SEGMENTATION AND CLASSIFICATION OF SKIN LESIONS IN DERMOSCOPY IMAGES USING DEEP TRANSFER LEARNING TECHNIQUES

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Abstract

In this article, a novel segmentation and classification model for skin lesions based on dermoscopic images is presented. The first performed BF-based pre-processing using the proposed model removes any noise that is present in the image. Additionally, the Non-interactive Grab-Cut Algorithm is used to segment the images. A relevant collection of feature vectors is then extracted using a DTL model built on the VGGNet-19 Network. A variation of the VGG model called VGG19 has 19 layers (16 convolution layers, 3 fully connected layer, 5 MaxPool layers and 1 SoftMax layer). It is more accurate, trains more quickly, and uses less training samples every time. Additionally, the weights are readily accessible with other frameworks, such as keras, so they may be modified and utilised whatever the user pleases. The last step is to determine the various class labels of skin lesions using XGBoost and LDA models. A number of tests were conducted to show the outstanding performance of the suggested technique in order to validate the competent diagnostic result of the provided model.

Keywords: Dermoscopic, Skin Lesions, Deep Transfer Learning (DTL), Convolution, Computer Vision, Detection, Sensitivity.

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1. Introduction

Skin cancer is now the most prevalent and terrible illness in the world. To reduce the fatality rate from skin cancer, earlier detection is crucial. The development of a Computer Aided Diagnosis (CAD) model for skin lesion detection is urgently needed due to the rapid increase in skin cancer cases. The potential of CAD models to assist doctors in the detecting process leads to better diagnostic outcomes. A number of Computer Vision (CV)-based techniques, such as object identification, medical image analysis, and others, have benefited from the emergence of Deep Learning (DL) models. Although there are a number of state-of-the-art models that have been published, DL-based strategies have performed better on dermoscopic skin lesion pictures since they don't need any hand-crafted features. This study focuses on the building of an ensemble of DL-based CAD models for dermoscopic skin lesion detection and classification due to the DL models’ effective performance.

Basically, CAD models are employed as cutting-edge modules and intelligence methods are facilitated as borderline for healthcare and computer related studies (Andrea Pennisi and Domenico D Bloisi, 2018 [1]). The CAD models in healthcare apply diagnosis rules for assisting well-trained professionals in clinical decision making. At this point, CAD models are facilitated as expertise in healthcare applications. The latest CAD methods are capable of examining medical data and gain novel experience. Then, the accomplished knowledge helps to maximize the diagnostic rules and activate the above-mentioned systems to enhance the performance within the limited duration. For this purpose, the systems have to be provided with feedback mechanisms so that new
experience can be acquired from various sets of clinical data, especially, from profit and loss. Here, the CAD systems are assumed as intelligent systems due to the effective learning ability. Intelligent CAD modules apply the Artificial Intelligence (AI), Data Mining (DM), and Machine Learning (ML) methodologies for examining the maximum and complicated medical information. These methods are capable of making decisions in extensive variety of diseases and clinical states (Annemie Ribbens, 2018 [2]). Figure.1 provides the process of CAD model.

![Pipeline of CAD Model](image)

Figure.1. Pipeline of CAD Model

Some of the factors intended in developing the CAD methods in clinical sector which include the difficulty of clinical diagnosing process and availability of maximum tedious clinical data related to many diseases, the diagnostic experience, and new advancements in computer science as defined previously. Hence, the development of CAD and better acceptance in clinical diagnosis results a fruitful environment for developers in expert models for pursuing the current and previous options in healthcare and computer science. Thus, the definition of these deployments is segmented effectively.

In past decades, biomedical studies are initialized in finding the feasibility of applying system to examine and resolve the issues contributed to biology and medicine. Few works are related to the deployment of systems in system relied medical analysis. The earlier diagnosing models are considered as “expert systems in healthcare”, applied patients traits and lab reports as inputs for generating the diagnosing result. But, it is apparent that the constraints in providing exact diagnosis while applying classical approaches like flow-charts, statistical pattern-matching, and probability theory. Earlier demands for deriving capable CAD system are intended to be highly beneficial. Initially, developers have concentrated on making complete automated CAD methods. It has been modified and the seminal involvement in theoretical computer science by Karp has defined the following. Specifically, the “Reducibility among Combinatorial Problems” was developed and few demerits are projected at the time of developing techniques to resolve the processing issues. Hence, merits and demerits of processing issues are relevant to clinical diagnosis could be learned by means of crucial deployment. Then, Barata, C, Marques et al., (2018) [3] have focused on applying AI and specialized computer models (pattern recognition and classification models) for diagnosing diseases relied on patient information. In recent times, the CAD system is assumed to be a significant portion of diagnosing ailments with maximum number of human professionals. Followed by, earlier deployments were initialized with CAD to predict the anomalies in clinical images. In recent times, diagnostic radiology as well as clinical image examination is crucial part of research in CAD (Bing Nan, 2019 [4]). Simultaneously, clinical errors and malfunctions are enhanced which has to be resolved effectively. The growing clinical malpractice liability insurance expense has resulted in negative impact on medical applications which again results in the enhancement of medical cost. The major evolution of CAD guides the physicians to eliminate clinical failures and negligence so that medical healthcare expenses can be reduced.

For delivering précised and effective medical diagnosis, medical experts should examine in
the (Capdehourat, G, 2019 [5]). Typically, the medical record of the patients such as lab reports and some other findings are assumed to be the symptoms of certain disease. Apart from the medical data, patient’s clinical historical data includes past medical information and relevant issues. Genetic factors are considered to be the crucial elements of diseases. Therefore, user’s family history also plays a major role in disease diagnosing process. Moreover, a patient’s social behavior has been assumed as significant measures in disease diagnoses such as habits, residence, diet, lifestyle, and many other aspects.

Several hospitals, medical services, and clinics send the patients details as digital documents which have applied Electronic Health Records (EHR). The CAD models with diseases or patient’s details have valid details regarding the disease's guides in examining the disease. Clinical information has been developed into sophisticated, complex and the size has been increased dramatically. When the data has become too large, then it is complex for medical experts to predict the patient’s state and define the actual problem. Therefore, CAD does not have the standard ability to compute and examine massive medical information using system power and dignified approaches. Figure 2. illustrates the different data used for CAD models.

![Figure 2. Different Data Used for CAD Models](image)

### 2. Related Work

This section elaborates the existing works done on the identification of skin lesions by the use of supervised learning, unsupervised learning, hybrid learning, and TL models.

Celebi, ME et al., (2019) [6] presented a DL-based model by applying CNN to compute automatic classification as well as prediction of skin lesions. It has applied a CNN method which is trained from end-to-end model from image pixels as well as disease labels that are facilitated as inputs to accomplish skin lesions classification. Here, two binary classifications task has been performed with keratinocyte-carcinomas vs benign seborrheic keratosis, and MMs vs benign nevi. Chunfeng Lian et al., (2018) [7] has applied a multi-resolution collection of CNNs with EN, SENet, and ResNeXt for prediction of skin lesions. As a result, considerable performance has been attained with tiny dataset of HAM 10000 as well as ISIC 2018. Daniel Ruiz et al., (2017) [8] processed an automated skin lesions classification with the help of TL and pre-trained DNN. Consequently, better classification accuracy has been accomplished on the applied datasets correspondingly.

The segmentation method called FCRN was deployed for computing skin lesion segmentation using complete resolution.
features of single image pixel of an input. It is validated on two commonly available datasets like ISBI 2017 as well as PH2 datasets. Hence, the projected approach has gained maximum accuracy for representative medical benign cases, melanoma cases, and seborrheic-keratosis cases from ISBI 2017 dataset (Dwarikanath Mahapatra et al., 2018). Emre Celebi et al., (2020) [9,10] developed a DL framework with dilated convolution on the basis of TL from four remarkable structures. A dataset with dermoscopic images of skin lesion classes with huge number of irregularities in training, validation, and sampling. Farag, AA et al., (2021) [11] implied a model which is applicable for Melanocytic Skin Lesions (MSLs) as well as non-melanocytic skin lesions (NoMSLs). A new model has been presented to find abnormalities by the application of features like color, sub region, and texture. It has applied layered as well as flat methodologies to be facilitated as performance estimation. It is sampled on dermoscopy images like above defined modules in conjunction with layered model that has performed well than flat models. Fekri-Ershad et al., (2020) [12] utilized GoogleNet and AlexNet with TL and optimization gradient descent Adaptive Momentum Learning Rate (ADAM) to classify the skin lesion images. These frameworks are employed on ISBI 2018 to carry out image classification as three major classes like benign, melanoma, seborrheic keratosis by two other technologies like classification of segmented as well as non-segmented lesion pictures. Pre-processing procedures like lesion image enhancement, filtration, and segmentation have been applied to lesion images to gain ROI (Feng Han et al., 2019) [13]. The handcraft features as well as DL features have been extracted. ABCD rules are employed in extracting features like shape, color, and texture whereas CNN has utilized DL for extracting diverse features. Also, CNN structure is employed as pre-trained object on ImageNet. ML values are employed as fusion rules to collect possible information from handcraft as well as DL attributes. Fengying Xie et al., (2018) [14] has employed a linear classification scheme which has been trained using extracted features from CNN. Moreover, a fully convolutional network (FCN) is applied for extracting multi-scale attributes by pooling and augmented feature space. At last, the deeply supervised multi-scale network Ferris et al., (2018) [15] has been applied for prediction and segmentation of skin cancer from the skin lesion photographs. Additionally, it has employed the side output layers to collect the details from shallow as well as deep layers and develop a multi-scale connection block which proceeds different changes in lesion size. In general, supervised models are effective when compared with alternate models in examining the skin lesion images. Unsupervised fully automated models were applied in last decades to handle the issues related to insufficiency of annotated clinical training datasets where the operations like analysis, segmentation, and classification of skin lesions images are performed. Moreover, it has applied specific principle which derives the inferences directly from a dataset that is employed in decision making (Ganapathy, 2019) [16]. Generally, it depends upon the models like iterative and statistical region combination, thresholding, and energy functions domains (Guoying Liu et al., 2019) [17]. In addition, a probabilistic generative scheme is utilized with the ability of learning hierarchy level of parameters and probability distribution over the input space especially in image classification process (Hadjarevic et al., 2018) [18]. Followed by, a limited capacity of accurate segmentation is considered to be challenging task of skin lesions like lesions which touch the image boundary and some of them with noise and outliers. In recent times, the above mentioned approaches are employed in clinical images analysis like Restricted Boltzmann Machines (RBM), Deep
Belief Networks (DBN), Deep Boltzmann Machine (DBM), Generative Adversarial Network (GAN) Auto-Encoders (AE), and various other applications (Hitoshi Iyatomi et al., 2018) [19]. Next, semantic segmentation of clinical images by using unsupervised models are challenging in experiment outcomes of life-based examination.

Ioannis Giotis et al., (2018) [20] deployed a DL method has employed RBM for unsupervised feature learning in brain lesion images. Also, RF classification model is applied to perform brain lesion segmentation. As a result, maximum dice coefficient accuracy has been attained on brain MRI image datasets. Additionally, Jianchao Fan et al., (2019) [21] employed DL scheme under the application of DBN for autism prediction. Here, a few series of unsupervised methods which include resting-state functional MRI (rs-fMRI), gray matter (GM), and white matter (WM) for DBN have been applied. A Deep Neural Network (DNN) scheme depends upon the RBM as developed by Jiachen Miao et al., (2018) [22] to classify the Histopathological breast cancer images. Therefore, moderate accuracy has been accomplished when estimated on breast-cancer image dataset. In general, TL methods are applied in training supervised DL methods for clinical image analysis. It is mainly employed resolving the issues involved in training labelled datasets. Also, TL is highly effective; however, it is suboptimal on healthcare image examination because of the maximum discrepancy which occurs in the target data of this study. Additionally, it is pursued from the visible images as well as class labels that result in feature extraction task which has been to the initial data and subsequently normalizes the target details (Karagas, MR et al., 2018) [23]. It is due to the methods which are actually pre-trained on are varied from clinical images. The images like animals, automobiles, equipment, nature, and many others are accomplished. These images are acquired in the form of clinical features like fuzzy boundaries, fine-grained differences, and heterogeneous depictions. The machine relied on this scheme are heavy-weight and demands for maximum variables for computational resource. The performance validation of such methodologies on clinical images has exhibited that, it has attained a better performance than state-of-the-art.

Langan et al., (2017) [24] developed encode-decode structure of a system which depends upon the DeepLab and PSPNet to perform skin lesion segmentation. Here, features extraction is carried out under the application of ResNet 101. Then, extracted features are mapped and induced for multi-scale blocks. Various sizes of pooling as well as dilation convolution have been employed for extracting a diverse set of features. The DL method is applied in the name of SegAN as presented by Maciel Zortea, (2017) [25], which is composed of two portions like Segmentor and Critic system. Initially, segmentor is used in generating possible label maps from input images are employed. Second, critic network is used for isolating two input types, and then it generates the effectual outcomes.

In addition, DL method deployed by Maglogiannis et al., (2019) [26] along with the network structure from deep-lab scheme applying pre-trained weight from PASCAL VOC-2012. The consequent method was being considered as ensemble one and bagging approaches are VGG16, U-net, DenseNet as well as Inception v3. The Conditional Random Field (CRF) which is post-processed segmentation mask attained consequent prediction for segmentation region has been applied. It is trained under various iterations. Here, convolution and decoder layers are fine-tuned with alternate iterations. Hence, state-of-arts function has been attained. The feature aggregation system which applied ResNet34 as the supportive network has been deployed by Manikandan, et al., (2016) [27]. It is applied in developing encoder method whereas decoder part is composed of various deconvolutional
processors used in recovering spatial resolution of feature maps. Also, dense connection methods are applicable in workflow among high-level as well as low-level feature deployed for making features among encoder as well as decoder units. It is also applied for effectual aggregation and recovers the spatial data with appropriate context. Moreover, auxiliary loss has been applied at the encoding portion which helps in reducing the complexity of model training.

Michal Drozdzal, (2018) [28] presented a CDNNs for generating binary masks for computing the skin lesion segmentation from dermoscopic photographs. Then, pixel-wise classification model has been applied for extracting the features of the input image for skin lesion classification. Also, training is utilized for reducing a loss function according to the Jaccard distance. Every N is composed of 29 layers, and hyper-parameters are attained using a grid search. The up-sampling and deconvolutional layers are employed for image restoration. RGB, HSV, and lightness in LAB spaces have also been applied for segmentation operation. Furthermore, the ensemble approach is comprised of CDNN as one of the fundamental classifiers for accomplishing consequent and effective segmentation results. Finally, supreme skin lesion segmentation is exhibited from this model.

Neda Zamani Tajeddin, (2018) [29] introduced a DL approach with FCRN for lesion segmentation as well as coarse lesion classification. Then, the classification results become more supreme by using the LICU, which estimates the importance of pixels according to the distances from the adjacent border. In particular, for generating the initial coarse maps, FCRN is trained on actual as well as flipped augmented images. Followed by, distance maps have been generated using LICU undergoes convolution for enhancing the coarse maps and acquire the feature maps. Consequently, the average probabilities of advanced maps are considered as final lesion classification results.

Omar Abuzaghleh, (2015) [30] applied an iterative color-related K-Means clustering as well as ensemble regressions methodologies for segmenting skin lesions. In this method, image pre-processing, color clustering, feature extraction, and Jaccard score calculation have been utilized. Therefore, the regression framework undergoes training under the application of training as well as ground truth images that have been produced by the ISIC 2017 data set. The count of features with region area, location, circularity, solidity, and the average color was attained from the isolated area. Moreover, RF and SVR methodologies are employed to forecast the segmentation from the Jaccard Index. Hence, this process is followed until reaching the count of clusters with a significant rate in the Jaccard score.

Then, Pedro Pedros et al., (2019) [31] performed a comparison task among U-Nets and clustering methods in order to select effective skin lesion segmentation. The U-Net with presented histogram-related pre-processing model has been executed. It is composed of contracting and expansion steps which undergo training with the help of a single epoch in conjunction with actual and flipped augmented images. Moreover, for the clustering mechanism, FCM is applied for clustering the images into different ROI. Subsequently, KM is applied for further classification of defined clusters according to the color features. The collection of darkest color features is considered a lesion. The U-Net scheme has surpassed clustering models; however, with poor trade-off among the working function and processing efficacy. Besides, EA is employed along with clustering approaches for clinical image segmentation tasks.

Generally, TL is one of the reputed models but it is suboptimal on clinical image analysis because of the massive discrepancy in target
data. It is employed in images and class labels that intend to extract features for biasing the source data. Finally, it normalizes the target data (Qaisar Abbas et al., 2019) [32]. It is due to the fact that the actual pre-training of images which are defined from diverse clinical images. Models that depend upon heavy-weight require huge parameters and computational resources. But the limitations involved in this model limit the efficiency of clinical image investigation. The performance validation of these approaches on clinical images implies that it still performs well than the state-of-the-art system.

From the existing studies, it is evident that there exist no standard assessment procedures to evaluate the performance of the CNN models. Besides, the datasets utilized for CNN training process involves regionally homogenous images. The creation of a large, open-access, standardised skin tumour image collection that encompasses all races and unusual tumors/subtypes is necessary to increase the robustness of the CNN classifier. Additionally, a reliable, uniform measuring technique should be devised for system assessment and comparison.

3. Skin Lesion Diagnosis

In general, skin is considered as an important body part which comprises of two principal layers called Epidermis and Dermis, as depicted in Figure 3. Initially, the epidermis is defined as a stratified squamous epithelium which is a layered scale resembling tissue that protects from UV rays and alternate pathogens like injuries, infections, as water loss. There are four kinds of cells namely, Keratinocytes, Melanocytes, Langerhans cells, and Merkel cells and the responsibility of each cell are defined in the following:

### 3.1 Keratinocytes

It is the major portion presented in the epidermis which acts as a driving force for fast skin redevelopment (Rahman, MM, 2017) [33]. Normally, a skin is regenerated within the limited time interval that is applicable to discriminate and divide the basal layer to stratum corneum and horny layer. At this point, daughter keratinocytes are generated by the classification in basal layer (basal cells) that moves to upcoming layers by changing the morphology as well as biochemistry. Consequently, the movement and transformation, flattened cell with no filled keratin are emerged to develop the external layer of epidermis named corneocytes. Followed by, the end of differentiation model, corneocytes leaves the cohesion and isolate from the surface of desquamation task.

### 3.2 Melanocytes

The dendritic cell is suited in the basal layer of epidermis. The package of melanin pigment is distributed over keratinocyte in order to provide the respective pigmentation for skin as well as hair.

### 3.3 Langerhans Cells
Dendritic cells are similar to melanocytes, one of the major differences is that it predicts the foreign bodies (antigens) which have been intruded in epidermis and provide to local lymph nodes.

3.4 Merkel Cells

Obviously, it is retrieved from keratinocytes. It is served as mechanosensory receptor that responds to physical touch. The important skin layer is dermis, which is developed by collagen and flexible fibers. Similar to the epidermis, it is also composed of sub layers like papillary and reticular dermis. When the top layer acts as “glue” with epidermis and dermis jointly, then second layer has blood and lymph vessel, nerve terminals, sweat gland as well as hair follicle. It is responsible for supplying energy and vitamins for epidermis which plays a significant role in thermoregulation, fast recovery, and sensing the external touch.

4. Challenges Involved in Skin Lesion Diagnosis

The complexities in predicting skin lesions are qualified to difference in image varieties and sources (Rangaswamy et al., 2018) [34]. The maximum difference in the skin color of a human being intends to make skin prediction more complicated and difficult. These methods are depicted in Figure 4. Different challenges from tedious visual features of skin lesions image are pointed in Sanghoon Lee et al. (2019) [35]:

![Figure 4. Challenges in Skin Lesion Identification](image)

(a) Hair artefact (b) ruler mark artefact (c) low contrast (d) color illumination (e) bubbles (f) irregular boundaries (g) blood vessels (h) frame artefact

4.1 Various Shapes and Sizes

The major difference in skin lesion enhances the difficulty of the images and develops exact prediction of skin lesion into complicated process. A drastic difference is viewed in lesion position, size as well as shape. Mostly, image analysing models for skin lesion images demands to carry out the image pre-processing in order to gain exact analysing results.

4.2 Existence of Noise and Artefacts

The noise is considered to be objects developed at the time of image collection. The skin lesion prediction could be affected by the existence of noise and unwanted objects. It is defined as compromising signals which are not actually the portion of image which influences the image interpretation by manual approaches and affects the computer-aided skin lesion segmentation models. Some of the samples are hair artifacts, bubbles, as well as blood vessel.

4.3 Uneven Fuzzy Borders

The skin lesion photographs are classified using fuzzy as well as irregular borders which makes complex for massive approaches like contour refinement as well as lesion boundaries localization. In pre-processing phase, it is highly challenging to gain exact skin lesion images for simple detection of asymmetry.

4.4 Poor Contrast

Here, the minimum contrast from adjacent tissues has posed excess complexities. The low
contrast from and between the lesion segments as well as the neighbouring skin results in accurate lesion segmentation.

4.5 Color Illumination
Some of the objectives like skin lesion image, colors, textures, light beams, and inverse reflection could disturb the lighting of dermoscopic pictures and results in multi resolution images.

5. Computer Aided Diagnosis Model for Skin Lesion Identification
Despite of using effective models like dermoscopy and several other standard approaches, the clinical analyzing process is still considered to be challenging with limited prediction accuracy, particularly with equivocal pigmented lesions (Soumen Biswas et al., 2017) [36]. Even though the application of dermoscopy is better, accuracy of better melanoma prediction is still at a considerable rate. Furthermore, medical analysis of melanoma is subjective and experiences inter as well as intra observer differences. And, this kind of problems exhibits the requirement to receive in vivo 2nd opinion which (i) maximizes the diagnosing accuracy, and prolong the lifetime of patients, (ii) reduces the count of false deletion of non-cancerous lesions and mitigates the clinical as well as emotional expense posed by unwanted invasions. Image Processing (IP) and Computer Vision (CV) methods were employed to resolve the issues involved in disease prediction. Additionally, CAD model in melanoma prediction gives measurable as well as objective estimation of skin lesion, vs the subjective medical evaluation. It enables the reproducible analysis by reducing the inter-observer as well as intra-observer differences which have been identified in dermatologists investigations. Moreover, it makes automatic diagnosis and mitigates the redundant and irregular process to be operated by physicians. Because of these advancements in skin imaging and IP model, repeated patterns from skin lesions are assumed to be intriguing issues to be resolved and a drastic enhancement in developing CAD system for melanoma prediction. Figure 5. shows the workflow involved in skin lesion classification.

![Workflow Involved in Skin Lesion Classification](image-url)
5.1 Image Acquisition
Initially, in CAD model the acquisition of digital image is processed. The major application employed for this process: digitized colour slides applied in earlier melanoma detection, acquisition of medical images by applying the pictures and video clippings, ELM seizes the brief data regarding surface of a lesion. Transmission Electron Microscopy (TEM) which is more applicable to learn the development and inhibition of melanoma. Nevoscope, is meant to be non-invasive trans-illumination relied imaging method for analyzing melanoma. Confocal Scanning Laser Microscopy (CSLM) is defined as a non invasive imaging method applied for in vivo inspection of skin lesions. It applies laser light to concentrate on particular spot inside the tissue and seizes high-dimensional images of skin lesions are comparable to comprehensive histologic pictures. Recently, the high depth of images is 200-300 μm from the intensity of papillary dermis. Additionally, the morphologic variations among melanoma and melanocytic nevi and CSLM method are employed in computing the edge of melanoma lesions. Then, existence of CSLM for melanoma prediction is performed in the recently developed literature.

Moreover, Ultrasound has been employed in medical dermatology, especially in Europe; and not highly preferred in US. It is operated on the basis of acoustic features involved in skin tissue. Ultrasound scan is operated in three states namely: (i) A-mode which defines 1D and exhibits the amplitude of intensity at various levels of skin tissue, (ii) B-mode, generally applied in medical settings which develops 2D images from brightness level of several A-mode scans; then, (iii) C-mode, is under development and makes 3D appearance using computer guidance. Alternate imaging models applied for dermoscopy image analysis are CT, PET which applies fluoride-oxy-glucose which has represented maximum sensitivity and specificity in melanoma detection using MRI, multi-frequency electrical impedance, and Raman spectra.

5.2 Image Segmentation
Image segmentation is defined as a task of classifying images as disjoint as well as homogeneous blocks by means of certain properties like color, texture, and so on. Apart from this, it is the task of placing the edges among regions named as border prediction. Also, segmentation is meant to be the prerequisite in developing CV models. Likewise, it is the preliminary process to develop automatic analysis and estimation of clinical photographs in CAD methods. Followed by, accuracy of segmentation outcome is highly effective because of bias on consecutive phases of diagnostic mechanism, which refers that the feature extraction and experiment outcome is effective. In CAD melanoma prediction, segmentation is applied for predicting the border of skin lesion and differentiates the lesion, Regions of Interest (ROI), from background skin. Therefore, the accurateness of predicted border is significant since exclusion of lesion results in dermoscopic patterns, colour, as well as texture-relied data which has been extracted from interior of lesion. Additionally, the geometric structure of lesion and structural features of border is comprised of diagnosing significance which is relied on predicted border. Various image characteristics like shape, colour, texture, and illumination could be applied in order to compute skin lesion segmentation. Thus, enormous techniques were deployed for automatic border prediction in dermoscopy pictures in recent times.

5.3 Feature Extraction
Extraction of special features to generate collection of useful descriptors from the image is named feature extraction. The central premise of feature extraction in CAD of melanoma is to gain different attributes from the skin image that classifies lesions as cancerous and non-cancerous. Here, feature extraction method of systematic melanoma
prediction schemes depends upon the former medical ABCD-rule of dermoscopy because of the effective, simple, and ease of execution. Next, features applied by classification method have to generate maximum sensitivity (maximum relation of feature with malignancy and results in greater True Positive (TP) response) as well as optimal specificity (to generate maximum True Negative (TN) response). Even though the classification models have considered sensitivity and specificity more effective (trade-off is estimated by enhancing area under the receiver operating characteristic curve (AUC) measure), the cancerous melanoma prediction has attained maximum TP or it reduces the False Negatives (FN) value.

5.4 Feature Selection
Actually, FS is considered a significant element in data pre-processing of several domains like CV, DM, image mining, and so on. The feature values can be reduced by the elimination of unwanted, repeated, and noisy data with immediate impact on simulating the classification, clustering, or DM methodologies, and enhance the performance efficiency. A common FS process is composed of four fundamental phases, like subset production, subset estimation, termination criteria, and performance verification. Initially, subset generation is defined as a search mechanism that generates candidate feature subsets on the basis of special search principle. Then, the accomplished candidate subset is evaluated on the basis of estimation criteria that are compared with existing optimal subset. When the novel subset is optimal than former one, then existing subset is interchanged by new model. The task of generation and estimation of subsets are followed till satisfying the termination condition. Eventually, the decided optimal subset undergoes validation and verification by former knowledge by the application of attained or practical data.

FS methods are classified into three classes: (i) Filter method, which applies typical features to estimate the features count and decides supreme feature subsets without classification schemes like correlation, entropy, mutual data, and so forth. (ii) Wrapper framework, which employs a learning technology and explores features to enhance the learning process which depends upon greedy or Genetic Algorithms (GA); finally, (iii) hybrid scheme is the combination of filter and wrapper models. Consequently, filter model FS are cheap when compared with wrapper-relied methods.

5.5 Image Classification
Classification is defined as a task of sharing items as classes with homogeneous types. In CV model, similarity is described by means of features gained from feature extraction approach. Various models were sampled with major attention for Artificial Neural Networks (ANN), Support Vector Machine (SVM), Decision Trees (DT), as well as k-Nearest Neighbour (KNN). Figure 6. depicts the ML based classification process.
DL is assumed to be block of ML supported by massive number of technologies that are intended to develop higher-level abstractions under the application of several processing layers, especially with complicated structures. Unlike, various non-linear transformations are also projected in these studies. DL model is evolved from ML approach; however traditional ML schemes resolve challenging image classification issues; unfortunately, the attained results are not so effective. Moreover, DL is one of the well-known and effective methods to be employed in ML as it depends upon the learning representations of data. Then, it exploits the pattern learning which can be viewed in different ways like vector of force values for each pixel, or in maximum abstract way as collection of acmes and definite structure. The maximum number of representations is optimal when compared with simplification of learning process. Therefore, the strides which make better representations and develop various count of unlabeled data. The representations are evolved by advancements in neuroscience and depend upon the interpretation of data processing as well as communication patterns of a nervous system like neural coding that tries to define the association from diverse stimuli and related neuronal responses from the brain.

6. PROPOSED MODEL
The proposed DTL based diagnosis model involves a series of processes namely pre-processing, segmentation, feature extraction, and classification as defined in Figure 7. Brief working processes of above-mentioned applications are described as follows.
6.1 BF based Image Pre-processing

BF is a well-known nonlinear filter that is capable of accomplishing an efficient edge and smoothing operations. The weight of BF considers the Euclidean distance of pixel and the affinity among the center pixel as well as neighbourhood pixel (Tamanna Tabassum Khan Munia et al., 2017) [37]. Additionally, it is a weighted average technology, which refers to the pixel’s intensity in conjunction with the weighted average of ambient pixel illumination. In general, the space weight applies a weighting calculation scheme of Gaussian filter (GF) under the calculation of distance among 2 pixels which is performed using the given function:

\[ g(i, j) = \frac{\sum_{k,l} f(k, l) \omega(i, j, k, l)}{\sum_{k,l} \omega(i, j, k, l)} \]  

(1)

The weighting coefficients \( \omega(i, j, k, l) \) depends upon the kernel product as well as the range where the kernel function is demonstrated as given below:

\[ d(i, j, k, l) = \exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma_d^2}\right) \]  

(2)

A range kernel is provided below:

\[ r(i, j, k, l) = \exp\left(-\frac{f(i,j) - f(k,l)^2}{2\sigma_d^2}\right) \]  

(3)

When two kernels are enhanced, BF weight functions are produced by the given function:

\[ \omega(i, j, k, l) = \exp\left(-\frac{(i-k)^2 + (j-l)^2}{2\sigma_d^2} - \frac{f(i,j) - f(k,l)^2}{2\sigma_d^2}\right) \]  

(4)

6.2 Non-Interactive Grab-Cut based Image Segmentation
After the completion of the BF based pre-processing step, image segmentation has been performed. The Graph Cut method is one of the conventional and well-known models in combinatorial graph theory. This is a class of image segmentation scheme which depends upon a graph cutting principle. Its necessities human communication markers, foreground as well as background pixels as input. It is modelled by making use of graph related degrees of identical background as well as foreground pixels. Moreover, an image segmentation scheme depends upon the Graph Cut mechanism where energy function is illustrated as given below:

\[
E(\alpha, k, \theta, z) = U(\alpha, k, \theta, z) + V(\alpha, z)
\]

\[
U(\alpha, k, \theta, z) = \sum_{n} D(\alpha_n, k_n, \theta, z_n)
\]

\[
V(\alpha, z) = \gamma \sum_{(m,n) \in C} [\alpha_m \neq \alpha_n] \exp(-\beta \|z_m - z_n\|^2)
\]

\[
D(\alpha_n, k_n, \theta, z_n) = -\log p(z_n | \alpha_n, k_n, \theta) - \log \pi(\alpha_n, k_n)
\]

The \(U\) function showcases the data item of an energy function. \(V\) function demonstrates the edge of the energy function and irregular penalty of neighborhood pixels among \(mm\) and \(nn\). When the variations among two neighbourhood pixels are minimum, then possibility comes under a similar foreground and background is maximum. Inversely, two pixels are edge and isolated as foreground and background.

The conventional interactive Grab-Cut methods require a user based image with marker rectangle and foreground target for foreground extraction. In order to satisfy the non-interactive requirements, an image with adaptive threshold segmentation has to be identified in the foreground as well as background target. The low-graded treatments apply pixels of an image with foreground target, and the pixel value 255 is employed to indicate the foreground target. The integration of foreground and background of two markers are used as input images in Grab-Cut technology. Simultaneously, the foreground target minimum is comprised of rectangles as input rectangles for the Grab-Cut mechanism. A Gaussian mixture model does not support the appropriate training data. Next, the feature extraction will be executed based on the DTL based VGGNet-19 model.

### 6.3 VGGNet-19 based Feature Extraction

VGG-19 uses the principle of modular design and develops a “5+3” structure with five convolution modules and three FC layers (Vardhana, M et al., 2018) [38]. The first and second convolution modules are composed of convolution and pooling layers. The third, fourth, and fifth convolution modules are comprised of massive convolution and pooling layers. Every convolution layer is linked with ReLU activation function. The architecture of VGG-19 is depicted in Figure 8.

The key objective of activation function is to enhance the non-linearity of NN approach. With no activation function, a layer of NN is identical to matrix multiplication. Thus, the experiment outcome of a layer is defined as a linear function of input, and these layers are determined in NN whereas the output is referred to as linear integration of inputs so called primitive perceptron. Followed by, a NN is used for numerous nonlinear approaches. When compared with the classical sigmoid activation function named ReLu (Eq. (9)) is highly beneficial in preserving the processing time and eliminates the gradient diminishing process.
When compared with classical 5x5 convolution kernel, VGG-19 network applies 3x3 small-size convolution kernel that limits model parameters and estimation time with no compromise in accuracy measure. The impact of feature extraction with two layers of size 3x3 is same as layer of size 5x5. It is predicted that by applying two layers of 3x3 convolution kernels rather than using a layer of 5x5 convolution kernels significantly limit the parameters and performance time is reduced.

In the pooling layer, the key objective of the maximum pooling model has is to limit the spatial features of input feature maps. It is also applied in conserving the texture features and mitigates the position weight. Here, the unit count of three FC layers is 512, 256, and 6 correspondingly. In earlier works, the experiment outcome is normalized using softmax function, and the output range is converted from (-∞, +∞) to [0, 1], and the sum is 1. The output measure of the FC layer is converted as a probability score as depicted in Eq. (10).

\[
S_i = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}}, \quad i \in (1, n)
\]  

where, \(x_i\) and \(x_j\) defines the output of \(i\) and \(j\) nodes of FC layer respectively, and \(S_i\) implies a probability value accomplished after the normalization function. DTL is a simple and efficient model of training a DL technique when adequate training data is not available. Applying every parameter in the pre-trained network in the initialization stage could utilize the feature which is learned from numerous images. They are mainly employed for feature extraction, and the attained parameters could assist in the training process. In addition, the DTL models do not necessitate high-end GPUs or CPUs for the training process. In this study, the DTL based VGGNet-19 model is employed, where the last FC layer is replaced by the classifier (i.e. LDA and XGBoost). It helps to increase the efficiency of classification while examining skin lesions from dermoscopic images.
6.4 Classification Models

In the final stage, skin lesion classification is carried out using LDA and GBT methodologies for evaluating appropriate class labels for applied images. Hence, the performance of LDA and GBT is given below.

6.4.1 XGBoost model

XGBoost is defined as a regression tree with similar decision rules as a DT. It applies to both regression and classification (Wiselin Jiji et al., 2018) [39]. It is a reputed and reliable variant of Gradient Boosting Machine (GBM), which is applied extensively for CV, DM, and other applications. In recent times, a type of GBM, XGBoost is classified into two factors: boosting tree development and presenting a novel distributed method for tree exploration. Using a dataset \( DD=\{(x_i, y_i)\} \), where \( x_i \) is a gene expression profile of lesion, \( y_i \) denotes the parallel binary label. Let the XGBoost model has \( K \) DT, an optimization for objective function is depicted as Eqn. (11):

\[
\hat{y}_i = \sum_{k=1}^{K} f_k (x_i), f_k \in F
\]

where each \( f_k \) corresponds an autonomous tree with leaf values, \( F \) depicts a space from regression tree which is expressed by Eqn. (12):

\[
L(f_i) = \sum l(\hat{y}_i, y_i) + \sum \Omega (f_i)
\]

where the initial term is defined as differentiable loss function, \( l \), which estimates the variations among predicted result \( \hat{y}_i \) and true output \( y_i \). Followed by, a regularization term \( \Omega \) has penalized the model’s complexity in order to resolve the over-fitting issues, where \( \Omega \) and \( \hat{y}_i \) is represented as

\[
\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i)
\]

\[
\Omega(f) = YT + 0.5\|\omega\|^2
\]

where \( T \) denotes a leaf node count and \( \omega \) refers to the value on a leaf. Therefore, the function is derived as

\[
L(f_i) \approx \sum \left[ (\sum_{i \in L_j} g_l) w_j + 0.5(\sum_{i \in L_j} h_l + \lambda) w_j^2 \right] + \gamma T
\]

where \( g_l \) and \( h_l \) are first and second order gradient statistics of a loss function. Additionally, parameters \( \gamma \) and \( \lambda \) means the constants used for controlling a regularization degree. Thus, it is applied to eliminate over-fitting problem.

6.4.2 LDA model

In general, LDA is concentrated on the correlation between numerous independent as well as categorical dependent parameters by developing a composite of autonomous parameters (Yao-Tien et al., 2019) [40]. The multivariate analysis has been applied for determining the expansion of composite parameters which is helpful in differentiating numerous pre-existing sets of subjects and makes a classifier to detect the collective membership in novel objects. Initially, a Linear Discriminant Function (LDF) which is passed by two groups is utilized in subject discrimination. When there are numerous groups, the group count is reduced from a function as required for observation [41]. For all the groups, LDA considers an explanatory variable for common distribution with symmetric covariance matrices. Such products are consolidated and summed up with a constant and a composite value is attained finally termed as discriminant value. The LDF is depicted as,

\[
LDF = b_0 + b_1 x_{11} + b_2 x_{12} + \cdots + b_k x_{ik} = bX,
\]

where \( b_j \) denotes a value of \( j \)th coefficient, \( j=1,\ldots,k \), and \( x_{ij} \) implies a value of \( i^{th} \) case of \( j^{th} \) predictor. Moreover, LDF is modified in a standardized format where it enables the comparison variables determined on diverse scales. In standardized \( LDF \), all variables are extended by reduction in mean value and division by corresponding Standard Deviation (SD). Next, LDF values are capable of
predicting the probabilities and estimated the collective membership for dependent variable. It depends upon the rationale which is highly independent as well as dependent parameters are relevant to the sum of squares is higher within-group sum of squares. Thus, ratio between-group is portioned under the application of within-group sum of squares are defined as analog to ratio of variances, where $FF$ is statistic and test which controls a probability with the observed relationship.

The discriminant coefficients are decided and improve the distance among two groups called as (centroids) $|\bar{y}_1 - \bar{y}_2|$. Fisher recommended a multivariate observation $x$ to univariate observations $y$ where the $y$’s derived from both groups 1 and two with higher distance. Hence, a linear combination $y=a’x$ enhances the ratio (squared distance between sample means)/(sample variance $yy$).

Furthermore, the vector of coefficients is projected by eigenvectors of matrix $B * S^{-1}$, where $B=(\bar{x}_1 - \bar{x}_2)'$ refers to a between-group matrix and $S$ represents an estimate of $\Sigma$. Mostly, the features of composite sums of squares are embedded with variability and covariability of all variables. Therefore, discriminant coefficients are determined in either unstandardized or standardized form; however, it is irrelatively informative when compared with regression. Consider that there are two phases, $x_1, x_2$ are means of all groups, and $S$ refers to a pooled covariance matrix which depends upon Fisher's discriminant functions as provided in the following:

$$X_i \in \begin{cases} 
\text{group 1, if } y = (\bar{x}_1 - \bar{x}_2)S^{-1}X_i \geq 0.5 \ (\bar{x}_1 - \bar{x}_2)'S^{-1}(\bar{x}_1 + \bar{x}_2) \\
\text{group 2, if } y = (\bar{x}_1 - \bar{x}_2)S^{-1}X_i < 0.5 \ (\bar{x}_1 - \bar{x}_2)'S^{-1}(\bar{x}_1 + \bar{x}_2) 
\end{cases}$$

(17)

7. PERFORMANCE VALIDATION

For investigating the classifier performance of the VGG19-LDA and VGG19-XGBoost models, an extensive experimental analysis takes place using the ISIC dataset. Figure.9. visualizes the working principle of the BF technique based on pre-processing on the applied dermoscopic images. Figure.9.(a) depicts the original images; Figures.9. (b) – 9. (c) illustrates the masked and pre-processed images. The figures clearly depicted that the dermoscopic images are effectively pre-processed and the noises are discarded.

![Figure 9](image-url)
Figure 10. showcases the sample outcome attained by the presented segmentation technique on the pre-processed skin lesion images. The figure portrayed that the pre-processed images are precisely segmented by the presented technique.

![Preprocessed Image](image1)

![Segmented Image](image2)

**Figure 10.** (a) Pre-processed Image (b) Segmented Image

Figure 11. demonstrates the confusion matrix derived by the VGG19-LDA and VGG19-XGBoost models at the time of execution. During the classification of distinct dermoscopic images, the VGG19-LDA model has classified a set of 21 images into Angioma class, 42 images into Nevus class, 36 images into Lentigo NOS class, 65 images into Solar Lentigo class, 46 images into Melanoma, 49 images into Seborrheic Keratosis class, and 34 images into BCC. On the other hand, the VGG19-XGBoost model has classified the skin lesion images with the total of 20 images into Angioma class, 45 images into Nevus class, 40 images into Lentigo NOS class, 68 images present in Solar Lentigo class, 48 images into Melanoma, 48 images into Seborrheic Keratosis class, and 34 images into BCC.

The table values portrayed that the VGG19-LDA and VGG19-XGBoost models have attained superior skin lesion classification process. The values in the confusion matrix of the VGG19-LDA and VGG19-XGBoost models are manipulated in the form of TP, TN, FP, and FN, as shown in Tables 1. and 2.

<table>
<thead>
<tr>
<th>Predicted Class</th>
<th>Angioma</th>
<th>Nevus</th>
<th>Lentigo NOS</th>
<th>Solar Lentigo</th>
<th>Melanoma</th>
<th>Seborrheic Keratosis</th>
<th>BCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Angioma</td>
<td>21</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Nevus</td>
<td>0</td>
<td>42</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Lentigo NOS</td>
<td>0</td>
<td>5</td>
<td>36</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Solar Lentigo</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>65</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Melanoma</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>0</td>
<td>46</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Seborrheic Keratosis</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>2</td>
<td>49</td>
<td>0</td>
</tr>
<tr>
<td>BCC</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>34</td>
<td></td>
</tr>
</tbody>
</table>

**Actual Class**

(a) VGG19-LDA
SEGMENTATION AND CLASSIFICATION OF SKIN LESIONS IN DERMOSCOPIC IMAGES USING DEEP TRANSFER LEARNING TECHNIQUES

(b) VGG19-XGBoost

Figure 11. Confusion Matrix of Proposed Models (a) VGG19-LDA (b) VGG19-XGBoost

Table 1. Manipulation from Confusion Matrix of Proposed VGG19-LDA Method

<table>
<thead>
<tr>
<th>Measures</th>
<th>Angioma</th>
<th>Nevus</th>
<th>Lentigo NOS</th>
<th>Solar Lentigo</th>
<th>Melanoma</th>
<th>Seborrheic Keratosis</th>
<th>BCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>21</td>
<td>42</td>
<td>36</td>
<td>65</td>
<td>46</td>
<td>49</td>
<td>34</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
<td>4</td>
<td>5</td>
<td>3</td>
<td>5</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>FP</td>
<td>1</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>TN</td>
<td>296</td>
<td>262</td>
<td>267</td>
<td>250</td>
<td>263</td>
<td>264</td>
<td>281</td>
</tr>
</tbody>
</table>

Table 2. Manipulations from Confusion Matrix of Proposed VGG19-XGBoost Method

<table>
<thead>
<tr>
<th>Measures</th>
<th>Angioma</th>
<th>Nevus</th>
<th>Lentigo NOS</th>
<th>Solar Lentigo</th>
<th>Melanoma</th>
<th>Seborrheic Keratosis</th>
<th>BCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>TP</td>
<td>21</td>
<td>42</td>
<td>36</td>
<td>65</td>
<td>46</td>
<td>49</td>
<td>34</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
<td>4</td>
<td>5</td>
<td>3</td>
<td>5</td>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>FP</td>
<td>1</td>
<td>10</td>
<td>10</td>
<td>0</td>
<td>4</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>TN</td>
<td>296</td>
<td>262</td>
<td>267</td>
<td>250</td>
<td>263</td>
<td>264</td>
<td>281</td>
</tr>
</tbody>
</table>

Table 3. exhibits the detailed classification results analysis of the VGG19-LDA and VGG19-XGBoost models under different class labels. Figure 12. analyzes the performance of the VGG19-LDA model on the categorization of skin lesions from the dermoscopic images. On the classification of Angioma images, the VGG19-LDA model has attained a sensitivity of 100%, specificity of 99.88%, and accuracy of 99.88%. At the same time, on the classification of Nevus class, the VGG19-LDA model has obtained a sensitivity of 93.30%, specificity of 97.42%, and accuracy of 96.60%. Besides, on the classification of Lentigo NOS images, the VGG19-LDA model has resulted in a sensitivity of 99.59%, specificity of 97.95%, and accuracy of 96.59%. Eventually, on the classification of Solar Lentigo images, the VGG19-LDA model has offered a sensitivity of 96.59%, specificity of 100%, and accuracy of 99.26%. Moreover, on the classification of Melanoma images, the VGG19-LDA model has reached a sensitivity of 92.20%, specificity of 99.40%, and accuracy of 98.17%. Also, on the classification of Seborrheic Keratosis, the VGG19-LDA model has exhibited better results with a sensitivity of 91.74%, specificity of 100%, and accuracy of 98.55%. At last, the BCC images are classified by the VGG19-LDA model with a sensitivity of 92.89%, specificity of 100%, and accuracy of 99.46%.
### Table 3. Performance Evaluation of Different Classes on Proposed VGG19-LDA and VGG19-XGBoost Method

<table>
<thead>
<tr>
<th>Classes</th>
<th>Proposed VGG19-LDA</th>
<th>Proposed VGG19-XGBoost</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sensitivity</td>
<td>Specificity</td>
</tr>
<tr>
<td>Angioma</td>
<td>100</td>
<td>99.88</td>
</tr>
<tr>
<td>Nevus</td>
<td>93.3</td>
<td>97.42</td>
</tr>
<tr>
<td>Lentigo NOS</td>
<td>89.8</td>
<td>97.52</td>
</tr>
<tr>
<td>Solar Lentigo</td>
<td>96.59</td>
<td>100</td>
</tr>
<tr>
<td>Melanoma</td>
<td>92.2</td>
<td>99.4</td>
</tr>
<tr>
<td>Seborrheic Keratosis</td>
<td>91.74</td>
<td>100</td>
</tr>
<tr>
<td>BCC</td>
<td>92.89</td>
<td>100</td>
</tr>
<tr>
<td>Average</td>
<td>93.78</td>
<td>99.17</td>
</tr>
</tbody>
</table>

Figure 12. Result Analysis of Proposed VGG19-LDA for Different Classes

Figure 13. examines the function of the VGG19-XGBoost method on the classification of skin lesions from the dermoscopic images. On the classification of Angioma images, the VGG19-XGBoost approach has accomplished a sensitivity of 96.24%, specificity of 100%, and accuracy of 99.88%. Simultaneously, on the classification of Nevus class, the VGG19-XGBoost framework has achieved a sensitivity of 98.83%, specificity of 100%, and accuracy of 99.79%. Followed by, on the classification of Lentigo NOS images, the VGG19-XGBoost technique has provided a sensitivity of 98.56%, specificity of 100%, and accuracy of 99.79%. Finally, on the classification of Solar Lentigo images, the VGG19-XGBoost framework has generated a sensitivity of 100%, specificity of 97%, and accuracy of 97.86%. In addition, the classification of Melanoma images, the VGG19-XGBoost scheme has obtained a sensitivity of 96.12%, specificity of 99.73%, and accuracy of 98.48%. Moreover, on the classification of Seborrheic Keratosis, the VGG19-XGBoost method has represented moderate results with a sensitivity of 89.89%, specificity of 99.44%, and accuracy of 98.48%. Finally, the BCC images are categorized by the VGG19-XGBoost approach with a sensitivity of 93.89%, specificity of 99.69%, and accuracy of 98.48%.
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Figure 13. Result Analysis of Proposed VGG19-XGBoost for Different Classes

Figure 14. Average Analysis of Proposed (a) VGG19-LDA and (b) VGG19-XGBoost

To further validate the outstanding performance of the VGG19-LDA and VGG19-XGBoost models, a detailed comparative study is made in Table 4. and Figure 15. On investigating the classifier results
interms of sensitivity, the SVM model has reached the lowest sensitivity over the compared methods. Similarly, the ResNets, CNN, and DLN models have accomplished slightly better and closer sensitivity values over the SVM model. On continuing with, the CDNN model has reached to even better sensitivity value of 82.5%. Likewise, the HLF model has attained moderate performance over the earlier modes. Followed by, the ensemble classifier and deep CNN models have reached near identical sensitivity values which are superior to other methods except for DCCN-GC, VGG19-LDA, and VGG19-XGBoost models. Though the DCCN-GC model has demonstrated near optimal results with the sensitivity of 90.82%, the proposed VGG19-LDA and VGG19-XGBoost models have outperformed all the compared methods by achieving a maximum sensitivity of 93.78% and 96.21% respectively.

Similarly, on examining the classifier outcomes by means of specificity, the SVM model has attained a minimum low specificity over the earlier technologies. Likewise, the HLF, CNN, and ensemble classifier approaches have attained considerable and identical specificity values over the SVM method. In line with this, a Deep CNN framework has attained an acceptable specificity value of 83.19%. Similarly, the DCCN-GC scheme has reached considerable performance when compared with previous approaches.

Table 4. Performance of Existing Methods with Proposed VGG19-LDA and VGG19-XGBoost Method

<table>
<thead>
<tr>
<th>Models</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed VGG19-LDA</td>
<td>93.78</td>
<td>99.17</td>
<td>98.31</td>
</tr>
<tr>
<td>Proposed VGG19-XGBoost</td>
<td>96.21</td>
<td>99.4</td>
<td>99.01</td>
</tr>
<tr>
<td>CNN</td>
<td>81.7</td>
<td>82.9</td>
<td>82.4</td>
</tr>
<tr>
<td>SVM</td>
<td>73.15</td>
<td>75.41</td>
<td>74.3</td>
</tr>
<tr>
<td>HLF</td>
<td>83.5</td>
<td>81.3</td>
<td>81.1</td>
</tr>
<tr>
<td>Deep CNN</td>
<td>84.64</td>
<td>83.19</td>
<td>84.27</td>
</tr>
<tr>
<td>Ensemble Classifier</td>
<td>84.16</td>
<td>82.64</td>
<td>83.98</td>
</tr>
<tr>
<td>CDNN</td>
<td>82.5</td>
<td>97.5</td>
<td>93.4</td>
</tr>
<tr>
<td>DLN</td>
<td>82</td>
<td>97.8</td>
<td>93.2</td>
</tr>
<tr>
<td>ResNets</td>
<td>80.2</td>
<td>98.5</td>
<td>93.4</td>
</tr>
<tr>
<td>DCCN-GC</td>
<td>90.82</td>
<td>92.68</td>
<td>93.39</td>
</tr>
</tbody>
</table>

Besides, the CDNN and DLN methods have attained closer specificity values which are supreme than alternate models except for ResNets, VGG19-LDA, and VGG19-XGBoost models. Even though the ResNets technology has implied closer results with the specificity of 98.5%, the presented VGG19-LDA and VGG19-XGBoost approaches have surpassed all the traditional schemes by accomplishing a high specificity of 99.17% and 99.4% respectively. Likewise, on examining the classifier outcomes with respect to the accuracy, the SVM approach has attained a low accuracy than the previous approaches. In line with this, the HLF, CNN, and ensemble classifier methodologies have gained moderate and identical accuracy values over the SVM algorithm.
Likewise, the Deep CNN scheme has attained a moderate accuracy value of 84.27%. Along with that, the DLN framework has reached an acceptable function over the existing modules. Then, the DCCN-GC and ResNets methodologies have attained closer identical accuracy values which are maximum than alternate technologies except for CDNN, VGG19-LDA, and VGG19-XGBoost technologies. Although the CDNN scheme has exhibited near identical results with an accuracy of 93.4%, the projected VGG19-LDA and VGG19-XGBoost methodologies have surpassed than related techniques by accomplishing an optimal accuracy of 98.31% and 99.01% respectively.

Finally, an AUC analysis of the proposed VGG19-LDA and VGG19-XGBoost models takes place in Figure 16. The figures depicted that the VGG19-LDA and VGG19-XGBoost models have accomplished superior outcomes with the maximum AUC of 0.9560 and 0.9711. After examining the abovementioned experimental results, it is evident that the VGG19-XGBoost model has showcased effective skin lesion diagnostic performance with a higher average sensitivity of 96.21%, specificity of 99.4%, and accuracy of 99.01%.

(a) VGG19-LDA
8. Conclusion

An innovative DTL-based segmentation and classification model for the identification of skin lesions from dermoscopic images has been proposed in this study. The proposed DTL based diagnosis model involves a series of processes namely BF based pre-processing, Non-interactive Grab-Cut algorithm based segmentation, DTL based VGGNet-19 Network for feature extraction, and classification. The distinct class labels of skin lesions are identified using the XGBoost and LDA models for classification. Several tests were run on the ISIC dataset to confirm the proposed model's competent diagnostic result. The experimental results showed that the VGG19-XGBoost model performed better than the comparison approaches, with a maximum sensitivity, specificity, and accuracy of 95.08%, 99.17%, and 98.65%, respectively.

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1. Galiveti Poornima / SEGMENTATION AND CLASSIFICATION OF SKIN LESIONS IN DERMOSCOPIC IMAGES USING DEEP TRANSFER LEARNING TECHNIQUES


