduction

Due to the obvious significance in learning how to cope with diseases and the disparities in differing remedies, skin or dermatological disorders are possibly the broadest and most diverse sub-fields of pharmaceuticals. Skin disorders are well-known among other disorders, particularly those that are rapidly spread [1] and can be harmful to melanoma if not detected in its early stages. Skin problems have tremendously increased in comparison to other types of disorders. According to many studies, skin disorders were the fourth leading source of nonfatal illness risk worldwide, highlighting dermatology's importance in the ever-growing field of global health [2]. Skin illness can only be identified by dermatologists with extensive clinical experience and is hardly recurrent due to its magnitude, diversification, and familiarity. An untrained dermatologist is prone to misdiagnose it, which can worsen the illness and restrict accurate diagnosis. As a result, a quick and proper categorization of such disorders is critical by evaluating several features such as skin lesion shape, biological characteristics, color, context, and defect location [3].

Recognition is extremely difficult based on a self-governing assessment of therapeutic dermatological characteristics, and epidermal features are not developed proactively. To overcome such challenges, a transfer learning model was built that uses deep learning structures to describe skin diseases [4]. Instead of implementing with the random initialization, pre-trained designs were applied to improve the weighting factors of deep learning through recurrent back-propagation. Over the centuries, several pre-trained DCNN variants, like AlexNet, GoogLeNet, VGGNet, and others, were deployed to discover skin abnormalities [5]. For adapting the skin disease classification system on the transient set, a 2-phase progressive transfer learning approach with a fully supervised Residual Network (ResNet152) model pre-trained on ImageNet [6] has been developed. Besides, cycle-Generative Adversarial Network (GAN) knowledge was employed as a transfer learning process for converting epidermal properties from the image domain to the target domain. Given the overall efficacy, DCNN's cognitive knowledge proved invaluable for skin-like images. To address this issue, epidermal images were segregated using the SegNet, a deep encoder-decoder structure, and the segregated images were classified using the DCNN [7]. But, the fine-delineation of the margins among the Regions-Of-Interest (ROIs) in the skin lesion was not accomplished.

As a result, a modified SegNet with Categorization known as SegClassNet [8] was developed, with the skin lesion images augmented by cycle-GAN giving as input. Initially, dilated convolution was employed rather than conventional convolution to get multi-scale contextual features while maintaining pixel density. The encoder then coded these features and transmitted them to the decoder, which was preceded by the dropout layer. In the dropout layer, Dynamic Conditional Random Fields (DCRFs) were employed to resolve the overfitting and obtain segregated skin images. Further, such segregated features were immediately submitted to ResNet18 to classify epidermal diseases. But, it uses a standard error function, which restricts the network's capacity to extract invariant features from epidermis images.

To address this issue, the F-SegClassNet [9] was constructed by modifying the ResNet18 layers with the integrated triplet and group losses. The ResNet18 classifier was used to learn the embedding from segregated images into the Euclidean space. Besides, l_2 gap was calculated amid the corresponding segregated images from Euclidean distance to learn invariant data of skin images using the integrated loss value. Then, these l_2 gaps were used to classify the segregated image features. Even though it uses cycle-GAN as an image enrichment system, it was not acceptable while the training samples were inadequate.

As a result, the BF-SegClassNet framework [10] was developed to overcome the imbalanced pictures in the training set by generating a set of pseudo-balanced training batches based on the features of the original epidermis image database. This BF-SegClassNet model was tailored to the particular characteristics of DCNNs, making it more capable of categorizing the skin infection image database with a highly unbalanced distribution of samples. Depending on this bootstrapping, a stronger balance across relatively complex image samples was accomplished to create a framework for robust automated skin infection categorization. In this model, the probability was calculated for the whole training examples and a novel collection termed bootstrap samples was constructed to keep the most important image samples. On the other hand, the knowledge transfer between source and target domains did not often increase the efficiency and it degrades the accuracy. The cycle-GAN domain adaptation was not highly efficient when the source domain varies largely from the target domain.

Therefore, this paper proposes the FTL model, which uses fuzzy logic to transfer knowledge from contextually differing atmospheres and model a target domain in an intelligent environment using the labeled source data. This model can understand the inherent uncertainty and dynamic nature of intelligent environments by adding estimation and better expressiveness of such uncertainty revealed within the data. This model comprises training and adaptation stages. During the training stage, the FIS is built by the source labeled data to extract knowledge from the source and transfer it to the target domain. The FIS includes the fuzzy sets and fuzzy rules, which are devised by an ADDL task. During the adaptation stage, the created source FIS and the target data are utilized to adapt the fuzzy rule and the fuzzy rule base from the FIS to extract dissimilarities in the data and support in bridging the contextual gap between the source and target. Thus, the FTL can be applied instead of cycleGAN as domain adaptation and the BF-SegClassNet model is applied to classify the skin disorder categories.

The phrase "advanced domain adaptation" refers to a strategy that makes use of specialised tools to modify a deep learning model to suit various and intricate skin disease domains. The process of precisely defining and classifying skin illnesses from medical image is referred to as "skin disease segmentation and classification" and is a crucial stage in the diagnosis and planning of treatment. To obtain stable performance across various skin disease datasets, the addition of "using bootstrapping of fine-tuned deep learner" suggests the use of iterative and increased fine-tuning methods inside deep learning models. This suggests the creation of a cutting-edge methodology that makes use of domain adaptation methods, powerful deep learning models, and bootstrapping techniques to efficiently segment and categorise skin diseases from medical images. This method, which uses flexible deep learning models to increase diagnostic accuracy, can revolutionise the detection of skin diseases and medical imaging. Its capacity to adapt to different domains guarantees correct performance across a range of datasets, improving generalisation and lowering retraining costs. The model is made more reliable and adapted to the characteristics of skin diseases through recurrent bootstrapping and fine-tuning. This not only quickens therapeutic processes but also makes telemedicine possible and makes dermatological research easier. This strategy has the potential to revolutionise dermatology and greatly enhance patient care by reducing variability and increasing model efficiency.

The following sections of the paper are outlined as (i) Section II focuses on the works regarding skin infection segmentation and classification, (ii) Section III explains the FTL model for domain adaptation and Section IV demonstrates its performance. Section V summarizes the study and outlines the improvements that will be made in the future.

2 Literature survey

Hu et al. [11] designed a noel codebook learning method depending on Feature Similarity Measurement (FSM) to efficiently quantify the actual features of melanoma. Then, the mixture of the linearly independent and linear prediction methods was used to calculate feature similarity. Also, a melanoma classification technique was applied depending on the FSM codebook learning method. The Bag-of-Features (BoF) histogram fusion method of different feature descriptors was adopted to classify benign and melanoma. But, it needs to adopt deep learner for automatically extracting high-level features, which defines the lesions.

Garcia-Arroyo et al. [12] presented an algorithm to partition the skin lesions in dermoscopy images depending on the fuzzy classification of pixels and histogram thresholding. But the threshold value was fixed and it needs to properly select the fuzzy membership functions. Nida et al. [13] designed a deep learning model using region-based CNN and fuzzy C-means clustering to automatically partition the melanoma region in the dermoscopic images. On the other hand, different categories of skin disorders were needed to classify simultaneously.

Qin et al. [14] developed the skin lesion style-based GAN to effectively synthesize high-quality skin lesion images and applied deep transfer learning to classify the skin tumor classes. This was used to help physicians in more proper diagnostic decisions. But it needs to solve the mode monotony of a few diagnostic types in synthetic images.

Gazioğlu & Kamaşak [15] analyzed the effects of objects and image quality on melanoma classification using different CNN structures. First, the melanoma image dataset was acquired and data augmentation was performed to increase the number of images per class in the dataset. Then, the CNN model was trained and tested using the degraded images to classify benign and melanoma lesions. But the accuracy was degraded because of the ruler in the images.

Tumpa & Kabir [16] applied a preprocessing of dermoscopic images to eliminate hairs with the maximum gradient intensity method and enhance the image quality. Then, partition was applied using the OTSU thresholding method to divide skin lesions from the images. Also, various features were extracted from the partitioned images to train the Artificial Neural Network (ANN) and classify the skin diseases. But it has a high computation burden while increasing the number of images.

Abdelhalim et al. [17] developed the Self-attention Progressive Growing of GANs (SPGGANs) to create more fine-grained skin lesion images for CNN-based melanoma recognition. In this model, the image was created by aggregating details from each feature position. Also, the discriminator was used to observe that highly detailed features in distant regions of the image were reliable with each other. Moreover, the Two-Timescale Update Rule (TTUR) was applied to SPGGAN (SPGGAN-TTUR) to enhance the stability while creating skin lesion images. But its training was influenced by the artifacts in the images and it needs to extract multi-level dependencies across skin lesion image areas.

Rahman et al. [18] designed a weighted mean ensemble learning-based framework to classify the variety of skin lesions. First, the skin lesion images were collected and preprocessed to remove the noise from the images. Then, the data augmentation based on rotation, flipping, shearing and zooming was performed to augment the training images. After that, different CNN models were trained and ensembled based on weights assigned to each model for classifying skin lesions. But it was complex to collect the data because they need a skilled clinician to manually annotate them.

Indraswari et al. [19] suggested the MobileNetV2 network classify the melanoma images into benign and malignant classes. But its efficiency was less because of an imbalanced dataset. Hasan et al. [20] developed an automated skin lesion classification using preprocessing and hybrid CNN. First, lesion segmentation, augmentation and class rebalancing were applied as preprocessing. Then, the hybrid CNN was applied to extract the different features and fuse them to predict a lesion class. But it fails to obtain satisfactory class-balanced outcomes.

3 Proposed methodology

In this section, the proposed FTL-based domain adaptation model is described briefly. Figure 1 demonstrates the block diagram of the proposed skin disease segmentation and classification system using FTL with the BF-SegClassNet model. First, the training and test dermoscopic images are acquired. Then, the training image set is fed to the FTL model as multi-domain adaptation, which maps the skin disease features from the source domain (input space) to the target domain (feature space). Based on this FTL, training images are augmented and given to the modified SegNet to segregate the skin lesion visuals with high-resolution pixels. Further, the BF-SegClassNet classifier is trained by the segregated images and tested by the test images to classify the types of skin diseases.

3.1 Dataset

The HAM10000 dataset [21] is initially obtained from the ISIC archive and is available at https://isic-archive.com/. It contains all skin images, with 505 lesions recognized by pathology, and has 10,015 skin images of seven different types. Actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, melanocytic nevus, and vascular lesion are seven different types of skin disorders. After acquiring the dataset, 70% of

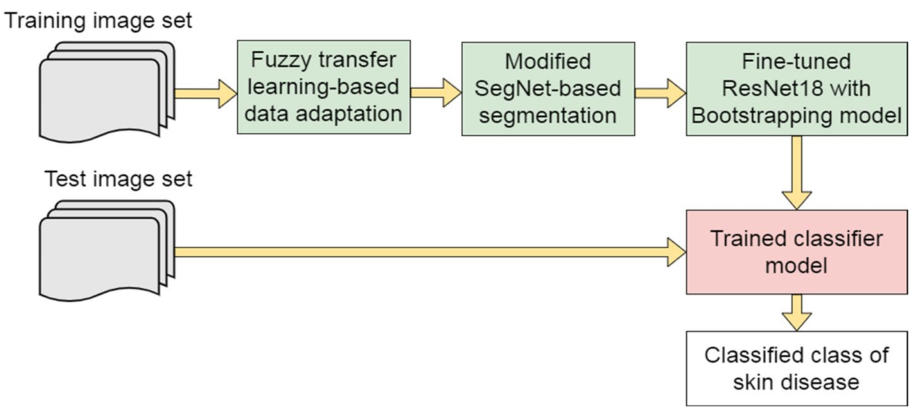

Fig. 1 Block Diagram of the Proposed Skin Diseases Segmentation and Classification System

the images (7011 images) are considered for the training set and 30% of the images (3004 images) are considered for the test set randomly. The training images are then augmented based on the FTL as a domain adaptation scheme to enhance the classification accuracy.

3.2 Domain adaptation based on fuzzy transfer learning

The major modules in the FTL are illustrated in Fig. 2. In this architecture, 2 different tasks are executed: (i) transfer of the fuzzy concepts and their relationships and (ii) the adaptation of the fuzzy modules using knowledge of the application context. In the initial phase, this system utilizes the source of labeled data to commence the training task. The training task utilizes this source data to build the FIS. The architecture of the FIS comprises fuzzy sets and fuzzy rules.

The FIS is utilized to extract the knowledge from the source and transfer it to the target domain. This task of transferring data is a basic phase of the FTL model. The FTL extracts data from the source domain to serve as a primary training step for the target domain. The second phase of the model investigates the adaptation of the FIS, which utilizes the data from the unlabeled dataset tied with prior learned data. This task adapts the individual units of the FIS to obtain the deviations in the data. Modifications from the scenario to the scenario are absorbed via alterations made within the domains of the fuzzy sets and adaptations to the rule base.

Based on this structure, the FTL model can transfer the data to help in bridging the knowledge gap. By an online adaptation task, newly added data is absorbed. The source domain $\left(D_S\right)$ is described as:

$$D_S = \left\{\left(x_n^S, y_m^S\right)\right\}_S^P \tag{1}$$

In Eq. (1), $x \in X$ are input images, $y \in Y$ is output, n is the number of input, m is the number of output and P is the number of data tuples within the domain. Likewise, the target domain $\left(D_T\right)$ and adaptive domain $\left(D_A\right)$ are described. Also, the domain is described

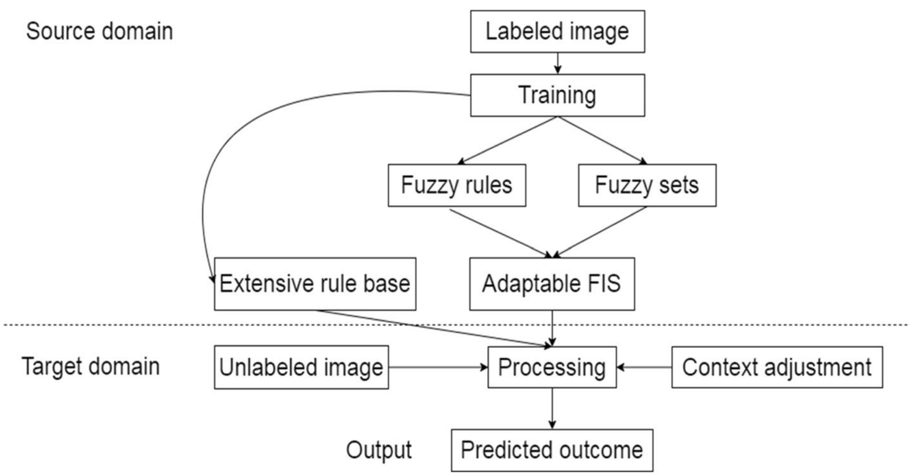

Fig. 2 Overview of FTL model

using time, which is applied to define the domains to enable the utilization of time arithmetic. In this model, a time is defined as a bounded collection of real numbers as:

$$A = \left[a_L, a_R\right] = \left\{a : a_L \le a \le a_R, a \in \mathbb{R}\right\} \tag{2}$$

$$B = \left[b_L, b_R\right] = \left\{b : b_L \le b \le b_R, b \in \mathbb{R}\right\} \tag{3}$$

In Eqns. (2) & (3), a_L and a_R are the left and right endpoints of the time A. When the respective endpoints of 2 time periods A and B are identical, these two time periods A and B are identical. Therefore, $A = B$, when $a_L = b_L$ and $a_R = b_R$. When $a_R < b_L$ or $b_L > a_R$, the intersection of 2 time periods is null ($A \cap B = \emptyset$). According to this description and using the time notation, the source domain time is described as:

$$D_S^I = \left\{\left[x_{1L}^S, x_{1R}^S\right]\left[x_{2L}^S, x_{2R}^S\right]\left[y_L^S, y_R^S\right]\right\} \tag{4}$$

As well, the domain is described using its relationship to fuzzy sets. The source domain with n inputs and m outputs is described by

$$D_S = \left\{fX_n^S, fY^m\right\} \tag{5}$$

In Eq. (5), fX_n^S denotes the collection of fuzzy input sets and fY^m denotes the collection of fuzzy output sets. Besides, fX_n^S is described as:

$$fX_n^S = \left\{vs^{fX_n^S}, s^{fX_n^S}, m^{fX_n^S}, l^{fX_n^S}, vl^{fX_n^S}\right\} \tag{6}$$

In Eq. (6), vs and vl are the sets very small, small, medium, large and very large, correspondingly. Such fuzzy sets are created as common, continuous and triangular.

The target domain with l inputs is described by

$$D_T = \left\{fX_n^T\right\} \tag{7}$$

In Eq. (7), fX_n^T denotes the collection of fuzzy input sets. The rule bases applied within the following tasks are described by a similar notation. A rule base that involves n antecedents and m consequent sets is represented by

$$R = \left\{fX_n^R, fY_m^R\right\}^P \tag{8}$$

In Eq. (8), R refers to the rule base, X refers to the input image, Y refers to the related output and P refers to the number of rules.

The initial phase of the FTL model is the formation of the FIS. Fuzzy rules and fuzzy sets are generated through the utilization of an ADDL task, which is determined from numerical data. This scheme utilizes numerical data to create the sets and rules.

The source domain D_S is transferred to model a predictive operation of a target domain D_T. The relationship between D_S and D_T influences the model output. The 2 domains are classified as correlated when there is an implicit or explicit correlation between them. The correlation can determine the need for knowledge adaptation from the source domain and the learning process. No adaptation is necessary when the domains are identical and the learning processes are addressing a similar issue; but this is uncommon in real-time systems. When the domains are partitioned, the adaptation procedure is required. The components of the adaptable FIS are changed to allow the model to understand these alterations from the source to the target domains. This domain adaptation via learning has the following phases:

Phase 1**: External source domain adaptation** During the transfer of learning structures from one contextual domain to another, a knowledge gap might emerge. Differences in the domains themselves, as well as variations in the learning structure can be represented. The FTL modifies the upper and lower bounds within the domain to adjust these variations in the source and target domains. The fuzzy sets initiate a stretching or expanding procedure. This model modifies the range of the period for an input instance of all databases based on any variance determined between the adaptable FIS and the new input values. First, D_S is defined as data tuples $\left(x_1, x_2, y\right)$, where x_1, x_2 are inputs and y is the output. The new domain is created depending on D_S including the variations obtained via the adaptation task. This is represented as D_A, which defines the missing data between the source and target domains.

Then, all data points are examined to capture data. The input period is adapted when the value enlarges beyond the left $\left(x_L\right)$ or right $\left(x_R\right)$ limits. So, a new set structure is created. Any domain adaption leads to a similar distribution across the sets because of the identical spacing. Domain expansion needs a simple update to the footprint of all sets. To adjust sets with unevenly distributed membership functions, a scaling function is essential. In this study, a triangular function is utilized and is described by

$$A(x) = \begin{cases} \left(1 - \frac{|x-c|}{w}\right), & \textit{if } c - w \le x \le c + w \\ 0, & \textit{or else} \end{cases} \tag{9}$$

In Eq. (9), x refers to the input value, c refers to the function centroid and w refers to the width. The sets are transferred by the centroid points when the domain is transferred in a negative or positive direction. The distance between each point is identical.

Any domain expansion or compression necessitates that the sets are transferred based on the scaling. When the target domain is embedded in the source domain, the alternated method is needed to adjust both set structure and domains.

Because the adaptation exists, the linguistic values allocated to the fuzzy sets remain unchanged. With the adaptation of the sets themselves, the linguistic labels provided to them are transferred from the source domain to the target domain. This relates to a linguistic label's contextual idea. Fuzzy subsets are defined as not being random and absolute, but rather depending on the criteria of a situation, according to a contextual idea. The situation is represented here by the timeframe of the array of an image. The adaptation essentially modifies the mapping of linguistic variables to the modified base set. The linguistic variables established during the creation of the sets from the source data remain constant throughout the situation in which the fuzzy sets are included.

Phase II**: Internal source domain adaptation** This phase is also subjected to the source domains. The source domain transfer will need adaptation to eliminate the knowledge gap, which is defined by variations in the domain periods. Phase I reduces the discrepancies by expanding the total size of the domain range by lowering the left bound or expanding the right bound if needed. But, when transferring the source to the target, the domain will need to be reduced, either partially or completely, to modify within the source bounds. In this phase, the following processes are performed:

1. Initialization: It initializes the FIS by analyzing the image from the source domain to increase an input period. The source domain input period is represented as $D_S^I(X) = [x_L, x_R]$ with x_L is the lowest range and x_R is the highest range of all inputs in the domain.
2. Correlation: The target domain contains very restricted image accessibility. To solve this problem, the adaptation model evaluates local highest and least ranges to source data. Because the target domain obtains data points, local minima and maxima are computed. When specific or both of such ranges exist within the period defined by the x_L and x_R, a proximity measure is used to determine whether the domain is adjusted or not. The proximity depends on the Gaussian membership function, which is according to the source input domain period. The outcome from the proximity factor is compared to the fixed threshold. If the threshold range is attained, the domains are adjusted according to the ranges from the target domain.
3. Negative impact: Adjustment of the input domains is forecasted depending on its effect on the entire fuzzy system. To determine the effect of this adjustment, an evaluation between the highest membership of the rule base prior to the transfer and equal after transfer. The system returns to its prior state when the value is reduced, which focuses on the adjustment and prevents the negative adaptation.

The initial 2 processes concentrate on the input variable domains and so the antecedent sets. Image is accessible to make adjustments within these domains. The unlabeled image makes direct adjustment of the target successive domains difficult. To solve this issue, the 3rd process merges the image created by the model with fresh domain data.

***Phase III*: Target domain adjustment via gradient control** This phase concentrates on the modification of the subsequent sets. This task utilizes an image from the target domain united with an image from the model itself. It enables feedback from the adjustment model. The processes performed in this phase are the following:

1. Image collection: A predefined n dimension sliding window (SL) of image is acquired from D_S and D_T for all input variables $x \in X$ and $y \in Y$. The output range for D_T is obtained from the FTL model. The source outcome is obtained from the given labeled image. Gradients are created depending on SL between the input and output range. It enables us to understand the correlation at all data points. The gradients are the basis of the consequent adjustment.
2. Gradient formation: Gradients are generated for all source and target inputs and the source output. The outcome from the FTL model is utilized to create the target output gradient. The image data is regularized by the typical score technique as:

$$z = \frac{x - \overline{x}}{\sigma} \tag{10}$$

In Eq. (10), z refers to the output, x refers to the input value, $\overline{x}$ and σ are the average and the standard variance of SL.

3. Gradient comparison: A comparison is performed at all individual input values by utilizing the gradients obtained across all source and target domain input and output variables.
4. Consequent adjustment: The gradients of the values are used to translate the source input and output values to the target input and output values. Variations emphasize the

need to adjust the consequent sets by mapping the source gradient to the target gradient. Adjustments to the target consequent domain period are influenced by changes between the source and target consequent gradients. The consequent adjustment is defined by

$$dD_A = \varphi \sum_{i=1}^{n} \left(g_{S_i} - g_{T_i} \right) \quad (11)$$

In Eq. (11), $\varphi(\varphi = 0.1)$ refers to the training variable to weight the effect of the gradient delta, g_S refers to the gradient of the source *SL* for *n* inputs that may be defined as $g_{S_{i...n}} \in [-1, 1]$, g_T refers to the gradient of the target *SL* for *n* inputs that may be defined as $g_{T_{i...n}} \in [-1, 1]$ and dD_A refers to the delta utilized to adjust the consequent sets.

The primary 3 processes of the adjustment task are concerned with changing the fuzzy sets. Also, it adjusts the fuzzy rule-base to observe the contextual alterations during all executions.

***Phase IV*: Rule base adjustment through source rule comparison** Earlier phases are concentrated on domain adjustment. As well, the variations exist within the rule base structure. The knowledge of the FTL model is included in the fuzzy sets and fuzzy rules. The knowledge gaps are addressed to employ adaptable FIS to the new situation via changing the rule base. The rule base is adjusted by analyzing prior pruned rules and integrating the target domain image. The usage of an extensive rule base is related to the transfer learning concept of the FIS development.

The initial process is to analyze the extensive rule base $\mathcal{A}$ to recognize the rules that strike by the image from D_T. The rule that strikes with the maximum membership value from all data points is retained in the dynamic rule base *C*. The collected rules are evaluated with the reduced rule base *B* depending on those with similar antecedent values. All reduced rule base rules that strike are evaluated with the dynamic rule base. Those rules that contain higher membership values are retained, eliminating the comparable rule from the dynamic rule base. The higher weighting defines higher applicability to the new domain. When the recognized rule in *B* is not within *C*, this is included. The addition of the rules from the extensive rule base helps in providing missing knowledge data needed by the new domain.

***Phase V*: Rule adjustment by Euclidean distance measure** The last phase of the adjustment is also concentrated on the fuzzy rule base. Earlier learned data can be used to bridge the gap in knowledge needed to execute a new assignment. Additional data is needed to bridge the gap and try to preserve each of the fragments where discrepancies exist. In the FTL model, data of the new domain can only be partially defined in the fuzzy rule base. Additional rules have to be created for supporting the rule base. Because the target domain is an unlabeled dataset, this method relies on a combination of learning from recently collected data and prior experience in the form of an extensive rule base. Different procedures are employed to create antecedent and consequent fuzzy sets.

The primary task is to obtain an output from all the input variables. The antecedent sets are adjusted depending on earlier acquired data. The unavailability of relevant data necessitates a new method. There is a mapping between the input values and the consequent output from a related rule. The mapping is produced by the Euclidean distance depending on the input values from the unlabeled image to localize the nearest related consequent set. All sets are provided a related input value during the creation of the extensive rule base.

Thus, this FTL as a domain adaptation can adjust the source and target domain images to augment the number of training images. Once the augmented training image set is obtained, the modified SegNet is applied to split the skin lesion images with high-resolution pixels. Further, those images are used to train the BF-ResNet18 classifier and so the trained classifier can be useful to classify the test images into different categories of skin diseases.

Algorithm for Proposed Skin Disease Segmentation and Classification Model:

Input: HAM image dataset and ImageNet

Output: Classified categories of skin diseases

Begin

Split the dataset into training and test sets;

$\boldsymbol{for}(training\ set)$

Map the epidermis visual features from the ImageNet (source domain) to the HAM (target domain) by FTL;

Get the enriched epidermis disorder images for learning;

Obtain the ROIs of skin lesions by learning the modified SegNet;

Partition the segmented image set into a positive and a negative set;

Create the bootstrapped samples to solve the class imbalance problem;

Train the fine-tuned ResNet18 classifier;

$\boldsymbol{end\ for}$

Get the trained model and validate it using the test images to classify the skin disease types;

End

4 Experimental results

In this section, the performance of FTL with the BF-SegClassNet model is evaluated through implementing it in Python 3.7.8. From the HAM dataset, 70% of skin lesion visuals from all classes are utilized for training and the remaining 30% from all classes are utilized for testing. Also, the performance is evaluated with the classical domain adaptation models depending on the precision, recall, f-measure and accuracy. The sample input images from HAM dataset for all skin disorder categories are given in Fig. 3.

Precision is calculated as:

$$Precision = \frac{No.of\ exactly\ classified\ skin\ disease\ images}{No.of\ exactly\ classified\ skin\ disease\ images + No.of\ inexactly\ classified\ skin\ disease\ images} \tag{12}$$

Recall is calculated as:

$$Recall = \frac{No.of\ exactly\ classified\ skin\ disease\ images}{No.of\ exactly\ classified\ skin\ disease\ images + No.of\ inexactly\ classified\ healthy\ images} \tag{13}$$

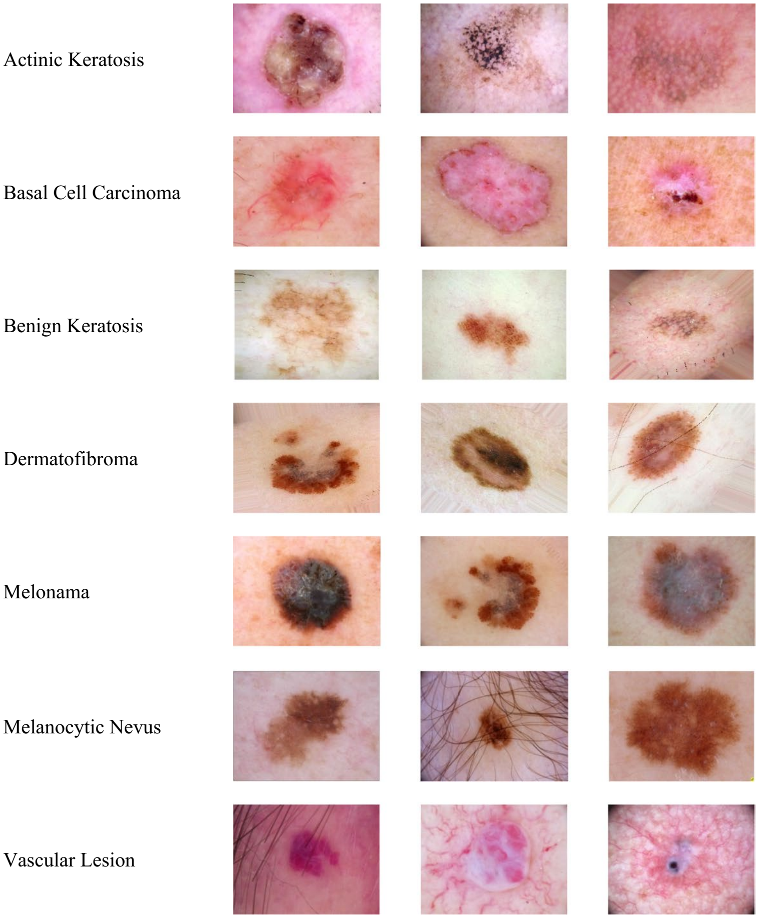

Fig. 3 Sample Input Images for Various Kinds of Epidermis Infections

F-measure is calculated by

$$F - measure = 2 \times \frac{Precision \cdot Recall}{Precision + Recall} \tag{14}$$

Accuracy is calculated as:

$$Accuracy = \frac{TP + True\ Negative\ (TN)}{TP + TN + FP + FN} \tag{15}$$

The values of precision, recall, f-measure and accuracy obtained by the different domain adaptation models such as FTL, cycle-GAN [6], style-based GAN [14] and SPGGAN-TTUR [17] on HAM10000 and ImageNet databases are listed in Table 1. The graphical depiction of these outcomes is presented in Fig. 4.

These test outcomes indicate that the FTL model as a domain adaptation realizes better efficiency compared to the different GAN models to transfer the knowledge from the

Table 1 Findings of Various Domain Adaptation Models on HAM Dataset

Metrics	Style-based GAN	Cycle-GAN	SPGGAN-TTUR	FTL
Precision (%)	85.74	89.35	90.61	93.98
Recall (%)	86.21	90.02	91.45	94.33
F-measure (%)	85.98	89.69	91.03	94.16
Accuracy (%)	86.26	90.11	91.52	94.74

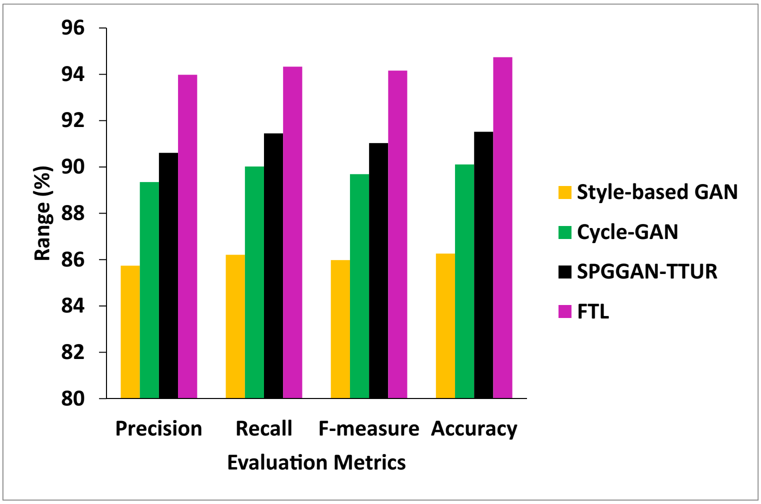

Fig. 4 Analysis of Different Domain Adaptation Models on HAM10000 Dataset

source domain to the target domain. As far as skin image augmentation is concerned, the FTL model is greatly helpful in terms of its efficiency.

The values of precision, recall, f-measure and accuracy achieved by the different classifier models such as FTL-BF-SegClassNet, MobileNetV2 [19], Hybrid CNN [20], ResNet-152 [6], SegClassNet [8], F-SegClassNet [9] and BF-SegClassNet [10] implemented on HAM dataset are listed in Table 2. The graphical illustration of these outcomes is provided in Fig. 5.

These test outcomes define that the FTL-BF-SegClassNet model accomplishes the maximum efficiency compared to the other classifier models to segment and classify the skin disease categories. As far as skin image segmentation and classification is concerned, the FTL-BF-SegClassNet model is very powerful in terms of its efficiency.

5 Conclusion

In this study, the FTL with BF-SegClassNet model was presented to improve the domain adaptation process for dermoscopic images. First, the HAM10000 dataset was acquired and given to the FTL model, which executes training and adaptation processes to augment

Table 2 Findings of Various Skin Disease Segmentation and Classification Models on HAM Dataset

Metrics	MobileNetv2	ResNet-152	Hybrid CNN	SegClassNet	F-SegClassNet	BF-SegClassNet	FTL-BF-SegClassNet
Precision (%)	86.88	88.40	89.52	90.94	93.26	95.98	97.53
Recall (%)	87.01	88.68	89.77	91.22	93.31	96.03	97.86
F-measure (%)	86.95	88.56	89.65	91.04	93.28	96.01	97.70
Accuracy (%)	87.17	88.78	89.83	91.28	93.37	96.14	98.08

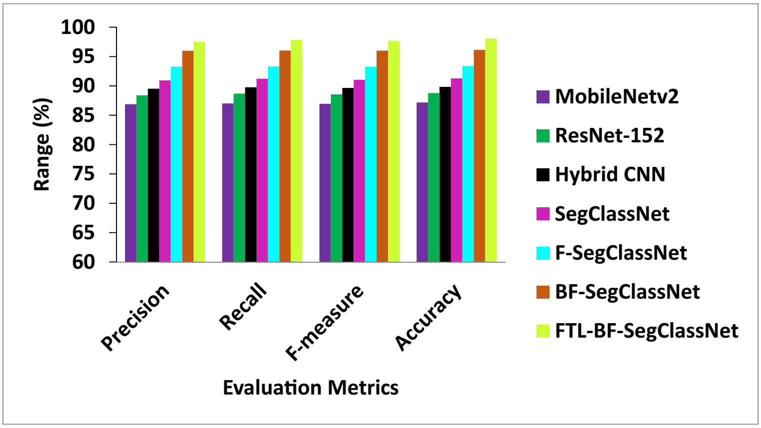

Fig. 5 Analysis of Different Skin Disease Segmentation and Classification Models on HAM10000 Dataset

the number of training images. In this FTL model, the source labeled image was utilized to create the FIS in the training phase, which captures data from the input space and transfers it to the feature space. Also, the ADDL method was applied to generate the fuzzy sets and fuzzy rules. In the adaptation phase, the created source FIS and the target data were considered to adjust the fuzzy rule and the fuzzy rule base to extract dissimilarities in the data and help bridge the contextual gap between the input and feature spaces. According to these processes, more skin images were created and segmented by the modified SegNet. Further, the BF-SegClassNet classifier was trained by the segmented images to classify the skin disease categories. To end, the findings proved that the FTL with BF-SegClassNet on the HAM database has 98.08% of mean accuracy than all other models.

Data availability All the data is collected from the simulation reports of the software and tools used by the authors. Authors are working on implementing the same using real world data with appropriate permissions.

Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

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