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A hybrid approach for melanoma classification using ensemble machine learning techniques with deep transfer learning

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ABSTRACT

Generally, Melanoma, Merkel cell cancer, Squamous cell carcinoma, and Basal cell carcinoma, are the four major categories of skin cancers. In contrast to other cancer types, melanoma, a type of skin cancer, affects a lot of people. Early identification and prediction of this skin cancer can avoid the risk of spreading to another part of the body which can be treated and cured effectively. The advancing machine learning and deep learning approaches create an efficient computerized diagnosis system that can assist physicians to predict the disease in a much faster way, and enable the affected person to identify it skillfully. The existing models either rely on machine learning models which are limited to feature selection or deep learning-based methods that learn features from full images. The proposed hybrid pre-trained convolutional neural network and machine learning classifiers are used for feature extraction and classification. This kind of approach improves the model's accuracy. Here the hybrid VGG16 and XGBoost is used as feature extraction and as a classifier, this integration obtains maximum accuracy of 99.1%, which is higher accuracy compared to other works represented in the literature survey.

1. Introduction

Skin cancer called melanoma develops in the skin cells that produce the color of the skin. Mainly it occurs outside the body which is mostly exposed to sunlight's ultraviolet rays, two person die every hour because of skin cancer [1–6], hardly found inside the body. It also occurs in other parts of the body such as the eyes, nose, throat, etc. The main cause of this cancer is not yet proven, but more exposure to ultraviolet rays may threaten this type of cancer [7–9], also because of pollution, and increased use of cosmetics [10]. The age groups fewer than 40 are get affected; mainly women. When this is diagnosed in the early stage melanoma can be medicated easily and the recovery ratio is also high [11–15]. Not only get the part exposed to sunlight affected, but also the areas which are rarely exposed to the sun. Some of the indications of melanoma include a sudden change in skin pigment or some growth in the skin, also the already prevailing mole may change [16,17]. Scarce moles should be taken seriously to mediate any harmful effects. To make the diagnosis easier and to increase the survival rate an automatic disease diagnosis system is more essential [18–22]. Here the proposed algorithm applies VGG16 as a transfer learning model to extract the features and that features are sent to the XGBoost classifier and Light Gradient Boosting Machine (LightGBM) in order to perform the severity checking and also to classify benign and malignant melanoma done by training the model and performance verification through validation. In this work, XGBoost and LightGBM obtain an accuracy of 99.1%, and 97.2%, respectively.

2. Related work

Skin cancer can be identified using dermatological photos. Machine learning and deep learning based algorithms play a key role in identifying skin cancer with tremendous performance. The literature review has reported the relevant studies on melanoma categorization. Early detection of skin problems [23,24] can be treated successfully [25,26]. Melanoma is one of the threatful skin cancer [27–30]. CNN based model provides a better result in early diagnosis which performance is similar

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to dermatologists [31–37]. Automatic detection of dermoscopy image lesions faces several obstacles due to the complicated detection backdrop and lesion attributes [38]. In [39] 2437 training and 660 test images are used with the transfer learning models ResNet-101 and Inception-v3 which acquire accuracy of 84.09% and 87.42% respectively. Data augmentation along with transfer learning models of deep learning in [40] uses DenseNet161, Inception-v4 and ResNet-152 trained with seborrheic keratosis and melanoma classification achieves accuracy of 86.3%, 82.0%, 88.7% respectively. In [41] deep learning model CNN and machine learning classifier is used with image feature extraction depicting the borders, texture, and color present in the input skin lesion image. The classifiers SVM and KNN achieve an accuracy of 77.8%, and 57.3%, respectively. Deep learning achieves an accuracy of 85.5%. In [42], it includes acquiring data, augmentation, developing the model, and successively predicting the input. Here CNN model and SVM obtain maximum accuracy of 85%. Computerized diagnosis overcomes the performance issue in skin disease prediction problems. Here segmentation, feature extraction, and classification done through image processing classify the unaffected skin and affected Melanoma skin. Resnet-50 is used as a classifier and obtained an accuracy of 85.18%. In [43] the MelaNet model was used to perform melanoma classification and obtain a value of area under the curve was 91.76%. In [44] Principal Component Analysis (PCA) algorithm is applied to skin lesion images to generate a feature extraction mechanism from low level features based on the properties of the input images such as color, texture etc. Here the SVM classifier provides an accuracy of 82.2%

Different image processing techniques assist the healthcare domain in the quick detection and prediction process [45–49]. The existing model comparison with specificity, sensitivity, and accuracy is shown in Table 1. From the knowledge obtained from the literature survey, a new kind of approach has been taken, and implemented and obtained a maximum accuracy of 99.1%. The approach has been explained in the proposed methodology.

3. Proposed methodology

Early detection of skin cancer will rescue the affected individuals and improve their survival probability. Fig. 1 shows the detection process which follows different steps which are elucidated as follows:

Table 1
Existing models comparison.

Refs.	Year	Methodology	Specificity	Sensitivity	Accuracy
Hekler et al. [50]	2019	CNN	60%	76%	68%
Seeja et al. [51]	2019	U-Net + VGG16	96.2%	95.5%	83.1%
Zghal et al. [52]	2020	ABCD rules	92%	87%	90%
Daghrir et al. [53]	2020	Majority Voting	–	–	88.4%
Vasconcelos [54]	2020	DCNN	84.5%	74.6%	82.5%
Lingaraj [55]	2021	VSVM	88.7%	87.6%	88.10%
Jojoa Acosta et al. [56]	2021	eVida M6 model	92.5%	82.0%	90.4
Gazioglu et. el. [57]	2021	DenseNet121	88.8%	89.5%	89.22%
Gazioglu et. el. [57]	2021	ResNet50	89.2%	86.8%	87.96%
Gazioglu et. el. [57]	2021	AlexNet	91.3%	86.8%	84.5%
Gazioglu et. el. [57]	2021	VGG16	91.1%	81.7%	86.2%
Brinker et al. [58]	2022	Ensembles of 3 individual CNNs	91.77%	88.88%	90.33%
Indraswari et al. [59]	2022	MobileNetV2	85%	85%	85%

3.1. DATA acquisition

Data acquisition involves data collection, which has been obtained from the International Skin Imaging Collaboration (ISIC) dataset which comprises 1000 skin lesion images of benign and 416 images of malignant Melanoma. Images of skin lesions were gathered from "siim-isic-melanoma-classification" datasets (http://www.isic-archive.com) [60]. The images are in JPEG format. The same data has been used in this work. The dataset images were given for training and testing with a test size of 20% and a training size of 80%.

3.2. Pre-processing

The data acquisition is followed by pre-processing the images obtained from the dataset. Fig. 3 exhibits illustrations of (a) benign and (b) malignant melanoma. This process in the lesion images eliminates undesirable data other than lesions which supports classifying images more accurately such as hair, skin colors, etc. Since all picture data should be at a single, standardized size before being fed into an ML or DL model, all images were initially downsized to the same size Images in this project are adjusted to be 224*224 (width*height). In order to find the hair contours, blackhat filtering is used to convert RGB images into grayscale. Then, the hair contours are intensified in order to prepare them for the inpainting algorithm, and the original image is then filtered using the mask as a guide. This highlights the region of the skin lesion. By carrying out this process, hair is removed and skin lesions are highlighted. This process iterates over all of the data in the dataset. The preprocessed results are shown in Fig. 4, which also includes the original image of the skin lesion, the RGB to GRAY image conversion, the BlackHat image filtering, the hair detection, and the hair removal.

3.3. DATA augmentation

This method is for addressing data imbalance that reduces model overfitting. Since there are 416 fewer malignant melanoma photos than benign images, the dataset's malignant melanoma skin lesion images are enhanced by randomly rotating the images between -25^0 and $+25^0$ before flipping and blurring them. The images are increased by 200, but there are still 384 of them that must be equalized with images of benign skin lesions. Generative Adversarial Networks (GAN) are utilized for the remaining images. Fig. 6 shows data augmented results.

(1) GENERATIVE ADVERSARIAL NETWORK (GAN)

Two neural networks compete with one another in the deep neural network design known as GAN [61]. Fig. 5 depicts the GAN. It was trained in a confrontational method to generate data that mimicked some distribution. Fig. 7 shows malignant melanoma images generated by GAN. The GAN loss function is calculated using (1).

(1) GAN LOSS FUNCTION

$$\min_G \max_D V(G,D) = E_x(X)[log(D(x))] + E_z(Z)[log(1 - D(G(Z)))] \quad (1)$$

- Ex represents actual data instances based on overall anticipated values.
- Ez is the generator's overall anticipated random inputs.

(2) DISCRIMINATOR

This architecture differentiates between fake data generated by the Generator with an indicator of 0 and real images with an indicator of 1.

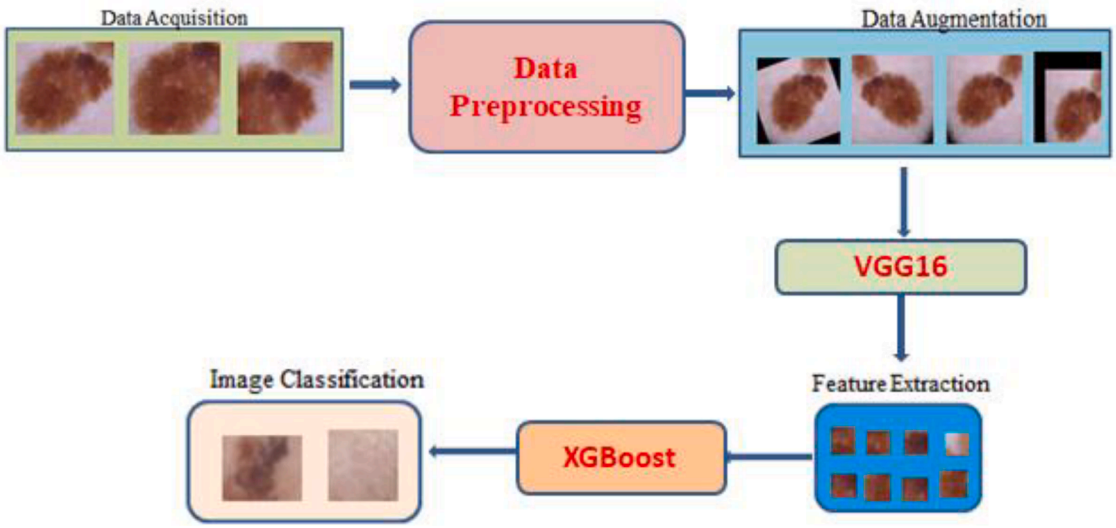

Fig. 1. Proposed architecture diagram.

Using (2) and (3), the loss function for the cost function, generator, and discriminator is created. To correct the discriminator for incorrectly categorizing an original copy as forged or a forged copy as original D(G (z)), however, discriminator training solely utilizes discriminator loss. The weights are updated by means of backpropagation from the discriminator loss through the discriminator network.

(1) DISCRIMINATOR LOSS FUNCTION

$$Discriminator \ : \ max_D E_z(z) \ [log(1 - D(G(z)))] \tag{2}$$

(2) GENERATOR

By leveraging the response from the discriminator together with some random noise "z," one of the neural networks named the Generator "G" attempts to trick the discriminator into classifying its output as real (z).

(1) GENERATOR LOSS FUNCTION

$$Generator \ : \ min_G E_x(x)[log(D(x))] \tag{3}$$

Here, 384 malignant melanoma images were created using this method with the support of GAN, making them equivalent to the dataset's benign images.

3.4. Feature extraction

In the fourth step, the skin dataset images are used to extract the key features. The feature extraction is done to get precise details on skin lesion data, such as border, color, textural nature of skin, etc., Here, feature extraction was carried out using the VGG16, which has already been trained and can assist the model to anticipate results more accurately.

VGG16: VGG16 has won the top 5 places in ImageNet Competition with 92.7% accuracy. Fig. 2 depicts the VGG16 Architecture for the feature extractor. ImageNet has 15 million high-resolution images with labels that fall under about 22,000 categories. Using the NVIDIA Titan Black GPU, VGG16 underwent weeks of training to extract in-depth characteristics from images. VGG16 has 16 layers with Conv and pooling layers with 3×3 kernels for convolution, 2×2 size for max pooling, and consisting of 138 million parameters, trained with ImageNet data.

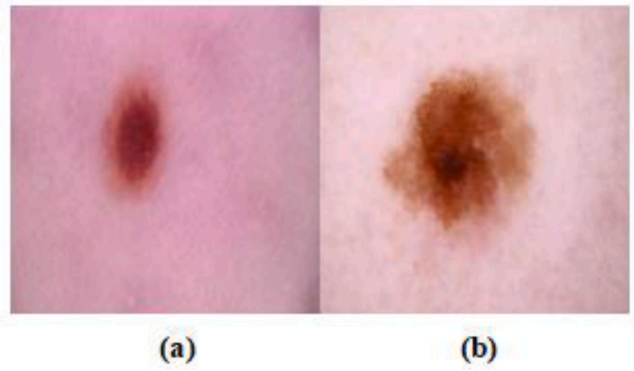

Fig. 3. Examples of (a) Benign image (b) Malignant Melanoma image.

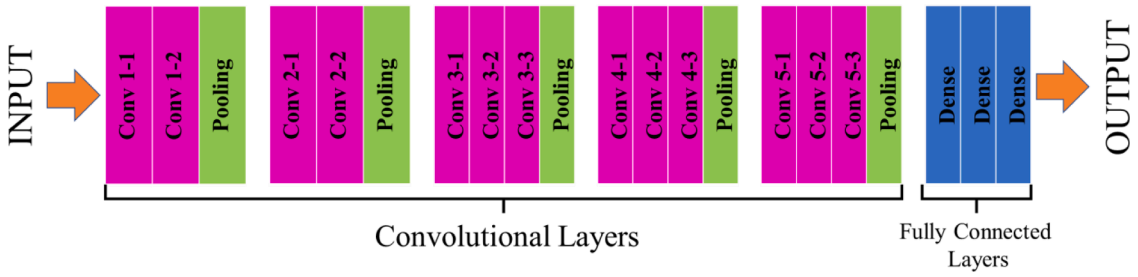

Fig. 2. VGG16 Architecture for feature extractor.

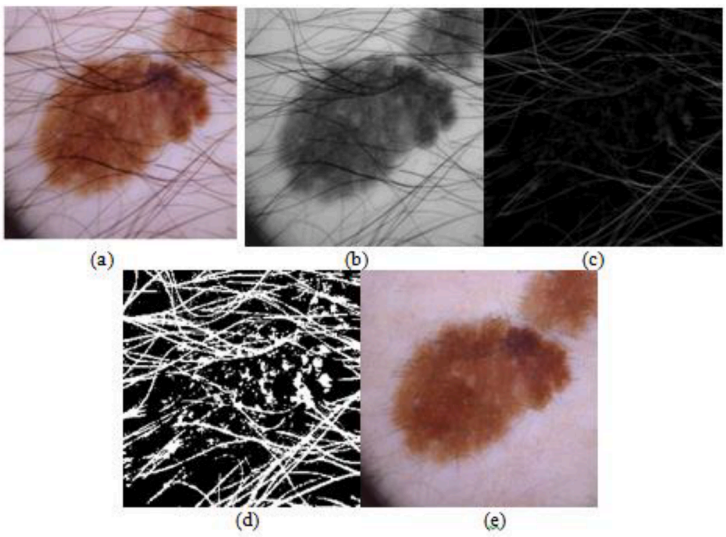

Fig. 4. Pre-processed results (a) original skin lesion image (b) RGB to GRAY converted image (c) BlackHat filtered image (d) Hair detected (e) Hair removed.

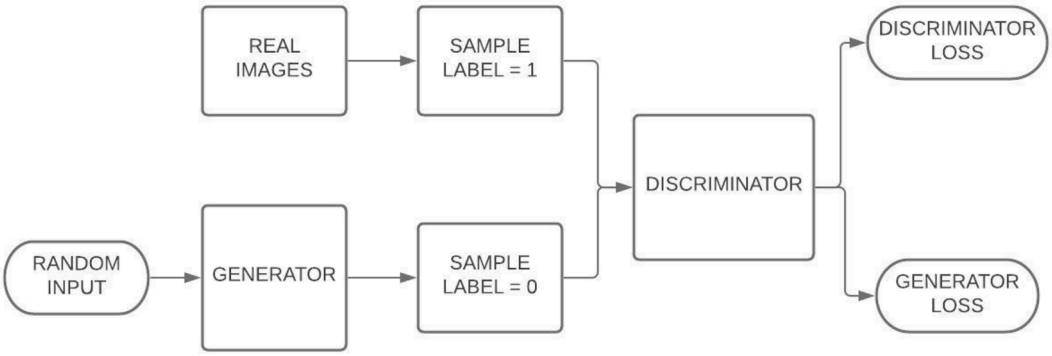

Fig. 5. Generative adversarial network architecture.

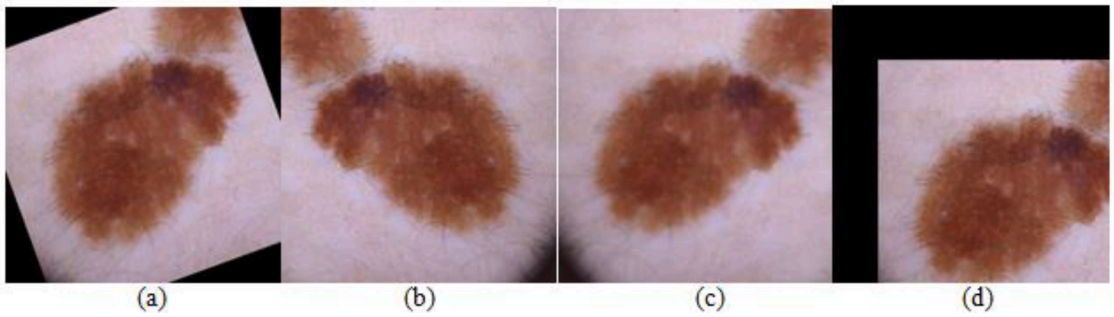

Fig. 6. Data augmented results (a) rotated image (b) flipped image (c) blurred image, and (d) translated images.

3.5. Classification

To categorize benign and malignant skin lesions there were many classification methods available. Supervised machine learning techniques for classification are KNN, SVM, Naïve Bayes, XGBoost, LightBGM etc. In this, XGBoost and LightBGM are utilized as classifiers. Here features derived from the VGG16 model are directly given to the XGBoost and LightBGM models to achieve classification.

(1) XGBOOST

The decision tree-based ensemble machine learning technique named XGBoost makes use of a gradient boosting framework. The main purpose is to classify unstructured data such as text, images, etc. Sometimes XGBoost algorithms perform better than neural networks when the dataset is of small size. Nowadays decision tree-based algorithms provide better results. After performing hyper parameter tuning the model parameters are changed. Where t learning rate was 0.05, max depth was 8, min child weight was 1, gamma was 0.3, and sample by the tree was 0.5.

Boosting creates models from individual 'weak learners.' Individual models in Boosting, unlike Random Forest, are not entirely formed on random selections of data/features. It successively gives credibility to instances with wrong predictions, learning from previous mistakes.

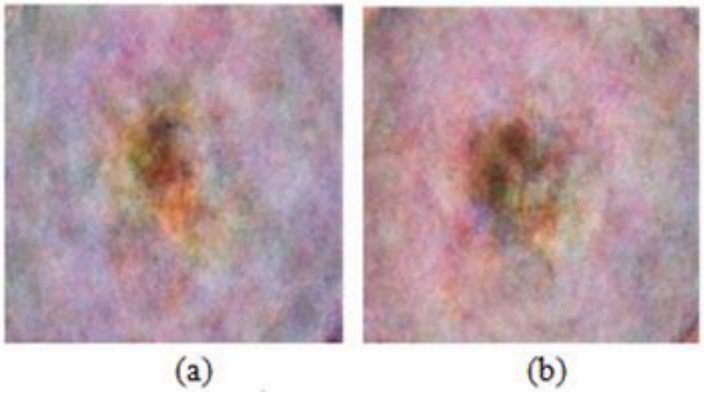

Fig. 7. Malignant melanoma images generated by GAN both (a) and (b).

XGBoost an efficient scalable optimized gradient boosting algorithm outperforms certain deep learning algorithms. To determine the direction of gradients, XGBoost uses second order gradients. To avoid overfitting, it employs advanced L1 and L2 regularization. It is also parallelized for fast computing. The simplified objective in iteration 't' of XGBoost is calculated by (4) (5).

$$\overline{L}^{(t)} = \sum_{i=1}^{n} \cdot \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{4}$$

Where the first and second order gradient statistics of the loss function is

$$g_i = \partial_{\hat{y}(t-1)} l\left(y_i, \hat{y}^{(t-1)}\right) \text{and } h_i = \partial^2_{\hat{y}(t-1)} l\left(y_i, \hat{y}^{(t-1)}\right) \tag{5}$$

Fitting a base learner to the negative gradient of the loss function with regard to the outcome of the previous iteration at each iteration yielded the $f_t(x_i)$ in the gradient boosting strategy. In XGBoost, a number of different base learners or functions is considered, and choose the one that minimizes the loss. XGBoost uses the Taylor series to approximate the loss function value for a base learner $f_t(x_i)$. The "gi" and "hi" refers to the first order derivative of loss and the second order derivative of loss with respect to previous iteration predictions, respectively.

(1) LIGHT GRADIENT BOOSTING MACHINE

Here the Light refers to a faster, more precise, and more efficient approach. In order to distinguish this from XGBoost, LightGBM does leaf-wise tree growth while XGBoost performs level-wise tree development. The model parameters are modified following hyper parameter tweaking.

4. Experimental results

Images of skin lesions obtained from the International Skin Imaging Collaboration are used to test the proposed approaches. The datasets contain 1000 benign images and 416 malignant melanoma images, which are then balanced with augmentation and GAN. The data has been divided into 80:20 train test ratios and the training data has augmented to make both classes data was equal to solve the problem of overfitting, 5- StratifiedKFold was performed with augmented data validated with test data. As explicated in the approach two classifier models one from machine learning techniques is XGBoost and LightGBM with VGG16 a deep transfer learning model as feature extraction is used.

Confusion Matrix: To assess how well the classifier models are performing, confusion matrix is used.

	Predicted 0	Predicted 1
Actual 0	TN	FP
Actual 1	FN	TP

Where, True Positive (TP) = properly categorized positive class, True Negative (TN) = properly categorized negative class, False Positive (FP) = inaccurately categorized positive class, False Negative (FN) = incorrectly classified negative class.

The Performance of the classifier models is evaluated mathematically as Sensitivity(8), Specificity(7), and Accuracy(6).

$$\text{Accuracy} = \frac{\text{TruePositive} + \text{TrueNegative}}{\text{TruePositive} + \text{TrueNegative} + \text{FalsePositive} + \text{FalseNegative}} \tag{6}$$

$$\text{Specificity} = \frac{\text{TrueNegative}}{\text{TrueNegative} + \text{FalsePositive}} \tag{7}$$

$$\text{Sensitivity} = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalseNegative}} \tag{8}$$

Sensitivity: patients that correctly identify with a disease. Specificity: patients that correctly identify people without the disease. Accuracy: It measures how many correct predictions there were compared to all the input samples the model received. The hybrid classification approach was simulated on a desktop computer operating on windows 10 with 16 GB RAM and GTX 1080 8GB GPU, which runs on an intel i7 processor which takes 24 s per epoch for VGG16 + XGBOOST and 11.466 s per epoch for VGG16+LightBGM for an image size of 224 × 224. LightGBM is substantially faster than XGBoost yet provides almost equivalent performance.

5. Discussion

From Table 2 it is observed that the XGBOOST classifier with VGG16 as a feature extractor achieves much better results than LightGBM with VGG16. But when it comes to fast prediction and training LightGBM performs much faster than XGBoost. Figs. 8 and 9 shows the confusion matrix of two models XGBoost and LightGBM. The sensitivity of both models are similar (99.4%), and (97.8%) respectively, where the specificity of XGBoost was more accurate with (98.8%), and LightGBM with (96.6%) illustrated in Fig. 10. Fig. 11 compares the proposed model's performance on specificity against that of existing models such as CNN, U-Net + VGG16, ABCD rules, DCNN, VSVM, DenseNet121, ResNet50, AlexNet, VGG16 [61], Ensembles of 3 individual CNNs, MobileNetV2. Fig. 12 compares the proposed model's performance on sensitivity

Table 2
Shows the accuracy of xgboost model and lightgbm model with VGG16 as a feature extractor.

Feature Extractor + Classifier	Specificity	Sensitivity	Accuracy
VGG16 + XGBOOST	**98.8%**	**99.4%**	**99.1%**
VGG16+LightBGM	**96.6%**	**97.8%**	**97.2%**

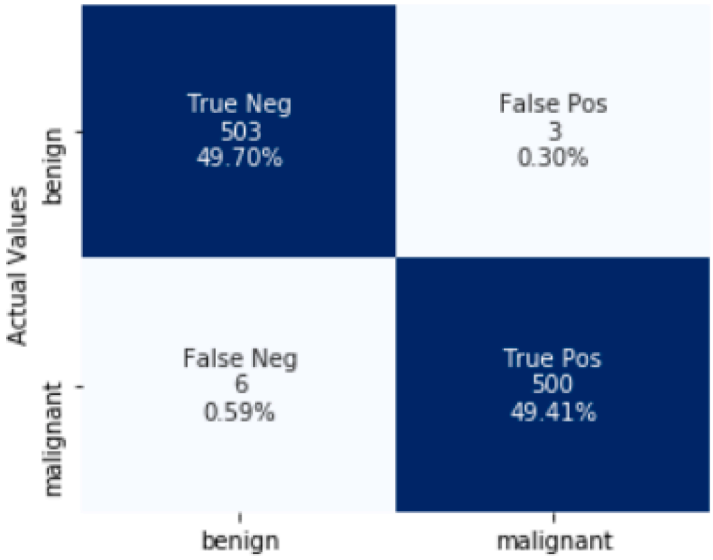

Fig. 8. Confusion matrix of XGBoost.

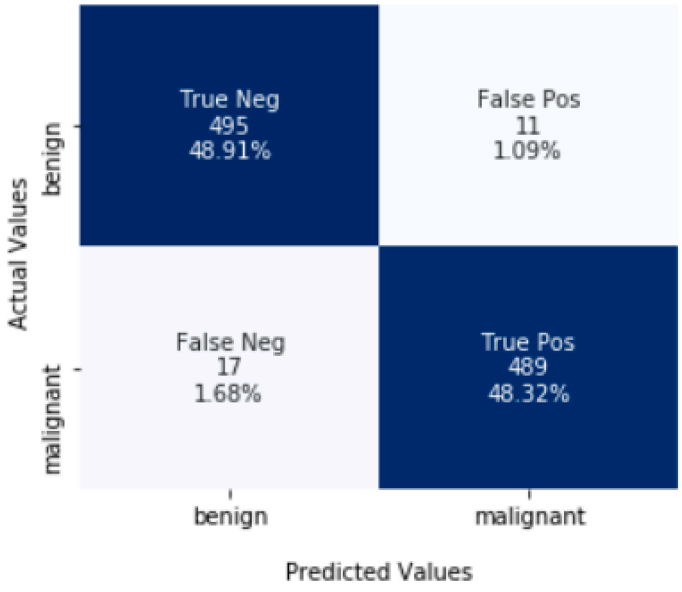

Fig. 9. Confusion matrix of LightBGM.

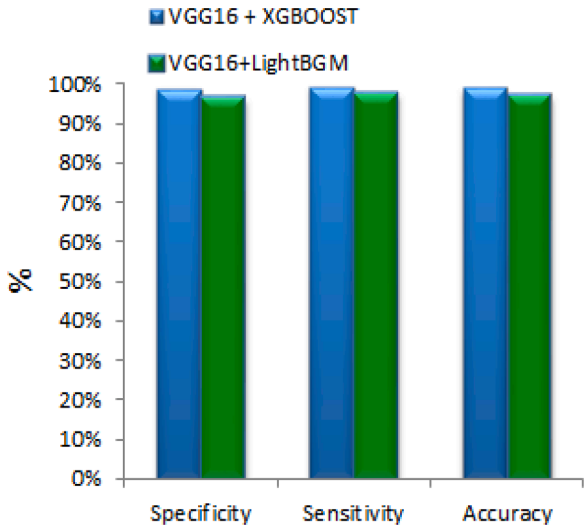

Fig. 10. Specificity, sensitivity, accuracy of the two models (a) VGG16+XGBoost, (b) VGG16+LightGBM.

against that of existing models as above. Fig. 13 compares the proposed model's performance on accuracy against that of existing models such as CNN, U-Net + VGG16, ABCD rules, DCNN, VSVM, DenseNet121, ResNet50, AlexNet, VGG16, Ensembles of 3 individual CNNs, MobileNetV2. These comparisons depict that the proposed method outperforms other existing methods and provides a better accuracy of 99.1%. Some of the other existing methods are SVM with CNN [62], Localizing the lesions using DTP-net specified in [63], the EfficientNet-based modified sigmoid transform used to contrast the lesion [64], the method to effectively categorize skin cancer images, using a hybrid deep feature creation and iterative feature selector [65].

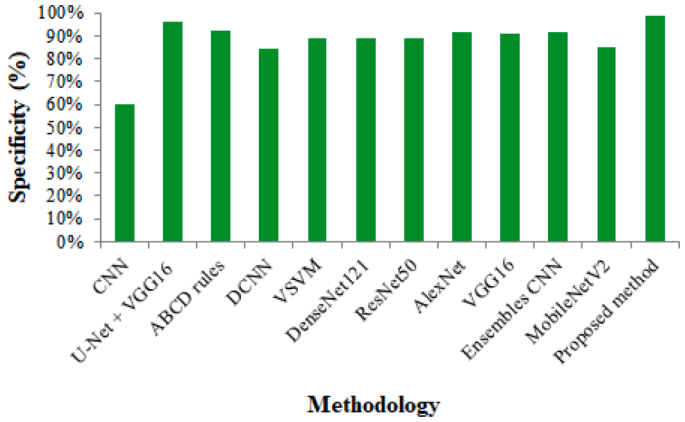

Fig. 11. Proposed method Vs existing models on specificity.

6. Conclusion and future work

Skin cancers are intermittently difficult to identify because of the misconception. Melanoma is one among them. When an appropriate computerized method is used, which ease the work of dermatologist to classify the skin lesions whether it is benign or melanoma. To automate

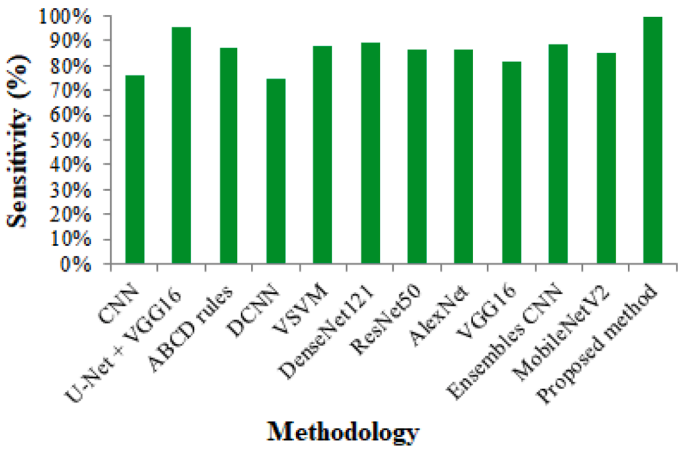

Fig. 12. Proposed method Vs existing models on sensitivity.

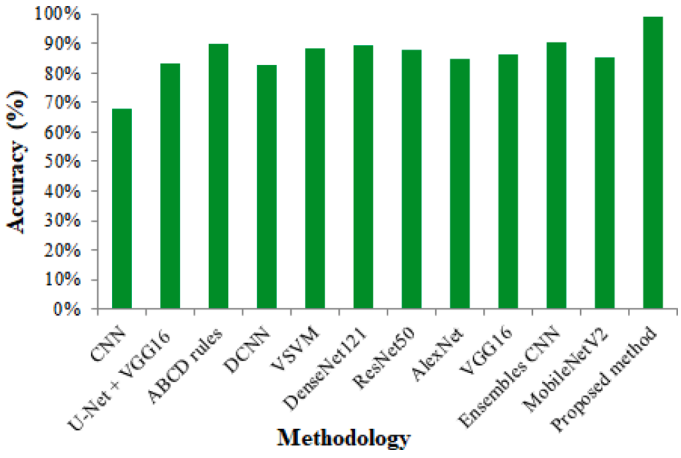

Fig. 13. Proposed method Vs existing models on accuracy.

this process and to increase the early stage prediction of this disease, a hybrid method that aggregates VGG16 and XGBoost is used, which extracts the feature and classifies the dermatological photographs to identify the skin cancer. XGBoost algorithm outperforms certain deep learning algorithms even when the dataset size is small which also avoids overfitting with its regularization techniques. The proposed technique when implemented on skin lesion images from the ISIC datasets, classification methods obtain the accuracy with the two models VGG16 + XGBOOST and VGG16+LightBGM as 99.1%, 97.2% respectively which depicts the significant improvement compared to the state of the art skin lesion classifiers. After the usage of feature extraction and data augmentation, the performance has been improved and the model is more accurate in discriminating benign and malignant skin lesions, unlike the previous models.

In future work, this method can be broadened for other kinds of skin cancer diseases. Further strengthening the dataset will reduce overfitting by calibrating the hyper-parameters. Segmenting the affected region will aid dermatologists in accurate findings even with different skin colors. Smart devices embedded with CAD will automate the diagnosing process of several skin lesions with accurate results. The methodology lacks scalability, which can be handled using suitable techniques.

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Abbreviations

Not applicable.

Availability of data and materials

Not applicable.

Authors' contributions

All authors contributed equally to this article. All authors read and approved the final manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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