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Melanoma Skin Cancer Detection using SVM and CNN

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Abstract

In the field of cancer detection and prevention, doctors and patients are facing numerous challenges when it comes to cancer prediction. Melanoma skin cancer is a deadly type of skin cancer with a multitude of variants spread across the world. Traditional methods involved manual inspection followed by various tests of samples. This time-consuming work and inaccurate predictions sometimes risk the overall health of the patient. The two aspects of solving skin cancer detection problems utilising both conventional image-processing techniques and methods based on machine learning and deep learning are elaborated in this article. It gives a review of current skin cancer detection techniques, weighs the benefits and drawbacks of those techniques, and introduces some relevant cancer datasets. The proposed method focuses mainly on Melanoma skin cancer detection and its previous stages (Common Nevus and Atypical Nevus). The methods being proposed employ a blend of colour, texture, and shape characteristics to derive distinguishing attributes from the images. Using CNN (convolutional neural networks) and SVM (support vector machine) algorithms to identify the type of skin cancer the patient is affected with and achieved an accuracy of **92%** and **95%** respectively.

Keywords: Skin Cancer Detection, Machine Learning, Image Processing, Deep Learning, Convolutional Neural Networks, Support Vector Machine

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1. Introduction

Melanoma is a fatal kind of skin cancer that spreads fast if not diagnosed and treated early. Accurate and dependable approaches for melanoma detection are becoming more and more necessary as its prevalence rises. This introduction to Melanoma Skin Cancer Detection explores various methods for detecting and diagnosing Melanoma, the importance of early detection, and the role that technology can play in improving the accuracy and speed of Melanoma diagnosis.

Detecting melanoma cancer early is critical for successful treatment and a good prognosis. Fortunately, there are several methods for detecting Melanoma Skin Cancer, including self-examination of the skin, clinical examination by a dermatologist, and the use of advanced technologies such as smartphone apps and AI-based screening tools. In recent years, melanoma from skin photos has been successfully identified using machine learning approaches. Support Vector Machines (SVM) and Convolutional Neural Networks (CNN). The Common Nevus and Atypical Nevus show only mild effects on a patient's health but when left unchecked they can lead to its derivative stage of Melanoma cancer which is deadly to humans, Therefore the detection of these stages has been concentrated in this research focusing more on the melanoma skin cancer.

SVM is a well-known machine-learning algorithm that has been applied in several medical fields, including the detection of cancer. SVM divides the data points into different classes, in this case, benign and malignant skin lesions, by locating the best boundary that can be used to do so. SVM can learn to distinguish between benign and malignant skin lesions by identifying features particular to each type of lesion. It can be trained on large datasets of skin lesion images.

Contrarily, **CNN** is a deep learning architecture created to automatically recognise and extract features from large amounts of complex image data. It has been demonstrated that CNNs are very efficient at identifying and classifying skin lesions, including melanoma. Large datasets of skin lesion images can be used to train CNNs, and they can be taught to recognise the distinctive characteristics that separate benign from malignant skin lesions.

The suggested approach leverages the benefits of both algorithms to obtain high melanoma detection accuracy. The outcomes of tests performed on a publicly accessible dataset show that the suggested approach is effective in detecting melanoma with high accuracy and low false-positive rates.

1.1. Techniques Used for Classification

When identifying skin cancer via image processing, there are many different strategies used. A few of these methods are:

1.2. Image Acquisition

The initial phase in the identification of skin cancer through image processing is acquiring images. To accomplish this, a camera or microscope can be utilised to obtain clear and high-quality pictures. The excellence of these pictures holds key significance; thus [4], there must be good lighting conditions while capturing them as well as controlling angles for optimal results.

1.3. Pre-Processing

Images must be pre-processed to enhance image quality before the examination. These techniques to eliminate unwanted noise from the photographs while emphasising their characteristics include hair removal, glare removal, and segmentation. These techniques shorten the processing time, speed up the identification of important details, and increase accuracy by allowing us to concentrate on the skin area that is afflicted by the malignancy.

1.4. Feature Extraction

The goal of the feature extraction procedure is to identify distinctive qualities that distinguish one type of skin cancer from another. These differentiating characteristics include, among other things, shape, colour, texture, and size [5]. To determine which of these many procedures produces the most pertinent distinguishing features for a specific malignant pigment patch, techniques like the Otsu segmentation method and the watershed segmentation method are used.

1.5. Image Classification

After the relevant features have been extracted, classification techniques are used to classify the specific skin cancer. Classification can be done using supervised or unsupervised learning techniques [4]. Some common classification algorithms used include support vector machines, Convolutional Neural Networks, and artificial neural networks [10].

1.6. Validation

To complete the process, it is essential to confirm the skin cancer identify- cation system's precision. The method used for this confirmation involves matching up outcomes acquired from the said system with those acknowledged by a specialist regarding the exact type of skin cancer distinctions [12]. To better enhance accuracy, adjustments can be made using feedback garnered through fine-tuning of aforementioned systems [8]. To evaluate and compare the performance of the trained SVM classifier and CNN on the testing set using the following metrics such as accuracy, precision, recall, and F1 score.

2. Literature Survey

They proposed the design using the deep recursive CNN model for classifying and detecting pests on plants. In this research, they gave about the ReLu, Max pooling and the feature pyramid networks. They proposed the recursive model for CNN. It has datasets which contain NBAIR and pest images in the agricultural field. They concluded the DR CNN images for the pest that will appear in the plant either on the upper side or lower side of the leaf [1].

This work is mainly focused on image processing as artificial neural networks for traps in greenhouse agriculture. The dataset they considered was whitefly (Bemisia tabaci) and thrip (Frankliniella occidentalis) in the greenhouse [2]. The methods they have taken are image acquisition and image insect algorithm and it is classified using the neural networks.

The work in this paper mainly focused on skin disease classification using Convolutional Neural Networks (CNN) [3]. They took the pomelo skin lesion dataset to detect plant disease [11].

The work in this paper mainly focussed on the Convolutional Neural Network for fruit image processing. In this, the data taken is RGB images, hyperspectral images and RGB-D images [4]. They proposed one formula for the CNN architecture in Filter banks or kernels and convolutional layers. They have also given the formulas for the dropout layer.

It mainly focuses on the detection of the pandemic COVID 19 using image processing techniques and also images with X-RAY and CT by CNN. They used the methods of the size of the image, image segmentation, image enhancement and Transfer learning. They used the augmentation technique for the case of the normal person and those who are affected by covid 19 they classified the images, and they got the accuracy as 93 percent [5].

The work in this paper is using the convolutional neural networks model based on fake image detection [6]. They used convolution neural networks for classifying the images. It also shows which training algorithm gives how much accuracy they used the machine learning algorithms such as KNN, Naive Bayes, decision tree and random forest etc [15]. Out of all these random forests gave high accuracy.

3. Description of Dataset

In this section, a dataset is chosen that's useful for determining accuracy.

3.1. Dataset

The PH2 Dataset fits right into the requirements of the data set in this research. The assortment of pictures that constitutes the PH2 Dataset consists of 3 different types of skin cancers (Atypical Nevus, Common Nevus and Melanoma. These skin cancers are chosen based on the most common and deadly cancers if not treated in the further stages. The motivating factor behind compiling this collection was to educate machine learning models about Skin cancer identification techniques which would ultimately aid the patients affected with such skin cancer better than the traditional methods still used around the globe. Featuring over Two-Thousand snapshots of melanoma skin cancer lesions. The PH2 Dataset has internal folders with images of the mentioned 3 types of skin cancers which are related in nature and can be used for prediction of the stage in which the melanoma skin cancer is currently. Common Nevus is diagnosed mostly as mild or close to zero risk on health but on the other side once the Common Nevus turns into Atypical Nevus it can be cancerous and can lead to melanoma if not treated beforehand.

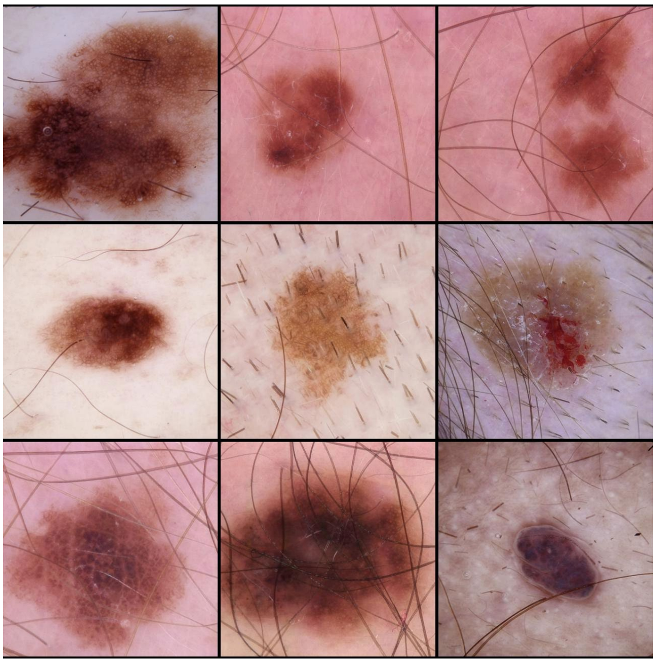

Figure 1. PH2 Dataset

4. Methodology

By using the computer vision techniques mentioned above there are five steps for the classification of the skin cancers in the patients. They are Image Acquisition, Pre-Processing, Feature Extraction, Image Classification and Classification results. In Feature Extraction, they are classified as shape, color, texture, Otsu segmentation method and watershed segmentation. Whereas in the classification they are divided into two types: base classifiers and Ensemble classifiers. In the base classifiers, they are KNN, Naive Bayes, SVM and CNN.
There are several algorithms which are used for the classification of skin cancer.

Convolutional Neural Networks (CNN): To use CNNs for image classification of skin cancers, one typically trains the network on a large dataset of labelled images that includes both images with melanoma skin cancer and images of other skin cancers. The CNN learns to recognize patterns and features in the images that are associated with the presence of skin cancer and uses this information to classify new images as either diagnosed with or without skin cancer [10].
Support Vector Machines creation of an optimal decision boundary - a line or curved surface, that possesses

unparalleled precision in segregating a multi-dimensional space into distinctive classes [15]. This superlative algorithm enables users to employ it as a model to categorize and classify novel data points with unmatched accuracy and efficiency.

Naive Bayes: The Naive Bayes algorithm is notable for its effectiveness despite being straightforward. It operates on the premise that each feature it evaluates remains unrelated to all other characteristics, ultimately deriving the probability of every class based on those features [15].

Decision Trees: Decision trees are a popular algorithm for classification in skin cancer detection. Interpretation of such insights is a cinch, thanks to their lucid nature. The decision-making process can be significantly elucidated with the help of these easily understandable inputs.

Now out of all these algorithms, the most thoughtful is **CNN** (Convolutional Neural Network) and **SVM** (Support Vector Machine) as the suitable algorithms for getting better accuracy results.

4.1. Preprocessing of the Dataset

One of the main obstacles is hair on the human body which will be the primary removal method in the pre-processing stage. And next, remove the glare and shade which is resulted sometimes while capturing the image of the lesion.

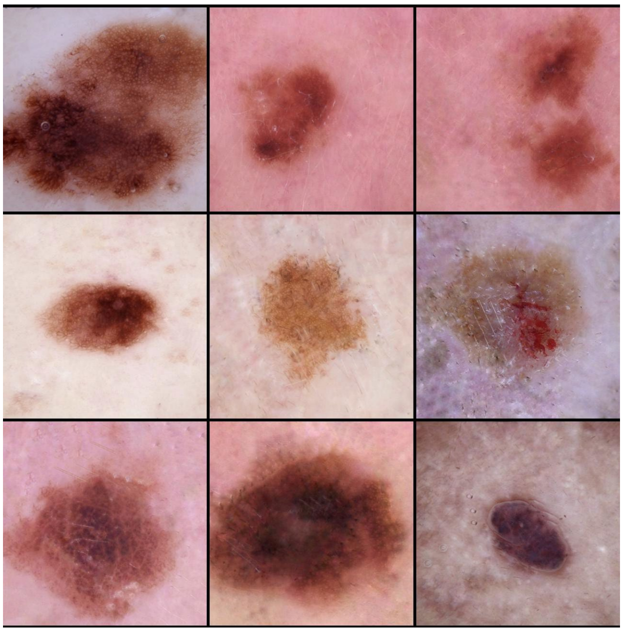

Figure 2. Pre-processing of image (Hair removal)

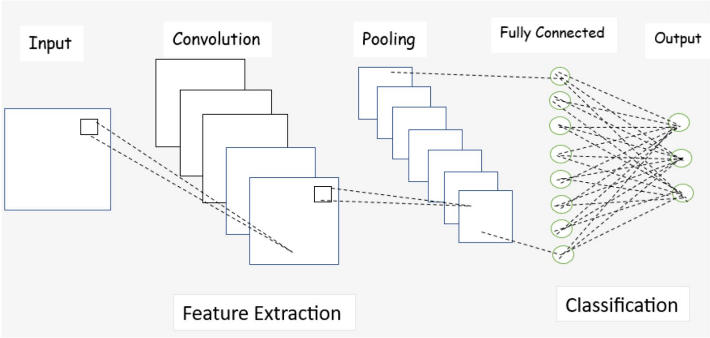

Figure 3. Architecture of CNN Model

4.2. Splitting of the dataset into training, testing and validation

Here splitting of the dataset as training, testing and validation. Take a small portion of the data and test that data and after training it at last validate it for accuracy.

4.3. Building Architecture

The convolutional neural network (CNN) ought, nay must, comprise layers that function convolutionally, distinctly geared towards the extraction and apprehension of features from images. In addition, pooling layers are implemented for the express purpose of reducing the feature dimensionality [13]. Finally, fully connected layers may categorically classify images by utilising said extracted features. Fig 3 shows the architecture of the CNN model.

4.4. Convolution Layer

In the convolutional neural network, applications of trained filters to input images are performed methodically through convolutional layers, resulting in the creation of feature maps that are considered an effective outline for the presence of these features within input [14]. This process serves to summarise and outline notable characteristics inherent in the image data. Convolutional layer efficiency cannot be denied, and when deep models are deployed with stacked convolutional layers, it allows the innermost layers closest to the input of the low-level features with elevated fine lines and layers deeper in the model to learn high-order or more abstract features like shapes or the specific objects.

4.5. Pooling Layer

Each feature map is processed separately by the pooling layer, which pro- duces a new set of the same number of pooled feature maps. To enable the feature maps to undergo pooling, much like in applying a filter, the process of pooling must be performed. When compared to those of the feature map, the dimensions of the pooling process and filter are minimal [7]. The dimensions of the pooling operation filter used are minor compared to those of the feature map. To specify, it is customarily 2x2 pixels administered with the stride of 2 pixels.

4.6. Fully Connected Layer

Neural networks that are fed forward are the Fully Connected Layer. The last few strata of the computational architecture are commonly characterised as Fully Connected Layers. The resultant output from the last pooling or convolutional layer, which is transformed into a flattened form before transmission to the former, is utilised as an input for the fully connected layer [10]. This transmission process through a flattened layer ensures the streamlined passing of information within connection paths.

```
# Create CNN model
model = tf.keras.models.Sequential([
    tf.keras.layers.Conv2D(32, (3,3), activation='relu', input_shape=(224, 224, 3)),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(512, activation='relu'),
    tf.keras.layers.Dense(256, activation='relu'),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dense(3, activation='softmax')
])
```

Figure 4. Layer Parameters

4.7. Train the CNN

Train the CNN using the training set, adjusting the model's weights and biases to minimise the loss function. By using the validation set to monitor the model's performance during training and prevent overfitting. In the training part, consider the images in the same size.

4.32. SVM Architecture

The Support Vector machine is used for classification of the dataset based on the features extracted from the dataset and it is also one of the most widely used kernel learning algorithms. It is used in this research for its robust pattern recognition performance using well-established concepts in optimization theory.

4.33. SVM Kernels

One of the important things in using an SVM algorithm is choosing the right kernel for the particular dataset. The opted kernels in this research are **Linear** kernel and **radial bias function** kernel also known as **rbf**.

4.33. SVM Training

Train the SVM using the training set by categorising the dataset into given types of skin cancers and by modifying the given image size to 100*100 so that the model can train much faster as the computational data is much lower in resolution. But it can always be tuned up for more accurate results.

5. Results

In this research, a total of **2158** images are taken of examples such as Atypical Nevus, Common Nevus and Melanoma skin cancers. As the dataset is large the resulting accuracy may also depend on the quality of capturing the photos. The below epoch representation of it shows the Model accuracy for the testing and validation datasets. Each epoch and its validation loss and validation accuracy are in Table 1.

Test loss: 0.217896029
Test Accuracy: 0.9260274178 ≈ **92.6%**

Table 1. Accuracy and Loss of CNN Model

Epoch	Test Loss	Test Accuracy	Validation Loss	Validation Accuracy
1/10	23.1671	0.8477	0.9183	0.8986
2/10	0.5542	0.9156	0.3362	0.8986
3/10	0.5219	0.9211	0.3944	0.9315
4/10	0.3178	0.9376	0.2219	0.9123
5/10	0.1557	0.9458	0.2257	0.9260
6/10	0.1344	0.9492	0.2025	0.9260
7/10	0.2135	0.9431	0.4169	0.8986
8/10	0.2843	0.9177	0.3159	0.8986
9/10	0.1680	0.9376	0.2008	0.9342
10/10	0.1277	0.9527	0.2179	0.9260

Training Time: 28 minutes (Feature mapping and extraction takes up more time, once trained the end-user experience will not be affected once the model is trained).

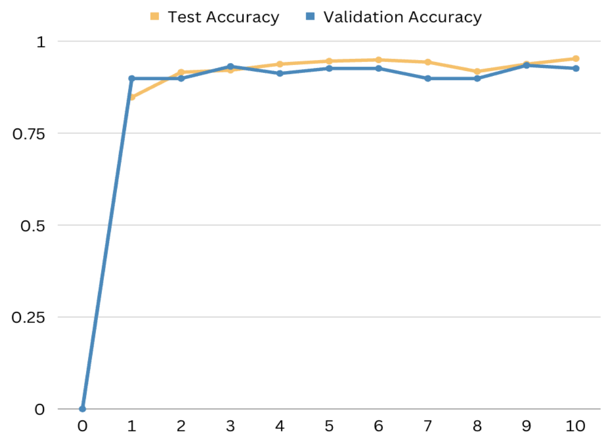

Figure 5. Plot for accuracy of CNN Model

SVM Approach Results:

For the same given dataset of images, the SVM model also gives accurate measurement in a multitude of metrics like accuracy, precision, recall, and F1 score. The final classification report represents the model accuracy in Table 2.

Table 1. Accuracy of the SVM Model

	Precision	recall	f1-score	Support
0	0.89	0.85	0.92	397
1	0.91	0.94	0.95	414
2	0.98	0.97	0.98	498
Accuracy			0.95	1309
Macro avg	0.89	0.88	0.88	1309
Weighted avg	0.95	0.95	0.95	1309

Demerits:

- **Limited dataset size:** CNN models often require a large amount of data for training to achieve optimal performance.
- **Imbalanced class distribution:** If the dataset has a significant class imbalance, where one class (e.g., melanoma) has far fewer samples than the other (e.g., not melanoma), the model may have a bias towards the majority class, leading to lower performance in detecting the minority class.
- **Hardware requirements:** Training CNN models can be computationally expensive, especially if the model is complex or the dataset is large. This might require access to high-performance hardware, such as GPUs, which can be a limitation in some settings.

6. Conclusions

In this study, the outcome is to identify skin cancer using Convolutional Neural Networks and Support Vector Machines methods. Despite ongoing research and improvements in the use of image-processing techniques to distinguish between various types of skin cancer, obstacles to their practical use continue to exist. Undoubtedly, obtaining high-quality images is a crucial challenge in putting this methodology into practice. This is a task that can be very difficult, especially in some situations. Additionally, skin cancers may have morphologies that resemble one another, making it difficult to distinguish them when using this method. A future application can be developed around this model to give the user an interface to upload their affected region of skin and predict the confidence rate after predicting the accuracy.

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