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SANTI BEHERA

Veer Surendra Sai University of Technology

PRABIRA SETHY (✉ [prabirsethy.05@gmail.com](mailto:prabirsethy.05@gmail.com))

Department of Electronics, Sambalpur University, Odisha, India

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## Research Article

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# Categorization of Common Pigmented Skin Lesions (CPSL) using Multi-Deep Features and Support Vector Machine

Prabira Kumar Sethy<sup>1,\*</sup>, Santi Kumari Behera<sup>2</sup>

<sup>1</sup> Department of Electronics, Sambalpur University, Odisha, India

<sup>2</sup> Department of Computer Science and Engineering, Veer Surendra Sai University of Technology, Odisha, India

\*Correspondence: prabirasethy.05@gmail.com, Tel.: +91-9439489214

**Abstract:** The skin is the main organ. It is approximately 8 pounds for the average adult. Our skin is a truly wonderful organ. It isolates us and shields our bodies from hazards. However, the skin is also vulnerable to damage and distracted from its original appearance; brown, black, or blue, or combinations of those colors, known as pigmented skin lesions. These common pigmented skin lesions (CPSL) are the leading factor of skin cancer, or can say these are the primary causes of skin cancer. In the healthcare sector, the categorization of CPSL is the main problem because of inaccurate outputs, overfitting, and higher computational costs. Hence, we proposed a classification model based on multi-deep feature and support vector machine (SVM) for the classification of CPSL. The proposed system comprises two phases: first, evaluate the 11 CNN model's performance in the deep feature extraction approach with SVM. Then, concatenate the top performed three CNN model's deep features and with the help of SVM to categorize the CPSL. In the second step, 8192 and 12288 features are obtained by combining binary and triple networks of 4096 features from the top performed CNN model. These features are also given to the SVM classifiers. The SVM results are also evaluated with principal component analysis (PCA) algorithm to the combined feature of 8192 and 12288. The highest results are obtained with 12288 features. The experimentation results, the combination of the deep feature of Alexnet, VGG16 & VGG19, achieved the highest accuracy of 91.7% using SVM classifier. As a result, the results show that the proposed methods are a useful tool for CPSL classification.

**Keywords:** Common Pigmented Skin Lesions; Multi-deep features; Support vector machine; Skin cancer; Convolutional neural network.

## 1. Introduction

The largest organ in the human body is the skin. Various forms of inflammatory, bacterial, and viral infections spread throughout the skin, leading to several skin diseases and health problems [1]. “Melanoma is the most dangerous type of skin cancer, which has been one of the most important challenges of public health in recent years [2].”

According to the latest statistics, in 2018, 91270 new melanoma cases are diagnosed and treated in the United States [1]. “Melanoma incidence rates and mortality from this disease are projected to increase over the next few decades [3].” “The latest study shows that the diagnosis of new melanoma cases has risen by 53% annually from 2008 to 2018[1, 4].” If it is possible to detect this type of cancer at its early stage by selecting the right treatment [5, 6], survival rates are very promising [7]. Otherwise, a patient's estimated 5-year survival rate would be decreased from 99% to 14% [8-10]. There was also a drastic rise in the diagnosis of new cases between 1994 and 2014, up to 77%, in the non-melanoma form of cancer. “The most common form of non-melanoma skin cancer is basal cell carcinoma, resulting in 3000 deaths per year [11].” Therefore, this will give rise to a strong demand for primary inspection and identification of various skin cancer forms to prevent it from getting worse and provide a better prognosis [3]. The normal way to diagnose melanoma is by examining the low-precision visual information [12,13]. “Dermoscopy, on the other hand, is a non-invasive technique that can capture a high-resolution skin image that helps dermatologists to identify features invisible to the naked eye [14].”

Several meta-analyses have shown that melanoma diagnosis is improved and reliable in naked eye examination using dermoscopy [15-17]. Even for experienced clinicians, the manual approach is challenging and subjective [18, 22-23]. Due to the similarity of visual characteristics between malignant tumors of the skin and benign lesions, dermatologists face difficulty distinguishing between them. Even if highly trained dermatologists and physicians have the average sensitivity for recognition of melanoma, it is less than 80% [24, 25]. Again, highly trained dermatologists are not available all over the world. Therefore, automatic skin lesion classification at the same level and accuracy as dermatologists or even higher is crucial in public health.

To solve the aforementioned issues, there have been plenty of publications on exploring methods to classify skin cancers by means of computer assistance. These algorithms use various approaches to the segmentation, detection, and classification of melanoma by

integrating areas such as image processing, computer vision, and machine learning [20, 26-29]. “The main problem of this type of scientific paper is the scarcity of data. However, skin cancer has been categorized into different stages according to 'man-made' methods, which is a major flaw in the classification method [30-33].”

In most current studies, the three main skin disorders, including seborrheic keratosis (SK), squamous cell (SC), and melanoma, are considered. In the last few decades, several researchers have developed various approaches to diagnose skin diseases. “In addition, natural computing system, region of interest (ROI), gray level co-occurrence matrix (GLCM), fractal-based regional texture analysis (FRTA) feature extraction methods, various machine learning algorithms such as Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Generative Adversarial Networks (GANs) with Support Vector Machine (SVM), Naive Bayes were implemented [34-36].” These approaches have produced improved classification accuracy in terms of skin disease detection. Still, they have few deficiencies in higher dimensional space computational complexity, more processing time, overfitting problems, a noisy environment, and so on. To overcome this, we have proposed a classification model that uses multi-deep features and SVM to categorize CPSL. The main contribution of the article is summarized as follows.

- The dataset images were collected from the HAM-10000 dataset belongs to seven classes of CPSL such as melanoma (mel), melanocytic nevi (nv), basal cell carcinoma (bcc), actinic keratosis and carcinoma benign keratosis (bkl), dermato fibroma (df) and vascular lesions (vasc).
- The performance of 11 CNN models is evaluated to classify seven CPSL based on their deep feature and SVM.
- High-dimensional features such as 8192 and 12288 are obtained by combining binary and triplet networks of three top-performing CNN architectures and feed to the SVM for classification.
- The performance is also evaluated by introducing dimensional reduction techniques like PCA.
- The LR+ is 49, which is greater than 10, and implicates the proposed method has a significant contribution to the diagnosis and an excellent diagnostic test.
- Finally, the AUC value of the proposed method is 0.99, which is within the range of 0.9 to 1. It reveals an excellent diagnostic approach as per STARD (Standards for Reporting of Diagnostic Accuracy Studies) guidelines.

The remaining of the manuscript is organized as follows. Section 2 discusses the related works. Section 3 detailed the dataset. The methodology is presented in section 4. Experimental results of the proposed method are given in Section 5. Finally, section 6 shows the discussion and conclusion section where the results are discussed by comparing with the previous methods.

## **2. Related Works**

Many approaches are reported towards the classification of different skin cancer lesions or CPSL, especially in machine learning. The integrated computer-aided mechanism [35] was proposed for the detection of skin diseases. They analyze the shape, color, texture, and irregular border of the skin lesion to create various quantitative features before classification. Textural information is quantified through a fractal-based regional texture analysis (FRTA) and a gray-level co-occurrence matrix (GLCM). The radial base function (RBF) and the support vector machine (SVM) evaluate the classification's efficiency. The experimental study delivers 99.65%, 97.54%, and 98.99% for BCC, dysplastic nevi, and melanoma classification, but the characteristic dimensional space is higher. The computer-aided classification system [36] was implemented to diagnose suspected pigmented lesions. Pre-selected single lesion images train computer-aided diagnostic tools for skin lesions. One hundred thirty-three patients with a multitude of skin lesions were selected for this study. The board-certified dermatologist investigates all lesions that are classified as normal or abnormal. The sensitivity of 100 percent of suspected pigmented lesions is achieved on the basis of the test set. At the population level, this computer-aided classification method is very useful for skin screening.

Dynamic Graphics Cut algorithm (DGCA) and Naive Bayes (NB), a classifier is proposed for the segmentation and classification of skin diseases [37]. Experimental datasets are taken from the International Skin Imaging Partnership (ISIC 207) [44], which shows better results compared to state-of-the-art approaches such as SegNet and FCN. Here, there are three kinds of cancers, such as keratosis, melanoma, and benign cases. The detailed analysis reveals 92.9%, 91.2%, and 94.3% for keratosis, melanoma, and benign disease classification. It was proposed that the deep convolutional neural network (DCNN) classifier should be used to identify skin diseases [38]. DenseNet-201, InceptionResNet-v2, ResNet-50 and Inception-v3 are used in the convolutional neural network classifier. The full resolution convolutional

network (FrCN) segments the skin lesion boundary of the entire dermoscopy image. The ISIC 2016 [27], ISIC 2017 [44], and ISIC 2018 [45] datasets are used to evaluate the performance of convolutional neural network classifiers in the case of skin disease classification.

Multi-label classification techniques are proposed [39] to identify skin disorders such as SK, BCC, nevus, and melanoma. Cross-spectrum and cross-correlation approaches for the extraction of features have been adopted. The extraction of both spectral and spatial features is clarified by suitable kernel patches and related visual impacts. Classifications of epidermal, benign melanocytic, and benign melanocytic skin lesions are performed using a multi-label multi-class skin lesion classification mechanism. Generative adversarial networks (GANs) have been developed to identify skin lesions [40]. The GAN-based data increase process improves the efficiency of the skin lesion classification. High-quality skin lesion images are synthesized by changing both the discriminator and the generator. Quantitative assessment measures such as Recall, Accuracy, Inception Distance (FID), and Inception Score (IS) assess GAN-based skin lesion's efficiency. The experimental analysis, 96.6% average precision, 74.3% specificity, 83.2% sensitivity, and 95.2% accuracy are obtained. Present methodologies used in the classification of skin diseases are illustrated in Table 1.

**Table 1.** A literature review of CPSL classification

References	Methods	Name of the dataset	Advantages	Limitations	Accuracy
[35]	RBF and SVM	Real-time dataset	The higher degree of accuracy and sensitivity at every stage	Higher feature dimensionality space	98.79%
[36]	Computer-aided classification	Dermatological I databases	Low feature dimensionality with the fast-screening process	Lower classification accuracy	75.9%
[37]	DGCA and NB	ISIC 2017	Easy to implement the classifier with quick output prediction	Higher cost and complexity	94.3%
[38]	DCNN	ISIC 2016, ISIC 2017, and ISIC 2018 datasets	Better classification performances with accurate results	The limited size of deep learning networks for both training and testing	98.79%
[39]	Multi-label classification techniques	Real-time database	Malignant and benign lesions in the classes of melanoma, nevus, BCC and SK have been identified.	It takes more processing time.	98.79%

[40]	GANs	ISIC 2018 dataset	More accurate diagnostic decisions	Insufficient class imbalanced data or labeled data	95.2%
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### 3. About Dataset

We considered the image classification task of the most common lesions that should be distinguished in a skin cancer screening setting. About 90% of lesions found in the routine skin examination are covered by the following seven skin lesion classes: (1) Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), (2) basal cell carcinoma (bcc), (3) benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses, (bkl), (4) dermatofibroma (df), (5) melanoma (mel), (6) melanocytic nevi (nv), and (7) vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage (vasc). All images were obtained from the HAM10000 Dataset [41]. This dataset contains 10015 dermoscopic images, which can serve as a training set for academic machine learning purposes. There are different dermatoscopy dataset publicly available, illustrated in Table 2. In this study, the HAM1000 dataset is taken into consideration because: (1) the only dataset which contains seven kinds of CPSL, (2) all seven kinds of CPSL have more than 100 images, (3) 53.3% of images are pathologically verified.

**Table 2.** Summary of publicly available dermoscopic image datasets in comparison to HAM10000

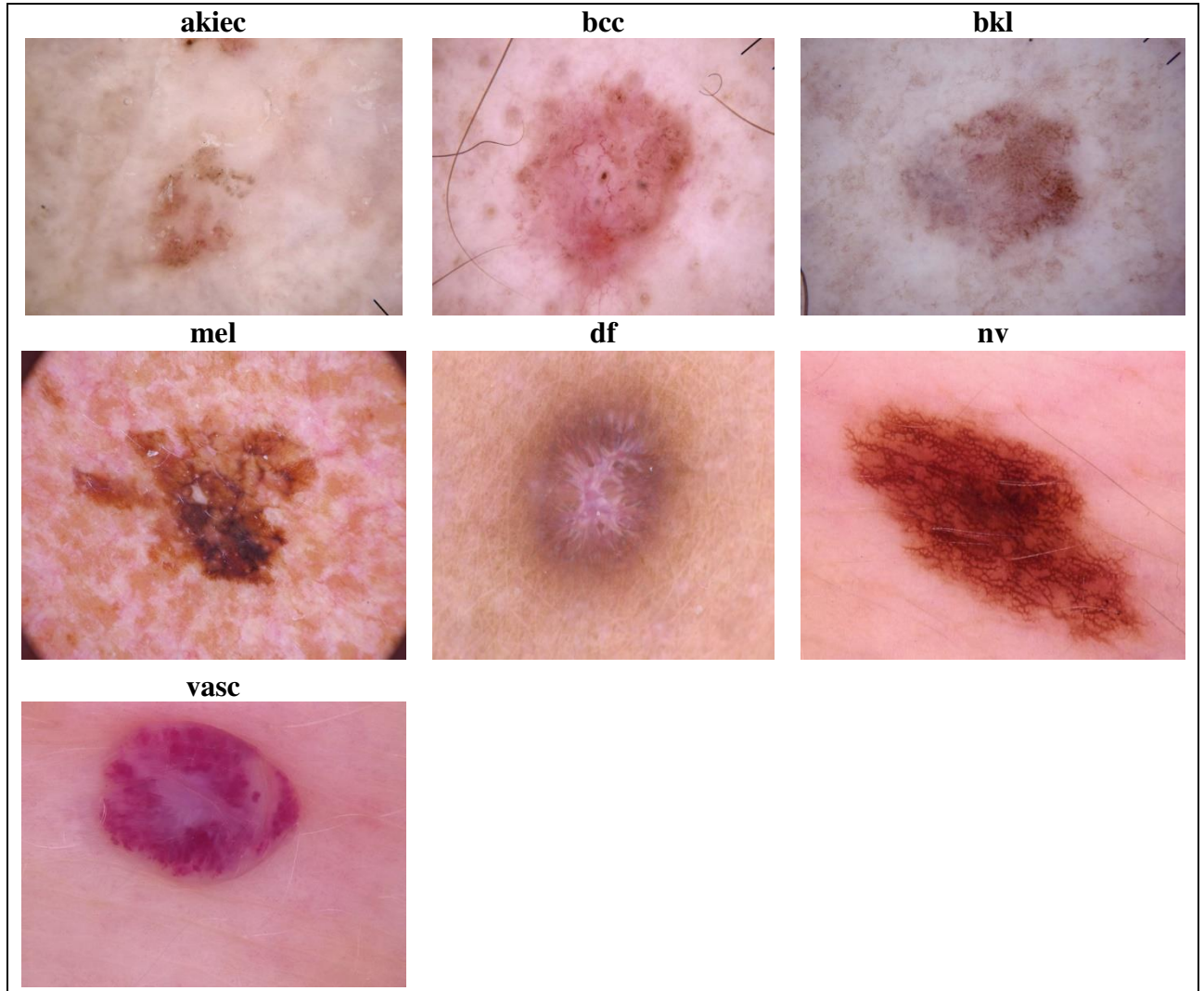
Dataset	Total images	Pathologic verification (%)	akiec	bcc	bkl	df	mel	nv	vasc
PH2	200	20.5%	-	-	-	-	40	160	-
Atlas	1024	unknown	5	42	70	20	275	582	30
ISIC 2017	13786	26.3%	2	33	575	7	1019	11861	15
Rosendahl	2259	100%	295	296	490	30	342	803	3
ViDIR Legacy	439	100%	0	5	10	4	67	350	3
ViDIR Current	3363	77.1%	32	211	475	51	680	1832	82
ViDIR MoleMax	3954	1.2%	0	2	124	30	24	3720	54
HAM10000	10015	53.3%	327	514	1099	115	1113	6705	142

To make the dataset balanced across all classes, we have horizontally and vertically flipped the images of df, akiec, and vasc class; and chosen a subset of images from bkl, mel, and nv class. The dataset distribution of CPSL is taken in this research is given in Table 3. Figure 1 illustrates the sample images of seven kinds of CPSL.

**Table 3.** Distribution of Sample images of CPSL

akiec	bcc	bkl	df	mel	nv	vasc	Total
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500	514	500	345	500	500	426	3285
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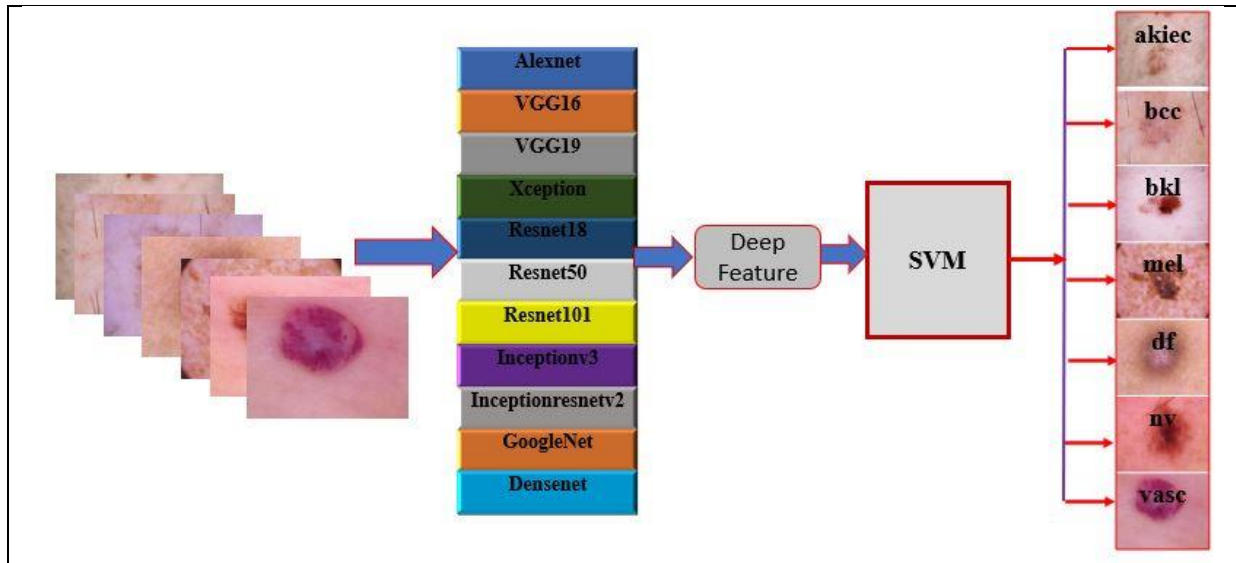
**Figure 1.** Sample images of CPSL

#### **4. Methodology**

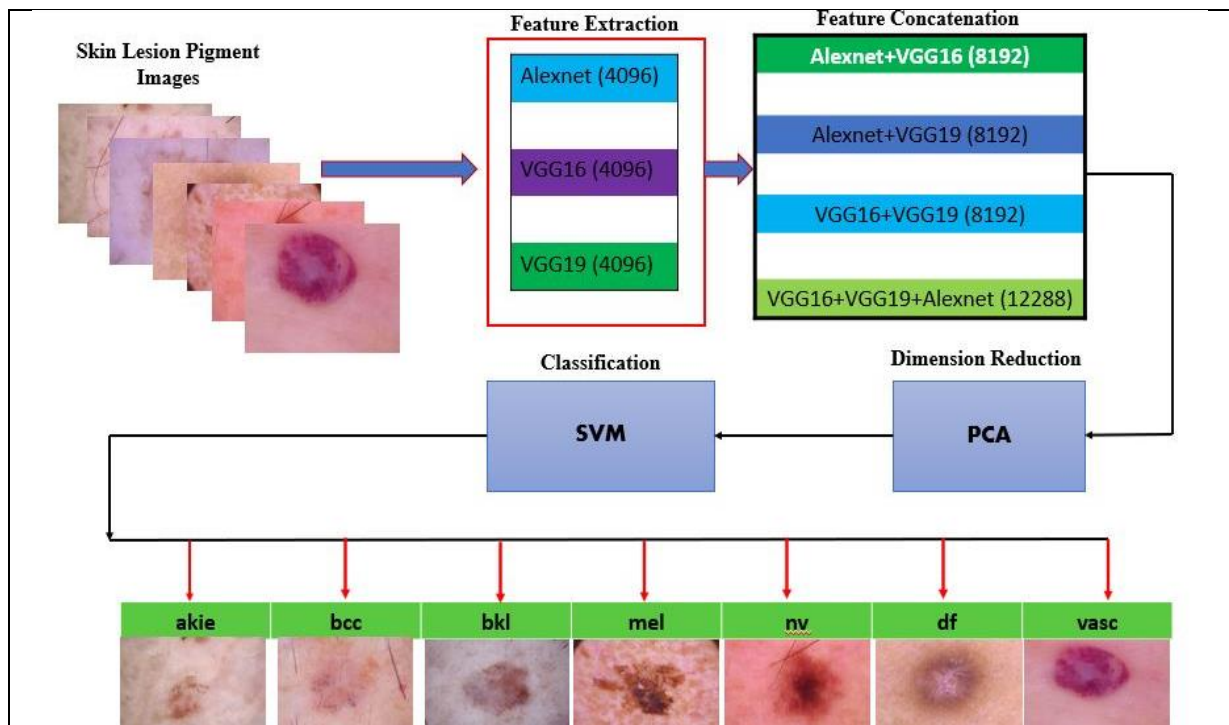
The proposed method comprises two phases: first, the 11CNN models are evaluated for classification of CPSL based on the feature extraction approach. Here, the features are extracted from fully connected layer and feed to the SVM for classification. The linear SVM is used for classification. When SVM is used as a classifier in CNN models, it increases accuracy [42,43]. The performance evaluation model of CNN for the classification of CPSL is shown in Figure 2. In the second phase, the features taken from three top performed models are combined and applied to the same SVM classifiers. In the last step of the experiment,



features are given to the classifiers after PCA. The architectural design of the proposed method is shown in Figure 3. The strategy for evaluating all classification models in this study is based on a training and testing ratio of 80:20.



**Figure 2.** Performance Evaluation model of CNN for classification of CPSL



**Figure 3.** The framework of the Proposed method based on multi-deep Features and SVM for the classification of CPSL

## 5. Experimental Analysis and Results

Evaluating a method is important in building a useful machine learning model. There are many performance criteria used to test the performance of the classification. The most commonly used classification evaluation metric is "accuracy." However, this criterion alone is not always correct and can be misleading in some cases. Therefore, it will be useful to provide an evaluation by looking at other criteria that support accuracy. The metrics we use to choose the top performed CNN model in this study; are accuracy, sensitivity, specificity, precision, FPR, and F1 score.

**Table 4.** Performance evaluation parameters computed using the deep feature of the CNN model and SVM

Model	Accuracy	Sensitivity	Specificity	Precision	FPR	F1 Score
Alexnet	0.717142857	0.717142857	0.952857143	0.771124988	0.047142857	0.713513735
VGG16	0.723095238	0.723095238	0.953849206	0.75281268	0.046150794	0.714124799
VGG19	0.735714286	0.735714286	0.955952381	0.749490933	0.044047619	0.732478894
Xception	0.584047619	0.584047619	0.930674603	0.652361318	0.069325397	0.568450918
Resnet18	0.428809524	0.428809524	0.904801587	0.648393615	0.095198413	0.394574751
Resnet50	0.58047619	0.58047619	0.930079365	0.705257431	0.069920635	0.576618549
Resnet101	0.677380952	0.677380952	0.946230159	0.730705187	0.053769841	0.678646795
Inceptionv3	0.613095238	0.613095238	0.935515873	0.679088471	0.064484127	0.603739113
Inceptionresnet v2	0.565	0.565	0.9275	0.636205758	0.0725	0.565969183
GoogleNet	0.525952381	0.525952381	0.920992063	0.622583676	0.079007937	0.526559175
Densenet	0.655952381	0.655952381	0.94265873	0.695805106	0.05734127	0.654849059

It was observed from Table 4, the Alexnet, VGG16, and VGG19 are the three top performed CNN model for classification of CPSL. The deep features of these three top performed models are now combined and feed to SVM for classification. The results are recorded in Table 5 in terms of Accuracy and AUC. The classification model is also evaluated with the employment of PCA, and corresponding results are recorded in Table 6.

**Table 5.** Performance of classification models with combined deep features

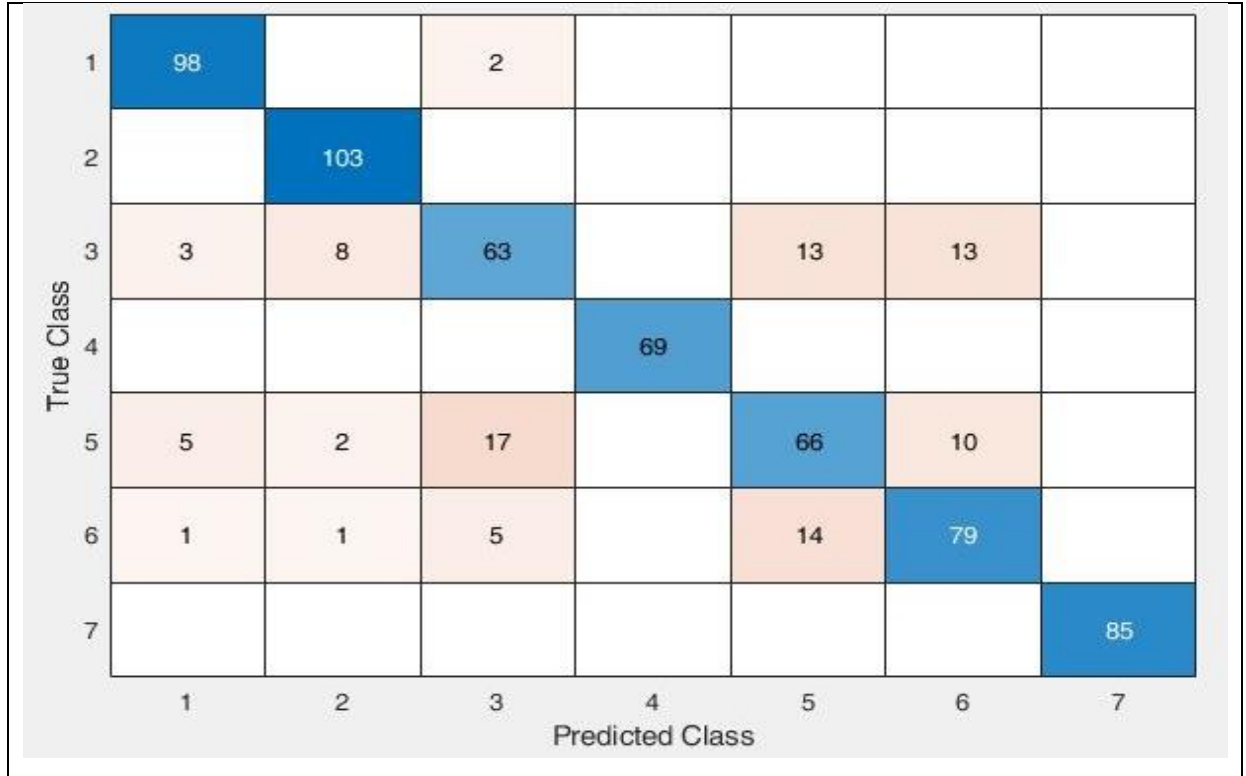
Models	Features	Accuracy (%)	AUC	Total misclassification
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Alexnet+ VGG16	8192	79.4	0.89	138
Alexnet+VGG19	8192	78.9	0.92	127
VGG16+VGG19	8192	82.5	0.95	102
Alexnet+vgg16+vgg19	12288	91.7	0.99	84

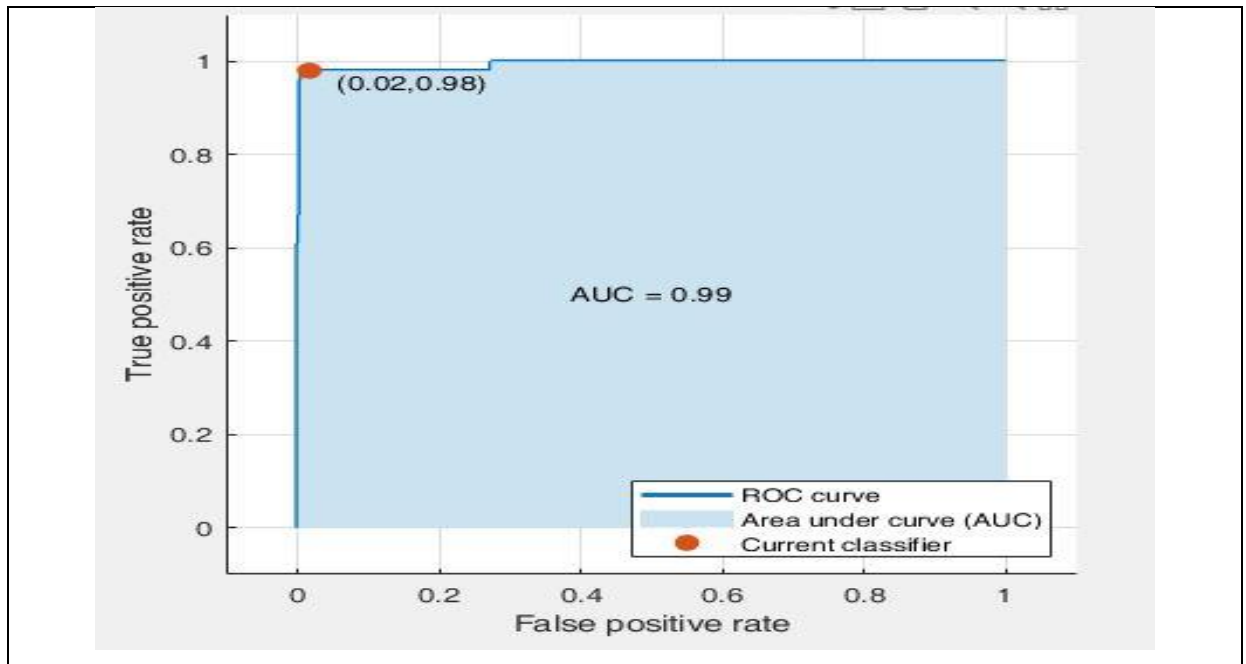
**Table 6.** Performance of classification models with combined deep features and PCA

Models	Features	Accuracy (%)	AUC	Total misclassification
Alexnet+ VGG16	8192	78.9	0.88	158
Alexnet+VGG19	8192	77.5	0.91	134
VGG16+VGG19	8192	79.9	0.95	112
Alexnet+vgg16+vgg19	12288	85.5	0.99	92

It was observed from Table 5 and Table 6; the performance of classification models is degraded with the employment of PCA. In the combination of deep features of binary and triplet CNN architectures, the performance of classification models is increased compared to an individual. Among the combined deep feature, the effectiveness of the deep features of triplet CNN architecture is more than the deep feature of binary CNN architectures. The confusion matrix and ROC plot of classification models, i.e., based on triplet deep feature and SVM, are presented in Figures 4 and 5, respectively.



**Figure 4.** Confusion Matrix of Proposed classification model for diagnosis of breast carcinoma



**Figure 5.** AUC of Proposed classification model for diagnosis of breast carcinoma

Figure 5 shows that the true positive rate (TPR) and false-positive rate (FPR) of the classification model are 0.02 and 0.98, respectively. The positive likelihood ratio (LR+) is calculated by equation 1.

$$LR+ = \frac{TPR}{FPR} \quad (1)$$

Hence, for proposed classification model  $LR+=\frac{0.98}{0.02}=49$ . So, as per STARD [46], the proposed method is a good diagnostic test. In addition, the AUC value of the proposed method is 0.99, which is within the range of 0.9 to 1.0. It reveals an excellent diagnostic approach as per STARD (Standards for Reporting of Diagnostic Accuracy Studies) guidelines [46]. Further, Table 7 presents the true positive rates (TPR) and positive predictive values (PPV) value of seven classes of CPSL.

**Table 7.** TPR and PPV values of each CPSL classes

Classes	TPR (%)	PPV (%)
akiec	98	91.6
bcc	100	90.4
bkl	63.0	72.4
mel	100	100
nv	66	71.0
df	79	77.5
vasc	100	100

It was observed from Table 7, the TPR or sensitivity of akiec is 98%, bcc is 100%, bkl is 63%, mel is 100%, nv is 66%, df is 79%, and vasc is 100%. The TPR values of classes are more than 60%, and the PPV values are more than 70%. Hence, it indicates the proposed methodology is going on a positive approach towards the classification of CPSL.

## 6. Conclusion

Our study aims to increase the classification accuracy values of the applied dataset with the models obtained by using two different forms of deep feature extraction approach with SVM. In the first, approach the deep features of 11 CNN models with SVM are evaluated for classification of CPSL. Then, the three top performed CNN architectures are chosen to prepared large dimensional deep features. The 8192 and 12288 dimensional deep features are prepared by combining binary and triplet network. Then, these features are fed to the SVM for classification of seven kinds of CPSL. Further, PCA is also employed to evaluate those classification model. It reveals from the experimental results that the 12288-dimensional deep feature with SVM performed well to classify seven kinds of CPSL. The achieved accuracy and AUC are 91.7% and 0.99, respectively, higher than the state-of-art.

Further, no research paper is published to classify seven kinds of CPSL, illustrated in Table 8.

Table 8. Performance Comparison of the proposed method with state-of-the-art techniques

Work	Database	CPSL Classes	Classification Performance
Oliveira et al. [46]	ISIC: dataset	Malignant and benign	Accuracy-94.3% Sensitivity-91.8% Specificity-96.7%
Kasmi et al. [47]	EDRA, Interactive Atlas of Dermoscopy	Malignant and benign	Sensitivity – 91.25% Specificity – 95.83%
Rastgoo et al. [48]	Vienna General Hospital	Melanoma and Dysplastic nev	Sensitivity – 98% Specificity – 70%
Shimizu et al. [49]	Keio University Hospital, University of Naples and Graz, Tokyo Women's Medical University	Melanoma, Nevus, BCC, and SK	Sensitivities-90.48%, 82.51%, 82.61% and 80.61%
González-Díaz et al. [50]	2017 ISBI Challenge database	Melanoma, Nevus, and SK	Sensitivity-95%
Esteva et al. [51]	ISIC Dermoscopic Archive, the Edinburgh Dermofit Library and data from the Stanford Hospital	Benign, malignant and non-neoplastic	Sensitivity-72.1%
Chatterjee et al. 2019 [39]	International Dermoscopic Society database, Dermoscopic Atlas database, ISIC: challenge 2017, and PH2 database	Melanoma, Nevus, BCC, and SK	Sensitivities-98.76%, 99.01%, 98.87% and 99.41%
AI-Masni et al. [38]	ISIC 2018	SK (AKIEC), Melanoma, Nevus, BCC, BKL, DF, VASC	Accuracy 89.28%
<b>Proposed Model</b>	ISIC 2018	SK (AKIEC), Melanoma, Nevus, BCC, BKL, DF, VASC	Accuracy 91.7% Sensitivity – 100%, 100%, 66%,100%,63%,79%,100%

It was observed in Table 8; the proposed methodology is the only method that deals with seven kinds of CPSL. Again, even if more kinds of CPSL are considered, the proposed method achieved better performance than the existing work. Also, the sensitivity of each class of CPSL is competent enough with the existing work.

The method achieved diagnostic effectiveness (accuracy) of 91.7%, AUC is 0.99, and LR+ is 49. As per STARD guidelines, the proposed diagnosis method is excellent (as AUC is within the range of 0.9 to 1) and an excellent diagnostic test (as LR+ > 10). In terms of definitely

solving skin cancer issues for the classification of CPSL, the findings obtained signify that we are in the right direction.

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**Funding:** Any organization or institution does not support this research.

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**Ethical approval:** This article does not contain any studies with human participants or animals performed by any authors.

### **Data availability statement:**

Data sharing does not apply to this article, as no new data were created or analyzed in this study.

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# Figures

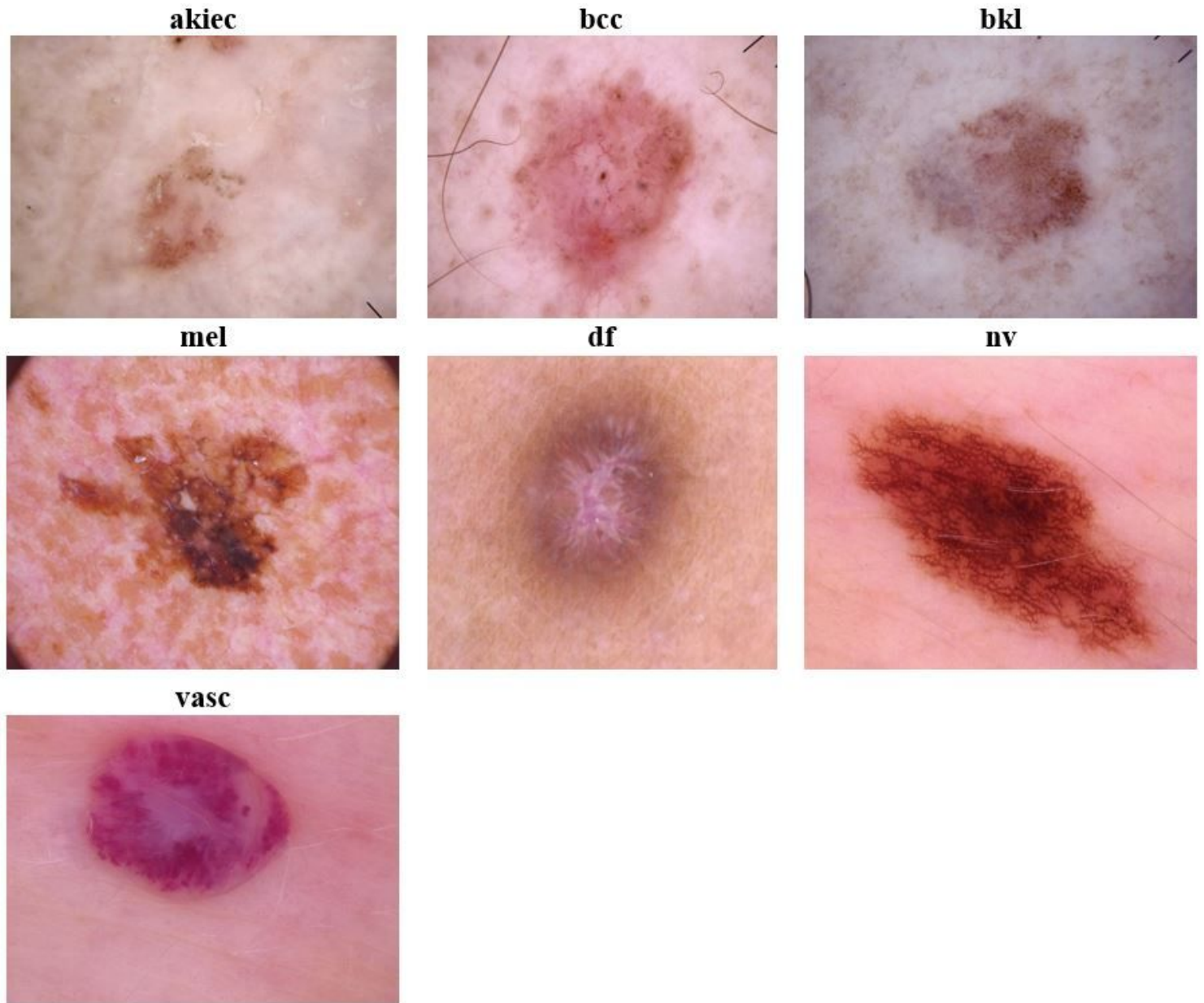


Figure 1

Sample images of CPSL

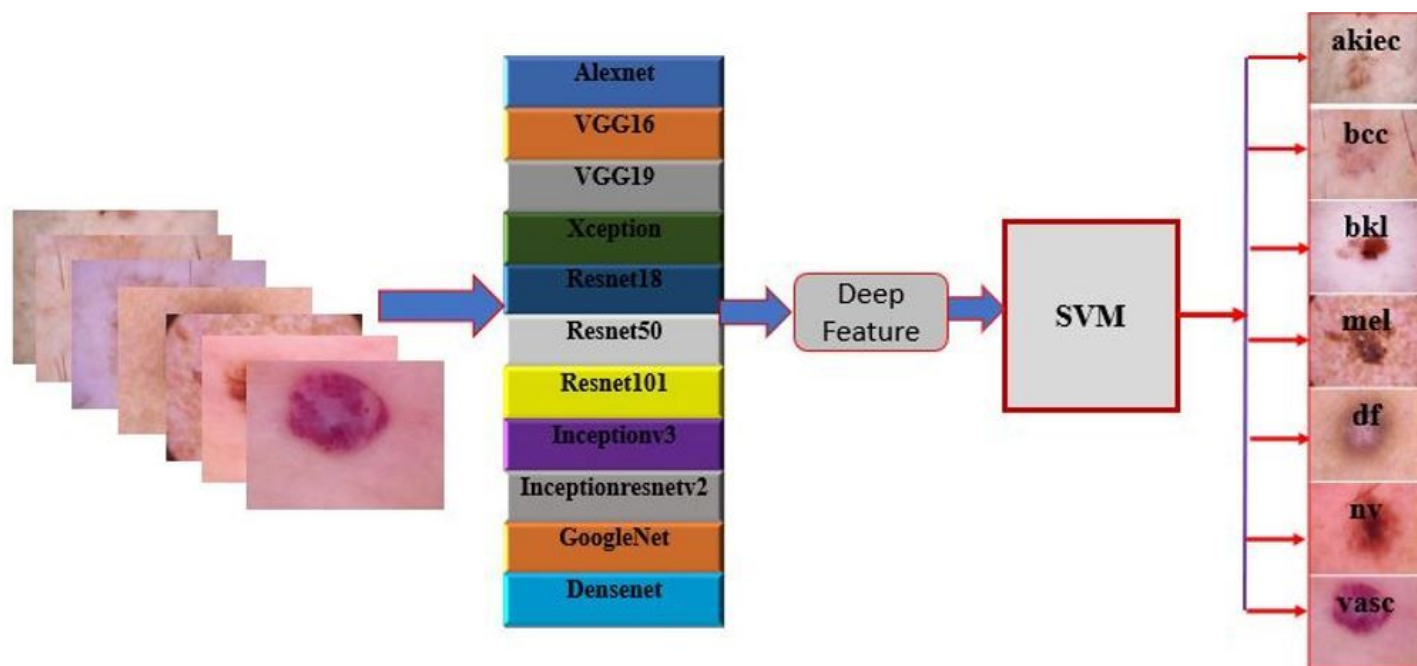


Figure 2

Performance Evaluation model of CNN for classification of CPSL

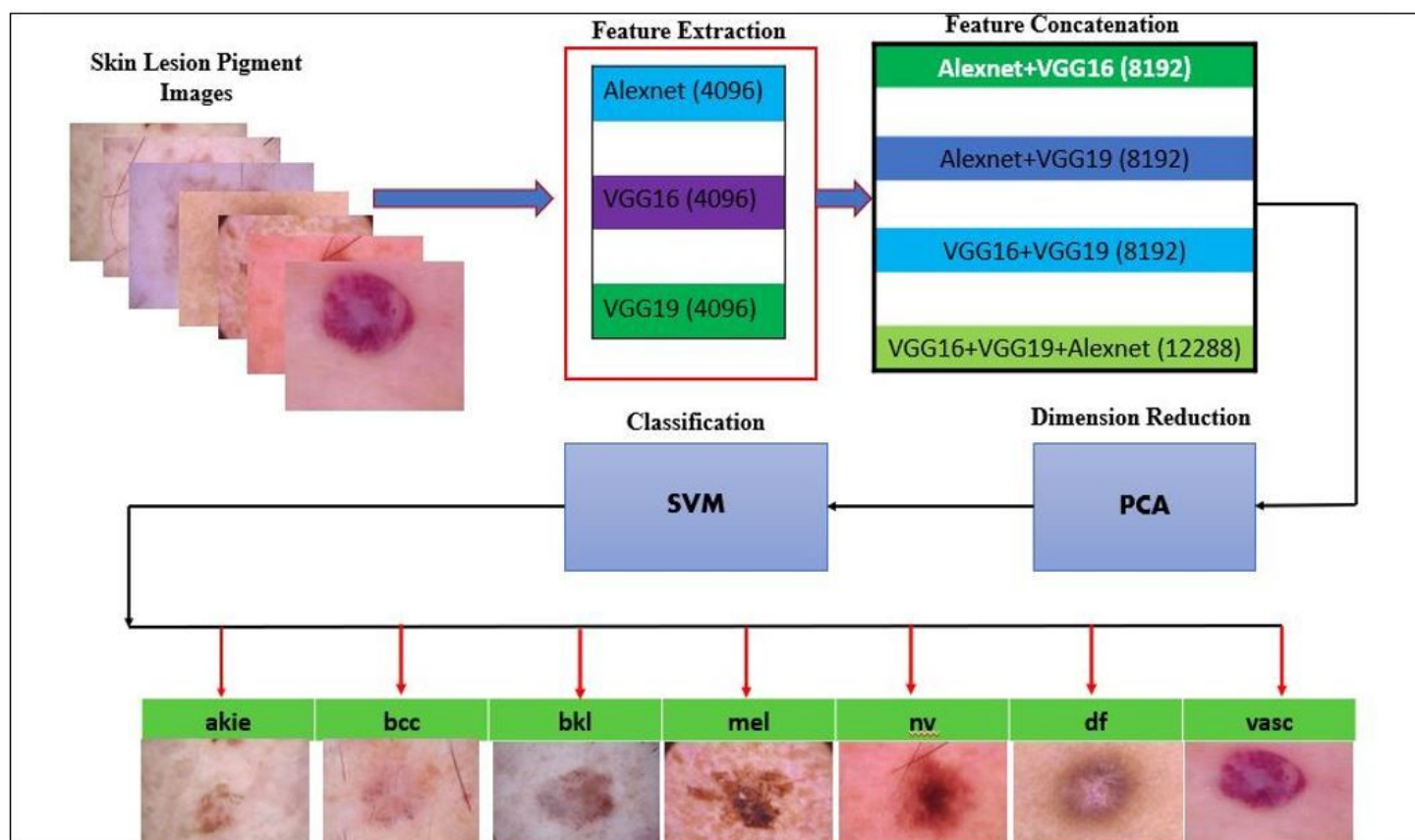
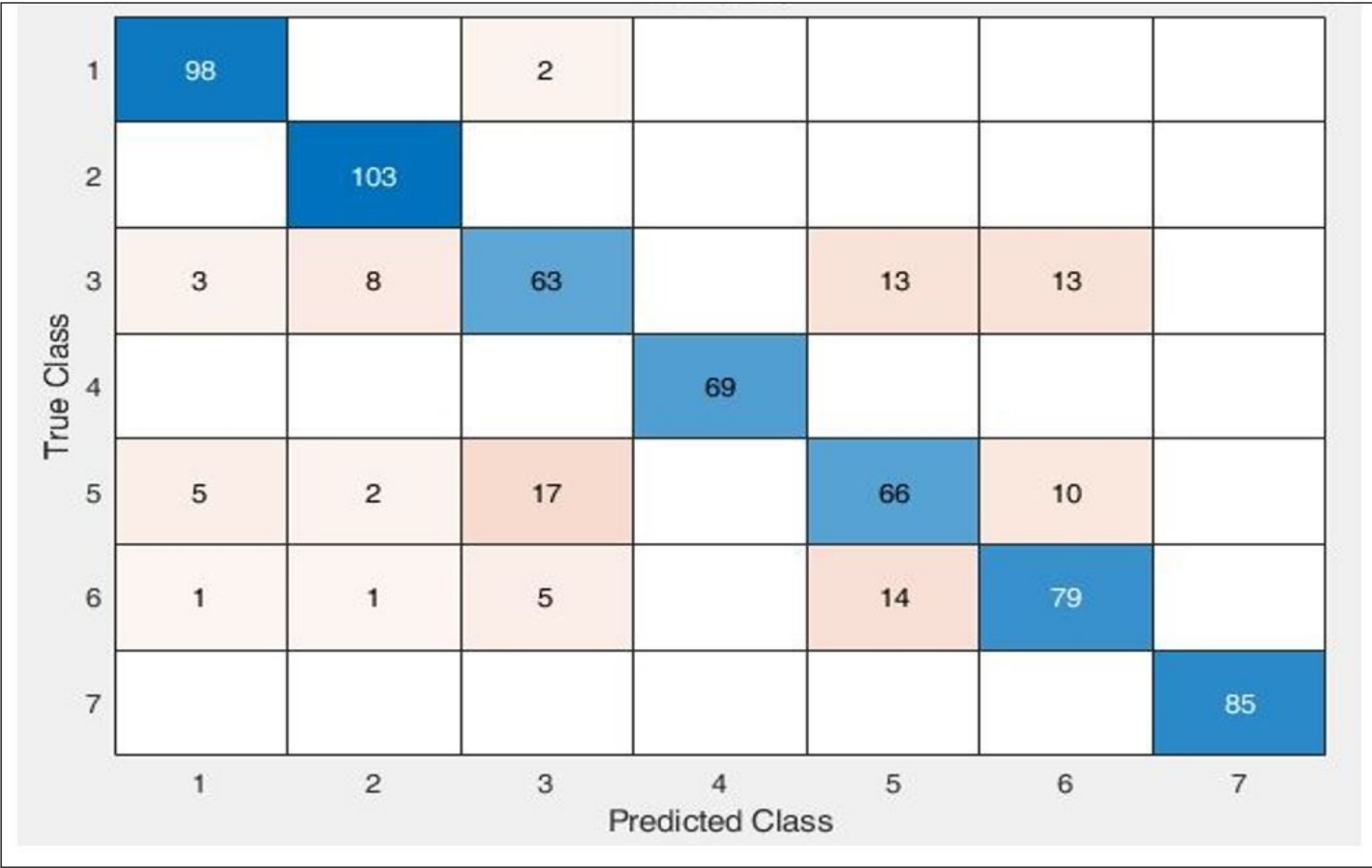
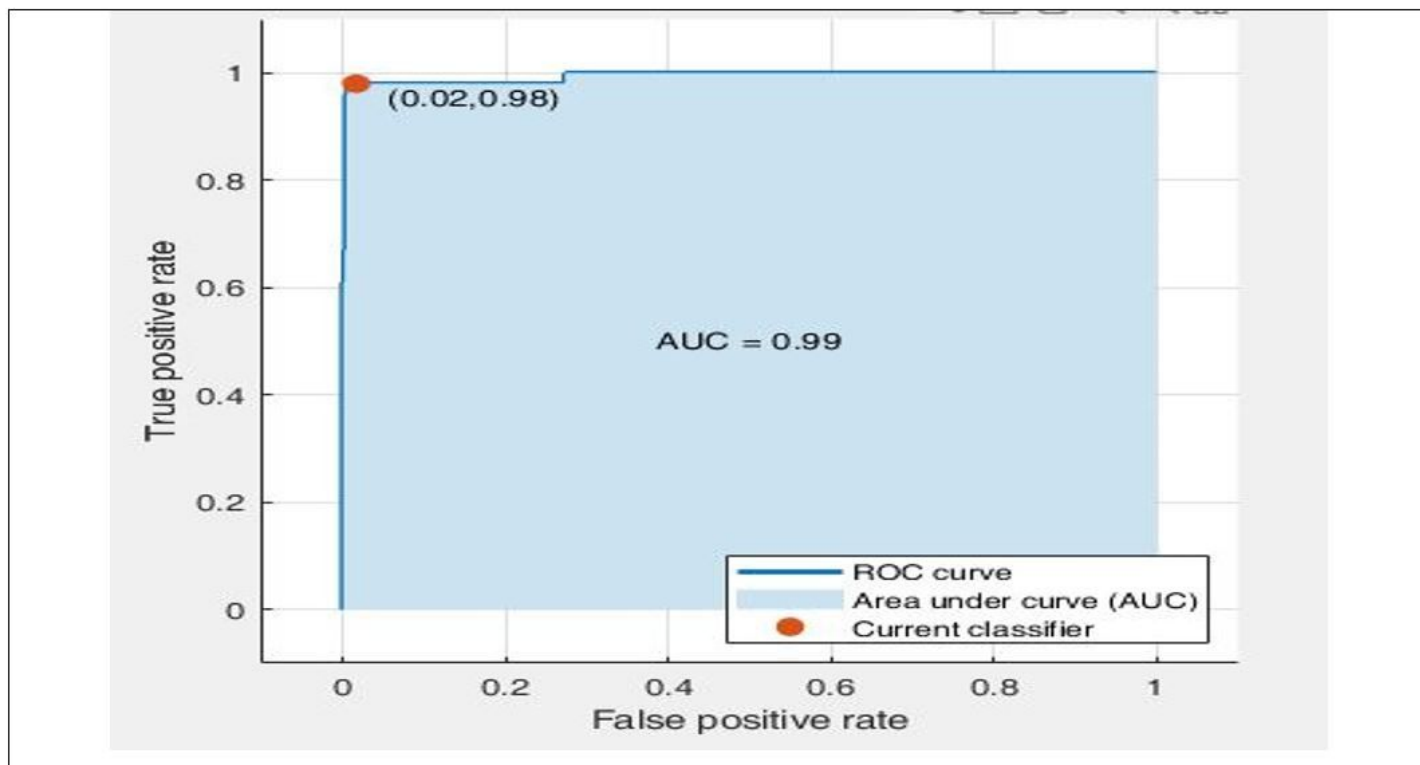


Figure 3

The framework of the Proposed method based on multi-deep Features and SVM for the classification of CPSL



**Figure 4**  
Confusion Matrix of Proposed classification model for diagnosis of breast carcinoma



**Figure 5**

AUC of Proposed classification model for diagnosis of breast carcinoma