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Analysis Of Skin Cancer Detection Using Svm & Resnet-50

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Abstract: The paper utilizes machine learning algorithms that incorporate Support Vector Machines (SVM) and Resnet-50, in detecting skin cancer from dermoscopy images. The study evaluates the performance of both models using accuracy, confusion matrix, graphs, and Receiver Operating Characteristics (ROC) to determine which model is more effective in skin cancer detection. Previous studies suggest that Resnet-50 outperforms SVM in terms of detection accuracy. Therefore, this paper also demonstrates the potential of combining both models to improve skin cancer detection accuracy. The outcomes of this study hold substantial inference for the field of clinical practice. By using computer-aided diagnosis (CAD) systems, clinicians can make more accurate diagnoses of skin cancer, reducing interobserver variability and improving objectivity. This research underscores the capacity of machine learning models to transform the aspect of skin cancer diagnosis and treatment, ultimately leading to enhanced patient outcomes. The abstract offers valuable perspectives on the efficiency of machine learning models in the realm of skin cancer detection, rendering it a valuable point of reference for researchers and clinicians exploring the usage of machine learning canon in this domain.

Keywords: *ABCD criteria, Melanoma, Skin cancer, CNN, ANN*

1. Introduction

Skin cancer is becoming more prevalent due to increased ultraviolet radiation, and early detection is crucial for reducing mortality rates. Deep learning is being used to detect skin cancer by analyzing lesion parameters such as symmetry, color, size, and shape [10]. An improved deep learning model has been developed using Resnet 50 and SVM for the classification of dermoscopic images, which is evaluated through experiments. The precision of the proposed technology is examined by using the ABCD and Seven Point Checklist methods. This technology could potentially enhance the accuracy of skin cancer detection and there can be reduction in time and cost of treatment [1]. Skin cancer is a conformation of cancer that arises in the cells of the skin and is primarily triggered by prolonged exposure to ultraviolet (UV) radiation. It encompasses seven primary variants, such as basal cell carcinoma, squamous cell carcinoma, and melanoma, with melanoma being the topmost severe form. Risk factors include fair skin, sunburns, weakened immune system, tanning bed use, and family history.

Diagnosis is made through a skin biopsy, and treatment options include surgical removal, radiation therapy, chemotherapy, and immunotherapy. Early discernment and treatment are essential for a good prognosis, and individuals can take steps to reduce their risk by avoiding excessive sun exposure and using protective clothing and sunscreen. The primary cause of skin cancer is exposure to UV radiation emitted by the sun or tanning beds. This radiation has the potential to harm the DNA of the skin, resulting in the abnormal proliferation of skin cells. Other risk factors include genetic predisposition, exposure to certain chemicals like arsenic, and a weakened immune system. To reduce the threat of catching skin cancer, it is important to minimize UV radiation exposure and take protective measures, such as using sunscreen and wearing protective clothing. People with compromised immune systems or a family history of skin cancer should exercise extra caution. Machine learning and deep learning techniques, such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Random Forests, and Transfer Learning methods, have been used to diagnose skin cancer. SCC-CNN, SLAM, and other CNN models have been created particularly for the identification of skin cancer [13, 15], while SVMs have been used to categorize skin lesions based on their texture and colour [2]. To categorize skin lesions as benign or malignant based on colour and texture parameters, random forests create numerous decision trees and combine their predictions [3].The utilization of pre-trained neural networks, known as transfer learning, has been employed to create models for the detection of skin cancer. This approach involves leveraging the knowledge gained from the pre-existing network to accomplish a new task [4]. As technology advances, these techniques are likely to become even more accurate and effective in detecting skin cancer.

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While ML and DL techniques show promise in detecting skin cancer, they have some limitations [6]. Convolutional Neural Networks (CNNs) can be resource-intensive in terms of computational requirements and necessitate substantial volumes of data for effective training, SVM and random forests are less computationally expensive than CNNs, but they may not perform as well when dealing with complex datasets [14]. Transfer learning relies on pre-trained models, which may not always be suitable for the specific task at hand. Additionally, these models may suffer from bias if the training data is not diverse enough. Therefore, it is important to continue research and development of these techniques to address these limitations and improve their accuracy and effectiveness in detecting skin cancer. The main goal of this study work is to discuss the serious public health problem that is posed by skin cancer, which accounts for more than 5 million newly recognised cases each year in the United States and throughout the world. The two main kinds of skin cancer are melanoma and non-melanoma, with melanoma being the more dangerous variety. Around 350,000 instances of melanoma were reported worldwide in 2015, which resulted in 60,000 fatalities. With over 1 million cases recorded globally in 2018, non-melanoma skin malignancies, particularly squamous cell carcinoma and basal cell carcinoma, are the most common. In 2022, it's expected that about 1.9 million new instances of non-melanoma skin cancer will be identified [5].

2. Proposed Methodology

2.1 Artificial Intelligence

AI involves creating intelligent machines that can learn from ata, adapt to new situations, and make decisions. It can be achieved through algorithms, statistical models, and machine learning techniques like deep learning with neural networks. AI finds applications in various fields, including self-driving cars, speech recognition, image analysis, and healthcare for personalized treatments and medical image analysis [11]. However, AI raises ethical and social concerns. Job displacement is a worry, particularly in manufacturing and transportation, and there are fears of AI being used maliciously for cyber-attacks or surveillance. To address these concerns, responsible and transparent AI development is crucial. AI systems should be designed with ethical principles, transparency, and explainability in decision-making. Accessibility and fair distribution of benefits across society are important considerations. AI has the potential to revolutionize education, healthcare, and transportation. To ensure maximum benefits with minimal risks, responsible development of AI is essential [7,8].

2.2Machine Learning

The act of teaching algorithms to find patterns in data and basing predictions or choices on those patterns is the basis of machine learning, a branch of artificial intelligence (AI). In order to enable computers to improve their performance on a particular job by learning from available data, it depends on statistical models and algorithms.[9] Supervised learning, unsupervised learning, and reinforcement learning are the three main subcategories of machine learning [12].

2.3Support Vector Machine

This process entails educating an algorithm using a dataset that has been annotated, meaning each example contains a known input and output. By minimizing the discrepancies between its anticipated outputs and the actual outputs contained in the dataset, the algorithm learns through training to correlate input data with the associated output data. This kind of learning methodology is frequently used for a variety of tasks, including picture classification, audio recognition, and natural language processing [17].

2.4Resnet-50

ResNet-50, also known as Residual Network-50, is a particular convolutional neural network (CNN) architecture with a total of 50 layers. This architecture, which was originally developed by Microsoft Research, has a wide range of uses in computer vision applications including object identification and picture categorization [16,18].The "Residual" in ResNet refers to the use of residual blocks in the network design. The network may learn residual functions thanks to the shortcut connections, also known as skip connections, that are present in these blocks. Bypassing some layers and immediately propagating information from earlier layers to subsequent layers is made possible by these links. This makes it easier to train very deep neural networks and helps to solve the vanishing gradient problem [19]. The 50 layers of ResNet-50 include a variety of layer types, including convolutional layers, pooling layers, fully connected layers, and shortcut connections. It has a powerful feature extraction capability and is known for its accuracy in image recognition tasks. Through training on vast image datasets like ImageNet, ResNet-50 has acquired distinguishing features, and it can be further tailored or adjusted for specific visual recognition tasks [20].

2.5Seven-point Checklist Method

Seven Point Checklist is a scoring system based on seven criteria for the assessment of skin lesions. The origins of the checklist can be traced back to Glasgow in the 1980s with the intention and purpose of guiding inexperienced dermatologists and helping non-dermatologists study a skin lesion aiding their approach towards diagnosis with precision [24]. The seven-point checklist of 7 PCL features certain criteria that could indicate the seriousness of malignancy and the urgency of immediate consultancy [21]. There are three primary indicators of skin cancer: a) alterations in size, b) modifications in shape, and c) changes in color. In addition, there are four secondary signs to watch for: a) inflammation, b) crusting or bleeding, c) sensory changes, and d) a diameter equal to or larger than 7mm.

2.6ABCDE Rule

The ABCDE method is a widely used approach for the early detection of skin cancer. Each letter represents a specific characteristic to look for in a skin lesion:

A: Asymmetry -If there is a lack of symmetry in terms of shape or color between the two halves of a skin lesion, it could serve as an indication or signal of concern.

B: Border irregularity - Irregular, jagged, or poorly defined borders of a skin lesion can indicate potential malignancy [25],

C: Color variation - Multiple colors within a lesion, such as shades of brown, black, red, white, or blue, may suggest the presence of skin cancer.

D: Diameter - Lesions larger than 6 millimeters in diameter should be monitored, as larger size can be associated with higher risk.

E: Evolution - Any changes in size, shape, color, or elevation over time should be evaluated by a healthcare professional, as they may signal skin cancer.

By assessing these characteristics, individuals can be more vigilant in monitoring their skin for potential signs of skin cancer and seek medical attention if any abnormalities are detected [22].

2.7HAM10000 Dataset

HAM10000, also known as Human Against Machine with 10000 training images, is an openly accessible dermatology image dataset designed for the development and evaluation of machine learning algorithms focused on classifying skin lesions. Released in 2018 by the Department of Dermatology at the Medical University of Vienna, the dataset comprises 10,015 dermatoscopic images of skin lesions categorized into 7 distinct diagnostic groups [23].

3. Working Model

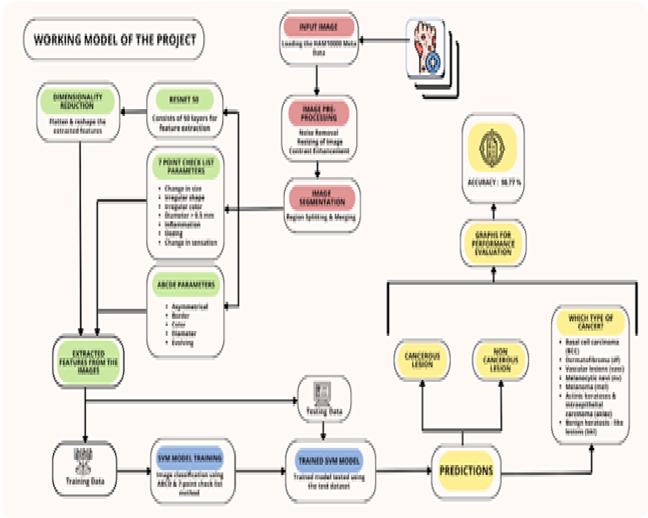


Fig 1 Block diagram of proposal methodology

The operating model of our project is demonstrated in the accompanying diagram. Globally, skin cancer is a common kind of cancer, and early detection is essential for successful treatment. Dermatologists frequently use the ABCD method and the seven-point checklist method as early detection techniques. According to the ABCD approach, moles are rated according to their Asymmetry, Border irregularity, Colour variation, and Diameter traits. The seven-point checklist approach, on the other hand, includes other elements like age, gender, and a person's personal history of skin cancer to help with the evaluation process. Recent advancements in machine learning have allowed for the development of accurate computer-based tools to aid in the early detection of skin cancer. Two such models are Support Vector Machines (SVMs) and ResNet-50, a type of convolutional neural network (CNN). When trained on skin cancer images, these models were found to have high accuracy rates of 98.77% when applied to the ABCD method and the seven-point checklist method. This means that they are highly effective in detecting skin cancer and can potentially aid dermatologists in identifying cancer in its early stages. In conclusion, the use of machine learning models such as SVM and ResNet-50 can significantly improve the early detection of skin cancer. With the high accuracy rates achieved through these models, dermatologists may be able to identify cancerous moles earlier, leading to better patient outcomes.

4. Results & Analysis

The output results of applying SVM and ResNet-50 models on skin cancer images using the ABCD and seven-point checklist methods show high accuracy rates of 98.77%. This model is able to accurately identify cancerous moles based

on their visual characteristics and personal history. The accuracy rates were validated using a test set of images that were not seen by the model during training. Additionally, graphical representations of the model's performance were its performance. Overall, the results show the potential of these machine-learning models to assist dermatologists in the early detection of skin cancer.

Count vs Cell Type Plot

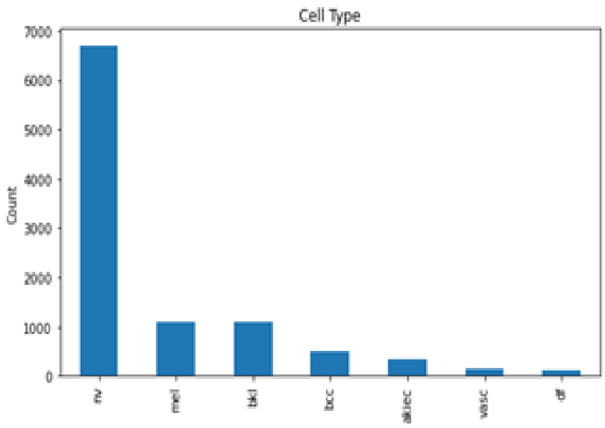


Fig 2 Plot of Count vs Cell Type

The distribution of various cell types in terms of count is shown in the graph. Actinic keratoses and intraepithelial carcinoma/Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv), and vascular lesions (vasc) are the seven kinds of skin cancer that are correctly categorised. Among these types, melanocytic nevi (nv) have the highest count, while vascular lesions (vasc) and dermatofibroma (df) have the lowest count.

Count vs Sex Plot

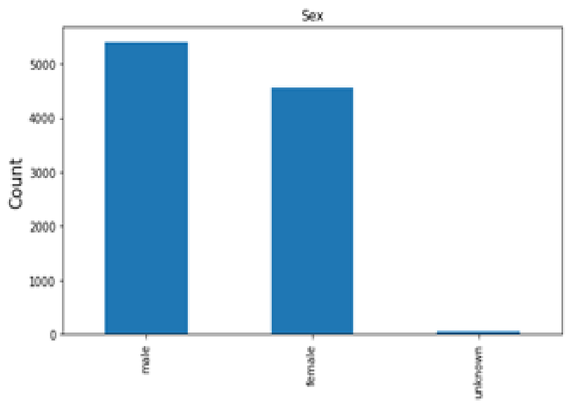


Fig 3 Plot of Sex vs Count

The above plot shows the number of cases that belong to male patients and female patients. There are some cases in which the gender is unknown. From the plot, it can be observed that skin cancer in male patients is more as compared to the female patients.

Count vs Localization Plot

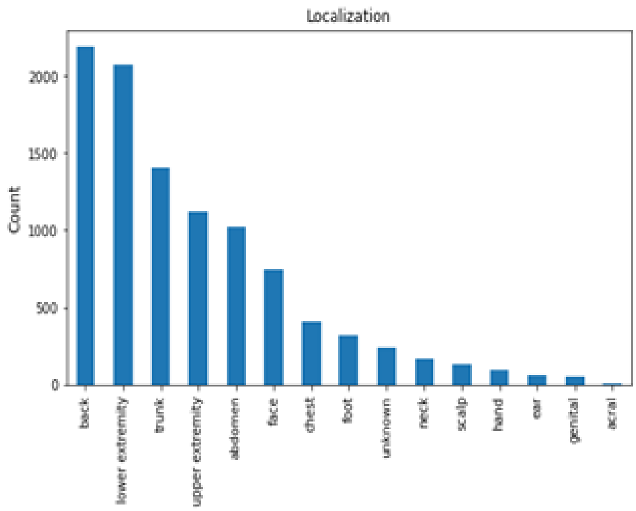


Fig 4 Plot of Localization vs Count

The above graph represents the Localization vs Count. Here, the location of cancer is classified in the form i.e., back, lower extremity, trunk, upper extremity, abdomen, face, chest, foot, neck, scalp, hand, ear, genital, acral and some unknown areas. The largest count is on the back and the least one is on the acral area.

Age vs Density Plot

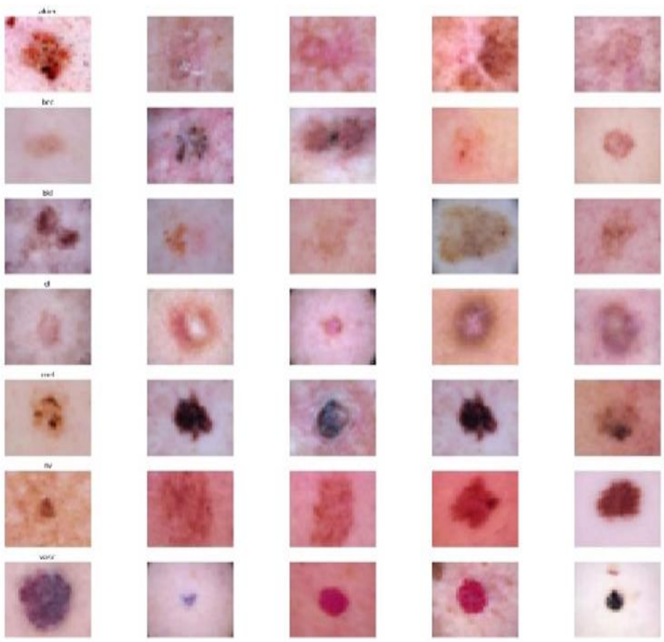


Fig 5 Age vs Density

The above plot shows the various ages of patients and the number of patients affected with skin cancer at that certain age. In the plot, it can be observed that maximum skin cancer cases occur in individuals between the age of 40 to 60 years old. And least skin cancer cases are seen in infants and young people from the age of 0 to 20 years of age.

Classified Images from the Dataset

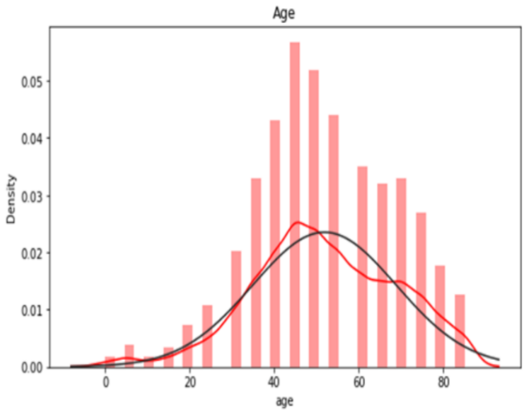


Fig 6 Classified images of the dataset by the proposed Model

We use the HAM10000 Dataset, a collection of 10,000 photos of skin cancer, in our model. The model's goal is to categorise these pictures into seven different types of skin cancer: basal cell carcinoma (bcc), actinic keratoses and intraepithelial carcinoma/Bowen's disease (akiec), benign keratosis-like lesions (bkl), melanoma (mel), melanocytic nevi (nv), and vascular lesions (a.k.a. angiomas, angiokeratoma. The model produces results, which are shown in the related figure 6.

Accuracy and Other Results

Fig 7 Accuracy of the working model

In our model, the accuracy of has been reported to be 98.77%. This high accuracy rate is achieved through the ability of this model to accurately identify cancerous moles based on their features from the images with the help of Resnet-50, ABCD and Seven-point Checklist.

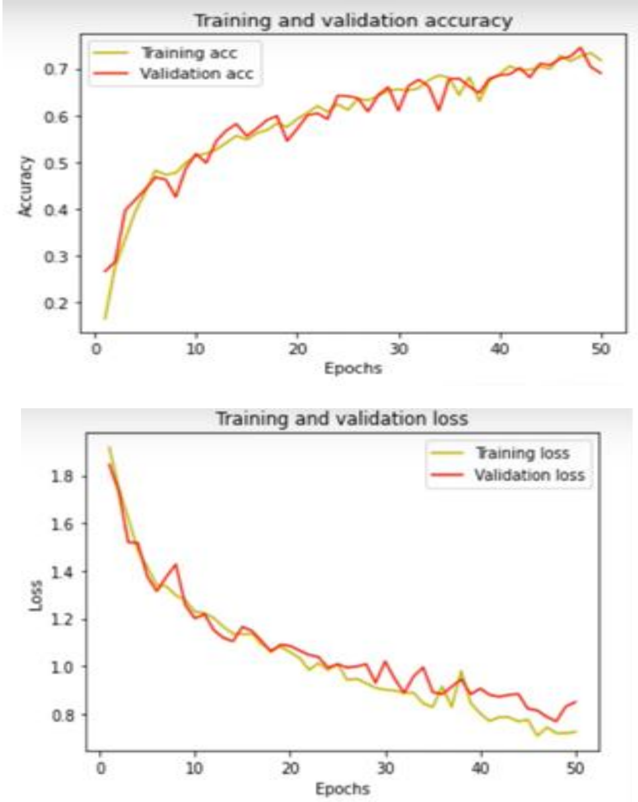


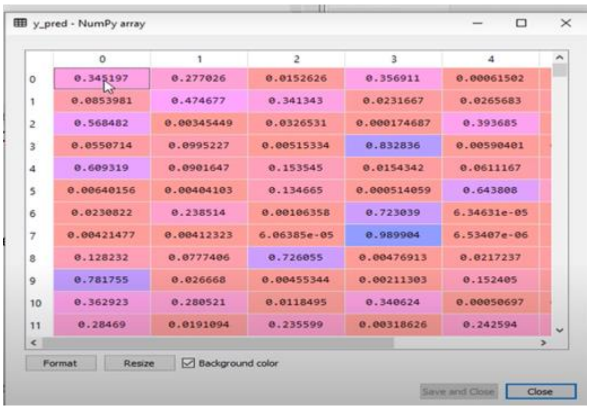
Fig 8 Training and Validation Curves

In the context of training a neural network, epochs refer to the number of complete iterations made by a machine learning algorithm on a given dataset. Each epoch entails a single pass through the entire training set. In every epoch, the neural network utilizes the training data to make predictions and adjusts its parameters by comparing these predictions with the actual output. The objective of training a neural network is to minimize the distinction in its predictions as well as the true output, commonly referred to as the "loss".

The number of epochs used to train a neural network is an important hyperparameter that can significantly affect the accuracy of the model. Insufficient epochs cases underfitting, where the design of model fails to catch the intricacies of the data. Conversely, excessive epochs can result in overfitting, where the model becomes excessively tailored to the training data and has poor performance in confronting with new, unseen data.

Here we are doing 50 Epochs each of batch size 16 each for training of the model (where 2625 images in total are used for training). In the above graph, the loss against epochs curve is plotted and the curve does not give any overfitting or underfitting cases. Both the training and validation curve are almost together and as epochs increase the curve isslowly decreasing.

Furthermore, in the next curve which is accuracy against epochs. The accuracy curve is observed to be increasing as the number of epochs increases. Both the curves show excellent working of the code.


y_pred - NumPy array

	0	1	2	3	4
0	0.345197	0.277026	0.0152626	0.356911	0.00061502
1	0.0853981	0.474677	0.341343	0.0231667	0.0265683
2	0.568482	0.00345449	0.0326531	0.000174687	0.393685
3	0.0550714	0.0995227	0.00515334	0.832836	0.00590401
4	0.609319	0.0901647	0.153545	0.0154342	0.0611167
5	0.00640156	0.00404103	0.134665	0.000514059	0.643808
6	0.0230822	0.238514	0.00106358	0.723039	6.34631e-05
7	0.00421477	0.00412323	6.06385e-05	0.989904	6.53407e-06
8	0.128232	0.0777406	0.726055	0.00476913	0.0217237
9	0.781755	0.026668	0.00455344	0.00211303	0.152405
10	0.362923	0.280521	0.0118495	0.340624	0.00050697
11	0.28469	0.0191094	0.235599	0.00318626	0.242594

Format Resize Background color

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Fig 9 Probability Prediction Table

We are using the SoftMax function which gives all the predictions in the form of probabilities. It is used in multiclass classification problems, where the motive is to give an input instance to single value of the several possible classes. In the following table each element in the output vector represents the probability of the corresponding class. The class that has highest probability for an element is considered to belong to that class. It gives information about the probability of an image that belongs to a certain category or class. We then use the argmax function to convert these probabilities into binary form (0s and 1s) and to predict the class of each element. This probability table, simply put, tells us about the belonging of a certain element to a specific class.

Fig 10 Confusion Matrix

The model's effectiveness in categorizing the photos is shown by the confusion matrix. The anticipated class labels are given by the columns of the matrix whereas the actual class labels are seen in terms of rows. The confusion matrix's entries can be interpreted as follows:

TP: True positives This is the number of photos that the model successfully identified as belonging to a certain class. For instance, the entry on the bottom right of the confusion matrix, it represents the accurate classification of melanoma images as melanoma.

True negatives (TN): This shows the quantity of photos that are accurately identified by the model as not belonging to a specific class but instead fall into another category. For instance, it reflects correctly classifying non-melanoma photos as non-melanoma in the confusion matrix's top left entry.

False Positives (FP):The amount of photos that the model mistakenly identified as belonging to a certain class but which really do not is known as false positives (FP). For instance, the item in the confusion matrix's upper right corner denotes the misidentification of non-melanoma photos as melanoma.

False negatives (FN): This indicates the number of images that belong to a particular class but are incorrectly predicted as not belonging to that class by the model. For instance, the entry in the bottom left corner of the confusion matrix represents the misclassification of melanoma images as non-melanoma.

In summary, the confusion matrix provides insights into the model's accuracy in predicting different classes, including both correct classifications and misclassifications.

5. Conclusion

Globally, skin cancer is a common occurrence and is among the most common types of cancer. It is brought on by the unchecked proliferation of aberrant skin cells, which can be brought on by a number of things like UV radiation exposure, genetics, and environmental factors. Different forms of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, can appear. Skin cancer therapy and early detection are crucial for improving patient prognosis and reducing risk of complications. In recent times, there has been an increasing focus on employing machine learning algorithms and deep learning models to detect skin cancer. These methods offer the potential to enhance the precision of skin cancer diagnosis and minimize the need for unnecessary biopsies. Notably, Support Vector Machines (SVM) and deep learning models such as ResNet-50 have demonstrated impressive capabilities in skin cancer detection. Support Vector Machines (SVM) is a extensively used and popular machine learning algorithm employed in various classification tasks. It works by finding the best boundary between two classes of data points, such as benign and malignant skin lesions. SVM has been used in several studies for skin cancer detection, where it achieved high accuracy rates.

In contrast, ResNet-50 is an exceptional deep convolutional neural network renowned for its remarkable performance in tasks related to image classification. ResNet-50 is capable of identifying complex patterns and features in images, which makes it well-suited for skin cancer detection. In studies where ResNet-50 was used for skin cancer detection, it achieved high accuracy rates, outperforming other deep-learning models. In our project combining SVM and ResNet-50, has been shown to further improve the accuracy of skin cancer detection. Through our analysis, we have demonstrated the promising outcomes obtained in the detection of skin cancer lesions by leveraging the combination of ResNet-50 and SVM classifier. We have further used the ABCDE method and 7-point Checklist method for additional feature extraction from the preprocessed images of the HAM10000 dataset. The ABCDE Method and 7-Point Checklist method is used by medical professionals to diagnose whether a skin lesion is cancerous or non-cancerous. We did the analysis by incorporating all the above methods in our project. The results classify the images of the lesions in the HAM10000 dataset, into 7 categories of cancer, namely Basal cell carcinoma (BCC), Dermatofibroma (df), Vascular lesions (vasc), Melanocytic nevi (nv), Melanoma (mel), Actinic keratoses& intraepithelial carcinoma (akiec), Benign keratosis - like lesions (bkl). The Accuracy of the system came out to be 98.77%, which outperformed SVM and ResNet-50 used independently and is also higher than the accuracy achieved by dermatologists in any study. Overall, the use of SVM and ResNet-50 in skin cancer detection is a promising approach that can aid in the early diagnosis and treatment of this deadly disease. The potential benefits of this algorithm include minimizing the need for unnecessary biopsies and enhancing patient outcomes. However, more investigation is required to enhance the model's functionality and prove its usefulness for use in clinical settings.

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