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# Skin cancer diagnosis using hybrid deep pre-trained convolutional neural networks

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**ABSTRACT**

As a variant of skin cancer, melanoma represents a substantial menace to the health and overall well-being of individuals. Statistics reveal that 55% of skin cancer patients succumb to this particular disease. However, early detection plays a crucial role in reducing mortality rates and saving lives. In the past several decades, there has been a rise in the adoption of deep learning algorithms, capturing the interest of researchers working in this field. One popular method involves utilizing pre-trained deep neural networks. In this study, a hybrid approach is employed to extract features from melanoma images. This approach integrates the utilization of pre-trained architectures, including AlexNet, ResNet-50, and GoogleNet. During the transfer training phase, these networks are fine-tuned to detect skin cancer by adjusting the learning rate. Subsequently, the maximum relevance minimum redundancy (MRMR) algorithm is employed to select optimal features based on the concepts of minimum redundancy and maximum relevance in order to minimize feature redundancy and enhance classification accuracy. The bagging technique is employed for the classification of various skin cancer types. The experimental results demonstrate the success of the suggested approach, yielding 98.9% accuracy. Furthermore, the results indicate the superiority of this method according to precision, recall, and F1-score in comparison with existing algorithms.



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## 1. INTRODUCTION

Skin cancer, a pervasive and potentially lethal class of neoplastic disorders, arises from the uncontrolled growth of skin cells, often triggered by cumulative exposure to ultraviolet (UV) radiation. While various skin cancers exist, the three primary types are basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma [1]–[3]. Each type possesses distinct characteristics, histopathological features, and prognoses, necessitating a nuanced understanding for accurate diagnosis and targeted therapeutic interventions. In addition to these major types, numerous other skin lesions merit attention, ranging from benign moles and cysts to precancerous actinic keratosis. The diverse spectrum of skin lesions underscores the challenge of accurate diagnosis, prompting the exploration of advanced diagnostic techniques and technologies [4], [5]. Timely diagnosis constitutes a pivotal role in the successful management and intervention of skin cancer, underscoring critical need for accurate and efficient diagnostic methods. Historically, visual inspection by dermatologists has been the primary means of diagnosing skin lesions.

However, the inherent subjectivity and potential for human error in this approach have prompted the exploration of advanced technologies and methodologies to enhance diagnostic precision [6]. Biopsies are commonly used to detect skin cancer, involving the removal of a specimen from a potentially afflicted area on the skin for medical testing to confirm its cancerous nature. This method, while effective, is invasive, discomforting, and demands a significant amount of time. The advent of computational technologies offers a faster, more convenient, and cost-effective alternative for diagnosing skin cancer symptoms. These systems aim to conduct an initial evaluation of potentially problematic skin lesions utilizing high-resolution, medical data and machine learning (ML) techniques. Although these systems cannot replace the crucial function of histopathology in cancer detection, the development of sophisticated detection techniques can substantially assist in the early detection of malignant tumors, particularly in regions with limited access to medical resources and healthcare professionals [7]–[9].

Numerous non-invasive methods have spurred researchers to detect signs of skin cancer and ascertain whether they indicate the presence of melanoma. Given its non-invasive characteristics, image processing has been widely recommended for the detection of melanoma. It has evolved as a valuable detection method for the analysis of clinical data, facilitating prompt and efficacious medical interventions for patients. Image processing equips professionals with a real-time detection method, facilitating the monitoring of patient's condition over time, supplying images for training and demonstration, and enabling swift image comparison. This could also prove to be cost-efficient for hospitals [10]–[12]. Dermoscopy, enabling non-surgical scrutiny of the hypodermis, can produce commendable outcomes; however, it demands extensive training and expertise in dermatology for effective application. Regrettably, the method fails to furnish a definitive melanoma detection, particularly at the initial phases. Consequently, the need for an automated diagnostic tool becomes indispensable. ML, a broad and advancing subset of artificial intelligence (AI), has been extensively incorporated into contemporary computer-based technologies. This technology, which allows computers to learn and evolve autonomously without explicit programming, originates from the study of pattern recognition and computational learning theory. Over the past few decades, it has found its application in a myriad of domains [13], [14]. In response to these challenges, the integration of AI and deep learning algorithms has surfaced as a compelling approach to enhance the efficiency and precision of skin cancer detection. Convolutional neural networks (CNNs) are a subset of artificial neural networks that are extensively used for processing visual data. They operate by acquiring the distinctive features from the training dataset for classifying the test dataset, employing a process involving backpropagation and feedforward, akin to other artificial neural networks. While CNNs outperform basic ML methods in terms of performance, they require more computational resources. The complexity of the network and its ability to identify patterns increase with the number of layers [15]–[17].

The present investigation introduces a novel model in detecting skin cancer by proposing a hybrid deep pre-trained CNN architecture. The hybrid model integrates the strengths of various pre-trained CNNs, optimizing the learning process for dermoscopic images. The major contributions are: i) a combination of three pre-trained deep learning models including AlexNet, ResNet50, and GoogleNet to extract an effective set of features from skin images; ii) using the transfer learning approach, in which pre-trained AlexNet, ResNet50, and GoogleNet is trained to detect skin cancer by reducing the network's learning rate at the fine-tuning stage; iii) achieving high detection accuracy in limited number of skin cancer input images and reducing detection error due to the use of fine-tuning method; and iv) selecting the optimal features using the two concepts of minimum redundancy and maximum relevance, in order to reduce redundancy between features and increase classification accuracy.

The remainder of this paper is organized in the following manner. Section 2 introduces the related works. Section 3 elaborates on the proposed methodology. Section 4 discloses the conducted experiments and their respective results. Finally, section 5 concludes the paper.

## 2. RELATED WORKS

Keerthana *et al*. [18] introduce the integration of CNN and a support vector machine (SVM) classifier, two innovative hybrid models. These models are designed to categorize dermoscopy images as either benign or melanoma lesions. The SVM classifier receives concatenated features extracted by the first and second CNN models for the classification task. The performance of these proposed methods is evaluated against labels provided by a professional dermatologist. When assessed using the publicly available ISBI 2016 database, these methods demonstrated superior performance compared to existing techniques. This suggests that the proposed framework could significantly enhance the accuracy of dermoscopy image classification.

Rahman *et al*. [19] stated a method based on anisotropic diffusion filtering is applied to dermoscopy images to mitigate noise. Then, the fast-bounding box (FBB) technique is employed for the segmentation of skin cancer regions. Two feature extractors are used for the representation of the images. The initial feature extractor utilized is the hybrid feature extractor (HFE), followed by a CNN modeled on VGG19. The HFE integrates three techniques-speed up robust feature (SURF), histogram-oriented gradient (HOG) and local binary pattern (LBP)-to generate a unified feature vector. The CNN methodology is then applied to provide supplementary features. Subsequently, these vectors are amalgamated to formulate the classification framework. According to the simulation findings, the suggested approach outperformed other methods.

Bozkurt [20] propose a potent data enrichment and a pretrained model for the skin lesions classification. Inception-ResNet-v2, as an integrated architecture, is introduced for the categorization of cancerous images. The primary objective is augmenting the number of images in the dataset leveraging data augmentation and examining its influence on the model. With the augmented dataset, the Inception-ResNet-v2 model achieved the highest recorded accuracy.

Maqsood and Damaševičius [21] introduce an extensive computer-aided diagnosis (CAD) model founded on a deep architecture designed for both the classification and segmentation of skin lesions. Initially, a pre-processing is performed utilizing an approach that involves modified bio-inspired multiple exposure fusion for contrast enhancement. Following this, a specialized CNN architecture comprising 26 layers is created to perform the segmentation of skin regions. In the subsequent phase, four pre-trained CNN models (VGG16, ResNet-50, Xception, and ResNet-101) are adjusted and trained through transfer learning using the segmented images. The feature selection process utilizes a Poisson distribution approach to identify optimal features for classification. The ultimate categorization is carried out through the application of the selected features in the multi-class support vector machine (MC-SVM). In comparison to established state-of-the-art algorithms, the suggested approach for skin lesion detection and classification exhibited superior performance.

Akilandasowmya *et al*. [22] utilize a technique known as sand cat swarm optimization with ResNet50 (SCSO-ResNet50) to differentiate between deep hidden and known features, thereby enhancing the accuracy of predictions. Authors employ an enhanced harmony search (EHS) strategy for feature optimization and reduction of data dimensionality. A range of ensemble classifiers, including SVM, k-nearest neighbor (KNN), random forest, linear regression, and naive Bayes are used for the timely detection of skin cancer. The effectiveness of the suggested approach is evaluated based on the Kaggle and the ISIC 2019 databases. As per evaluations on benchmark datasets, the suggested method enhances accuracy in comparison to leading techniques. These results illustrate the capability of the proposed model in improving the timely detection of skin cancer.

Chanda *et al*. [23] introduce a unique ensemble approach that incorporates three deep convolutional neural networks (DCNN), each customized with varying dropout layers to enhance learning. Consequently, the suggested framework, DCENSnet, attains an exceptional bias-variance balance. Upon assessment using the widely-utilized HAM10000 skin lesion dataset, the proposed model surpasses existing methods, showing potential to enhance the accuracy of diagnosis and treatment.

A pioneering method is suggested for multi-class classification of skin lesions, capitalizing on optimal deep learning feature integration and an extreme learning machine (ELM) [24]. The suggested model encompasses the following main stages: capturing and improving images; extracting deep learning features through transfer learning; choosing the most effective features utilizing a combined approach of whale optimization and entropy-mutual information (EMI); and merging selected features using an adapted canonical correlation-based method and, ultimately, classification according to ELM. The stage of selecting features enhances the precision and efficacy of the system. In contrast to novel techniques, the suggested approach enhances precision while maintaining computational efficiency.

Bansal *et al*. [25] suggest employing integrated extracted features, harnessing both deep learning model and handcrafted feature extraction techniques, derived from dermoscopic images to augment the classifier's functionality. EfficientNet-B0 and ResNet50V2 are then utilized for extracting features, while an artificial neural network (ANN) is employed for classifying stage. The outcomes reveal that the presented hair removal techniques, when combined with the features, enhance melanoma diagnosis accuracy in comparison with scenarios where i) no pre-processing is performed or ii) handcrafted or deep learning features are utilized independently. The suggested model outperforms other techniques in this field.

ElGhany *et al*. [26] explore that the potential of deep structures in detecting various dermoscopic images. The objective is to design and adjust a deep learning architecture for diagnosing various grades of skin cancer. Fine-tuning, a potent technique for achieving improved outcomes, is applied to pretrained model. The fine-tuning of the proposed deep network involves regularization, batch normalization, and hyperparameter optimization. The suggested ResNet50 network effectively classified 7 distinct classes of dermoscopic images within HAM10000 database. The experimental findings indicate the superiority of the suggested framework.

## 3. METHOD

The aim of this study is to propose a robust algorithm in order to diagnosing skin cancer, leveraging the power of pre-trained deep neural networks. The depth and effectiveness of convolutional filters make these pre-trained CNNs particularly beneficial for tasks related to images. For the purpose of feature extraction in this study, deep architectures such as ResNet, GoogleNet, and AlexNet are utilized. In the presented methodology, post the extraction and amalgamation of features, the minimum redundancy maximum relevance (MRMR) algorithm is employed to pick the most suitable features. The MRMR algorithm, utilizing the principles of minimum redundancy and maximum association, curtails the redundancy amongst features, thereby enhancing the accuracy of classification. Furthermore, the bagging algorithm is implemented during the classification phase. Figure 1 illustrates a block diagram depicting the proposed methodology.

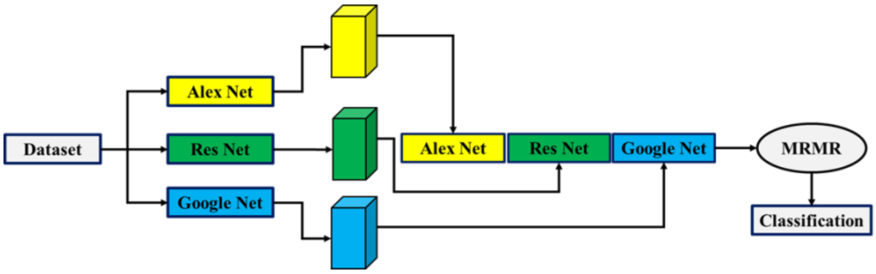


Figure 1. Diagram of proposed approach

### 3.1. Feature extraction

In the presented approach, pre-trained networks such as AlexNet, ResNet50, and GoogleNet are utilized for the purpose of feature extraction from images. Detailed descriptions of each of these networks are provided in the following sections.

#### 3.1.1. AlexNet

Essentially, AlexNet is an advanced type of the traditional LeNet. The comprehensive architecture of the AlexNet model is depicted in had been illustrated Figure 2. The model consists of several layers, starting with the input layer that determines the input data size. In the AlexNet network architecture, the size of the input image should be 227×227×3. The heart of the AlexNet is composed of the middle layers. The structure of these layers consists of five convolution layers, rectified linear units (ReLU), max-pooling layers, and fully connected layers. The final layer in this structure is the classification layer.

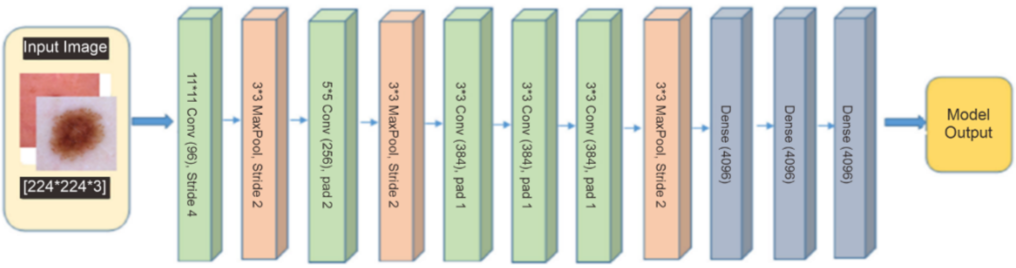


Figure 2. The architecture of AlexNet model [27]

#### 3.1.2. ResNet50

Residual networks, referred to as ResNets, are a type of deep convolutional networks. Their fundamental concept involves bypassing blocks of convolutional layers leveraging shortcut connections. The basic blocks, termed as "bottleneck" blocks, attend two fundamental lawes: i) layers with identical output feature map sizes have the same amount of filters and ii) when the feature map dimension is cut in half, the filter count is doubled correspondingly. The down sampling process is executed directly by convolutional layers with a stride of two. Batch normalization is implemented after any convolutional layer and before the ReLU activation function. Where the size of the output and input match, the identity shortcut is used. However, wherein the sizes increase, the projection shortcut is used to match sizes via 1*1 convolutions. then the shortcuts go across feature maps of two different sizes. Finally, network ends by a fully connected layer with 1,000 units, equipped with a SoftMax activation function. The network consists of a total of 50 weighted layers, with 23,534,592 trainable variables. The structure of the ResNet50 is illustrated in Figure 3.

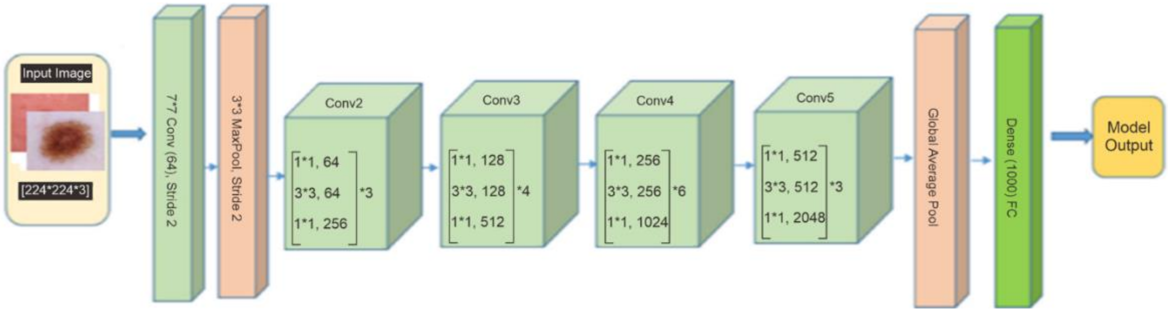


Figure 3. ResNet50 architecture [27]

### 3.1.3. GoogleNet

As a well-established pretrained deep CNN consisting of 22 layers, GoogleNet was specifically developed to outperform contemporary CNN networks in terms of performance. It demonstrated its superiority in accurately recognizing visual patterns from the source, earning it the victory in the ImageNet large scale visual recognition challenge (ILSVRC) challenge in 2014. The notable improvement in performance can be credited to the inception modules (IM) integrated within its framework, as denoted by the red circle in the illustration of Figure 4.

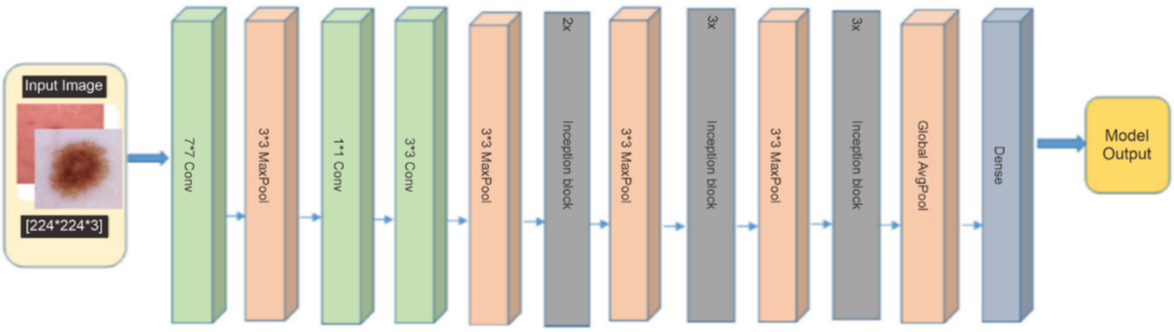


Figure 4. GoogleNet structure [27]

The IM enables the simultaneous application of various convolutions and max pooling operations within a unified layer. This guarantees that the network undergoes training with optimized weights and choose features that are more advantageous. To achieve this, each inception layer houses variable-sized convolutional kernels, specifically 1×1, 3×3, and 5×5, along with an additional 3×3 max pooling. This arrangement is devised to extract more distinctive features from the pattern transmitted from the preceding layer. The structure of the IM is depicted in illustrated Figure 3. Here, the 1*1 filters, in conjunction with the max pooling layer, perform a dual role of reducing encapsulating and dimensionality the content from the preceding layer. As illustrated in Figure 3, the nine IMs incorporated in the GoogleNet architecture are effective in extracting more discriminative features from the source image. Typically, features with greater complexity in their representations are favored, given their ease of handling in a new network and substantial contribution to expediting the training process.

## 3.2. Feature selection

The rationale behind employing the MRMR method is to optimize the relevance between features and their corresponding labels (class), while concurrently aiming to reduce the redundancy among individual features. The MRMR technique utilizes mutual information as a metric to assess the association among variables. The mutual information between X and Y is computed based on (1).

$$I(X;Y) = \sum_{x \in X} \sum_{y \in Y} p(x,y) \, log \frac{p(x,y)}{p(x)p(y)} \quad (1)$$

$p(x,y)$ denotes probabilistic density of X and Y variables, $xi$ is individual characteristics, c represents the classes. Maximum relevance measure is calculated based on (2).

$$MaxD(S,c), D = \frac{1}{|S|}\sum_{xi\in S} I(xi;c) \quad (2)$$

|S| represents the dimensionality of the features within the S space. $I(xi;c)$, $xi$ mutual information among features.

The subset S, which possesses the utmost correlation rate, is derived using the maximum relevance measure. Although, it's crucial to note that the properties chosen based on these measures may exhibit redundancy. Hence, the utilization of the minimum redundancy condition, as illustrated in (3), can also serve as a method to choose features that exhibit mutual exclusivity.

$$Min\ R(s), R = \frac{1}{|S|^2}\sum_{xi,xj\in S} I(xi,xj) \quad (3)$$

$I(xi,xj)$ represents the mutual knowledge among features $xi$ and $xj$.

The aim is to eliminate highly dependent features and minimize redundancy among them. The MRMR algorithm combines max-relevance and min-redundancy terms. As a result, (4) and (5) are utilized to concurrently optimize R (redundancy) and D (relevance).

$$max\ \Phi(D,R),\ \Phi = D - R \quad (4)$$

$$max\ \Phi(D,R),\ \Phi = \frac{D}{R} \quad (5)$$

Incremental search techniques are utilized for the identification of features that closely approximate optimality in various applications. The calculation of the optimal feature subset with m-1 features involves the computation of the $S_{m-1}$ feature subset, as outlined by (6).

$$max\ \ xj\varepsilon X - S_{m-1}[I(xi;c) - \frac{1}{m-1}\sum_{xi\,\in\,S_{m-1}} I(xi;xj) \quad (6)$$

### 3.3. Classification

In this investigation, the bagging technique is employed for skin cancer detection, wherein a subset of the original data is sent to the classifiers. Consequently, each classifier is exposed to a distinct portion of the dataset, constructing its model based on the specific subset it receives. Notably, the selection of this subset is performed with replacement, allowing for the possibility of multiple occurrences of each sample. The study has shown that the classification model can improve learning and detection capabilities, resulting in enhanced accuracy. The overall operation of this technique is displayed in Figure 5.

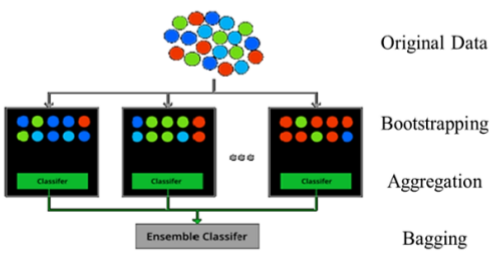


Figure 5. Classification model using bagging algorithm

## 4. RESULTS AND DISCUSSION

In this part, the efficacy of the proposed model is evaluated leveraging standard assessment metrics, and the functionality of the algorithm is compared with other state-of-the-art methods. The algorithm is simulated in MATLAB (2022b) software and an NVIDIA graphics card equipped with 8 Gigabytes of onboard RAM. In training phase, we allocate 70% of the data. Specifically, 7,011 data samples are fed into the proposed model as training input, while 3,004 data samples are set aside for the testing phase. Each image contributes 1,000 features, extracted by the pre-trained convolutional networks. Subsequently, the MRMR algorithm is employed to reduce the dimensions of each feature vector to 500 dimensions.

Ultimately, the classification of these feature vectors is carried out using the bagging method. Furthermore, the classification accuracy is assessed through a validation process, involving the partitioning of the dataset into ten folds. The model is iteratively trained and tested, with each fold serving as a validation set. Notably, the division of the dataset into training and test sets is accomplished through a random permutation process. The findings presented in the tables represent the average outcome of 50-times running the program.

### 4.1. Dataset

This work utilizes the HAM10000 database for the purpose of diagnosing skin cancer. The HAM10000 dataset comprises 10,015 dermatoscopy pictures, each exposing distinct forms of skin disorders. This database is collected from Austria and Australia patients. The pictures, which are centered crops, have dimensions of 600×450 pixels. The database is categorized into 7 classes, with each class signifying a distinct disease. The specifics of these classes are detailed in Table 1. Several instances of the dataset pictures are displayed in Figure 6.

Table 1. Categories in HAM10000 dataset

| Disease type | Class label |
|---|---|
| Actinic keratoses and intraepithelial carcinoma/Bowen disease (akiec) | 0 |
| Basal cell carcinoma (bcc) | 1 |
| Benign lesions of the keratosis (bkl) | 2 |
| Dermatofibroma (df) | 3 |
| Melanoma (mel) | 4 |
| Melanocytic nevi (nv) | 5 |
| Vascular lesions (vasc) | 6 |

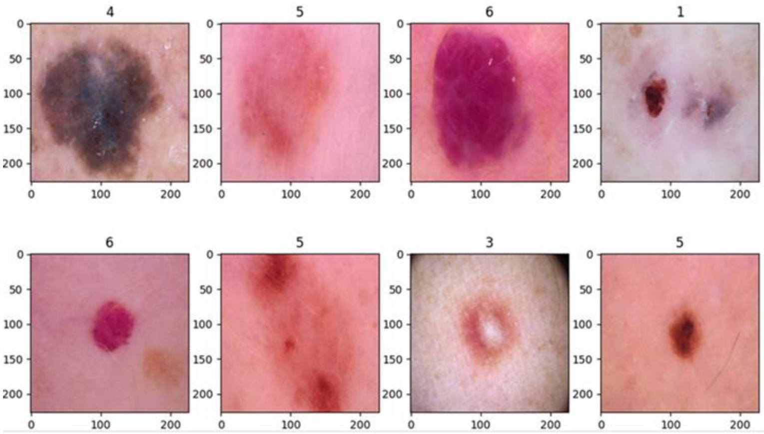

Figure 6. Dataset image examples

### 4.2. Evaluation criteria

The evaluation of our work is based on four key metrics; accuracy, precision, recall, and F1-score. The TP represents true positive detections, TN represents true negative detections, FP represents false positive detections, and FN represents false negative detections. The formulas for these metrics are presented in (7) to (10):

$$Accuracy = \frac{(TP+TN)}{(TP+FP+TN+FN)} \tag{7}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{8}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{9}$$

$$F1\ score = \frac{2*(Recall*Precision)}{(Recall+Precision)} \tag{10}$$

### 4.3. Evaluation and results comparison

In order to evaluate the system's effectiveness in detecting skin cancer, we utilized a confusion matrix. The confusion matrix for the test data is presented in illustrated Figure 7. The classification outcomes for each category as per the confusion matrix are displayed. The table suggests that the functionality of the suggested approach is deemed satisfactory.

Within the realm of ML, the efficiency of a binary classification at different thresholds can be represented by a receiver operating characteristic (ROC) curve. This curve is constructed using two key parameters: the true positive rate (TPR) and the false positive rate (FPR). The TPR, alternatively recognized as sensitivity or recall, denotes the fraction of actual positive samples accurately detected. In contrast, the

FPR represents the fraction of actual negative samples erroneously detected as positive. The definition of FPR is presented in (11).

$$FPR = \frac{FP}{TN+FP} \tag{11}$$

The relationship between a classifier's TPR and FPR is depicted by graphing TPR versus FPR for all potential thresholds. A high-performing classifier will gravitate towards the upper-left side of the ROC curve, signifying a high TPR and a minimal FPR. In contrast, a classifier with subpar performance will lean towards the lower-right corner, indicating a diminished TPR and an elevated FPR. A classifier that performs at a level equivalent to random guessing will coincide with the ROC curve's diagonal line, denoting an equal TPR and FPR.

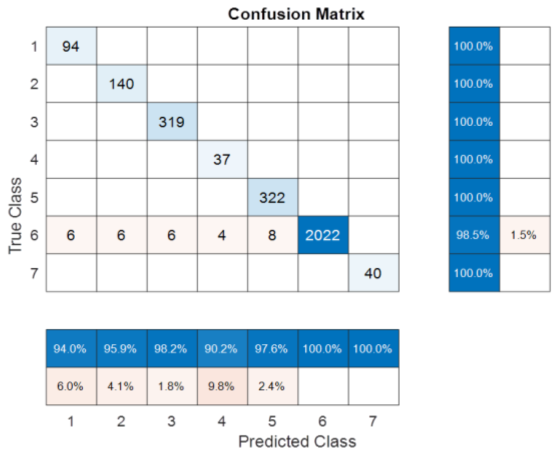


Figure 7. Confusion matrix of skin cancer detection

The ROC curve for the presented method is illustrated in Figure 8. The curve, positioned near the top-left corner, signifies a notable TPR and a correspondingly low FPR. This positioning indicates that our model is highly accurate in detecting skin cancer. Figure 9 illustrates a bar chart comparison depicting the outcomes of skin cancer diagnosis using our presented approach alongside various other models, including KNN, decision trees (DT), SVM, CNN, and DenseNet. As depicted in Figure 9, the KNN, DT, SVM, CNN, and DenseNet models achieved accuracy rates of 94.71, 95.14, 97.43, 92, and 83, respectively. The proposed method outperformed these models with an impressive accuracy rate of 99.

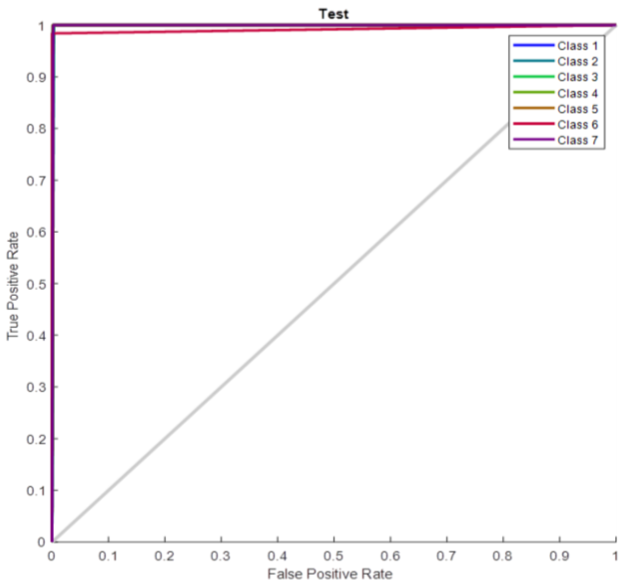


Figure 8. ROC curve for the presented approach

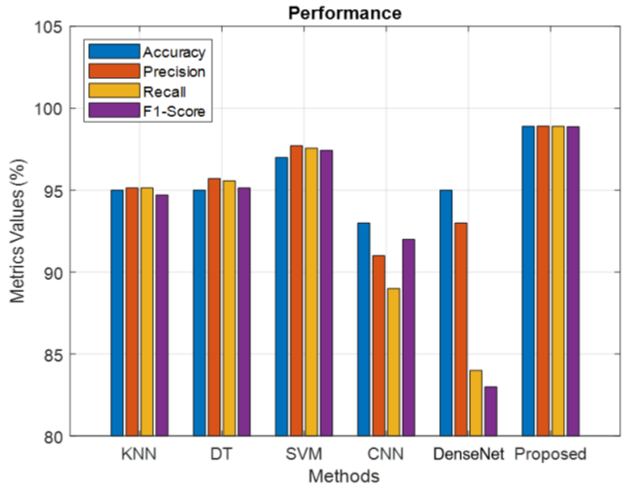


Figure 9. The efficacy of the suggested methodology and pre-trained methods

We conducted a comparative evaluation of our proposed approach against various other methods for skin cancer detection. As per the data in Table 2, our model achieved a high classification accuracy exceeding 99%. This demonstrates the superior performance of our method in comparison to other contemporary algorithms. Our research indicates a higher recall does not correlate with lower precision. The presented algorithm can improve recall metric without negatively affecting on precision criterion. Moreover, we discovered a correlation between the recall and precision metrics with the F-score criterion. The method presented in this research aims to achieve a significantly higher F-score ratio compared to previous studies.

It is noteworthy which this study has examined all the metrics of precision, F-score, accuracy, recall, ROC curve, and learning curve simultaneously. In contrast, prior studies have not explored the combined effect of all these criteria, focusing instead on only some of them. in addition, this article is presenting a comprehensive study on the automatic detection of skin cancer based on transfer learning using a hybrid method including three pre-trained neural networks AlexNet, ResNet50, and GoogleNet in order to extract features and bagging technique in order to classifying. However, more in-depth researches can be applied to prove the method efficiency on a larger patient population. In this research, it was displayed that mathematical optimization methods same as MRMR technique are more efficient than traditional algorithms for selecting optimal features. Future works could explore other novel mathematical methods inorder to optimal features selection. Recent findings in researches in the field of skin cancer recognition display that hybrid deep learning approaches can achieve high performance in feature extraction from images. Our observation displays conclusive evidence where feature extraction by hybrid pre-trained deep neural network can lead to higher effectiveness of skin cancer detection system. The experimental results that achieved in this study proves this matter.

Table 2. Results comparison in terms of evaluation parameters

| Method | F-score | Recall | Precision | Accuracy |
|---|---|---|---|---|
| KNN [28] | 94.71 | 95.14 | 95.14 | 95 |
| DT [28] | 95.14 | 95.57 | 95.71 | 95 |
| SVM [28] | 97.43 | 97.57 | 97.71 | 97 |
| CNN [29] | 92 | 89 | 91 | 93 |
| DenseNet [29] | 83 | 84 | 93 | 95 |
| The proposed method | 98.88 | 98.90 | 98.91 | 98.9 |

## 5. CONCLUSION

Melanoma, skin cancer known for its aggressive metastatic behavior, represents a formidable and widespread malignancy within the spectrum of skin-related cancers. Prompt and accurate diagnosis of melanoma is crucial in enhancing the chances of effective treatment. The major focus of this research is to put forward a sturdy model to skin cancer recognition, utilizing the potential of pre-existing deep neural networks. The inherent depth and effectiveness of convolution filters render pre-trained CNNs particularly advantageous for image-related tasks. Deep architectures, including ResNet, GoogleNet, and AlexNet are employed for extraction of features. Following the extraction and integration of features, the MRMR algorithm is applied in the methodology to select the most pertinent features. Additionally, the classification phase incorporates the bagging algorithm to enhance the model's robustness. An exhaustive comparison was conducted, wherein our proposed methodology was juxtaposed against various alternatives including KNN, DT, SVM, CNN, and DenseNet in the domain of skin cancer recognition. The results underscore the outstanding performance of our approach, surpassing that of other contemporary algorithms in the field.

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## AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

| Name of Author | C | M | So | Va | Fo | I | R | D | O | E | Vi | Su | P | Fu |
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| Amir Lakizadeh | | ✓ | | ✓ | ✓ | ✓ | | | | ✓ | | ✓ | ✓ | |

| | | |
|---|---|---|
| C : **C**onceptualization | I : **I**nvestigation | Vi : **Vi**sualization |
| M : **M**ethodology | R : **R**esources | Su : **Su**pervision |
| So : **So**ftware | D : **D**ata Curation | P : **P**roject administration |
| Va : **Va**lidation | O : Writing - **O**riginal Draft | Fu : **Fu**nding acquisition |
| Fo : **Fo**rmal analysis | E : Writing - Review & **E**diting | |

## CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

## DATA AVAILABILITY

The data that support the findings of this study are openly available in [Kaggle] at https://www.kaggle.com/datasets/kmader/skin-cancer-mnist-ham10000.

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