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Skin Cancer Classification and Detection By Deep Learning

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ABSTRACT

Malignant melanoma stands as a formidable manifestation of skin cancer, posing a significant threat to human health. Contemporary dermatology acknowledges the paramount significance of timely detection in mitigating the aggregate mortality rate and guaranteeing that individuals are subjected to minimally intrusive therapeutic interventions. The escalating popularity of computer-aided diagnostic (CAD) mechanisms utilized for the timely identification of skin lesions is becoming increasingly apparent. These systems encompass a multitude of sequential stages, each necessitating a judicious selection that aligns with the inherent attributes of the digital images, thereby culminating in a dependable diagnostic outcome. The successful advancement of automated diagnosis for life-threatening lesions like melanoma necessitates the conquering of various challenges encompassing acquisition, pre-processing, the process of segmentation extraction of features and selection, and ultimately categorization of dermoscopic images. In the suggested method, Random Forest and Resnet-50 are combined. The experiment improved precision by 9-10%.

INDEX TERMS: Melanoma, Skin cancer, Classification, Random Forest, Deep Learning

I. INTRODUCTION

Melanoma is a highly lethal and rapidly spreading form of skin cancer that affects people worldwide. It is a particularly severe type of skin cancer, as it grows fast to lymph nodes, well before the cancer is detected [4-6]. In 2016, the United States is expected to see 76,380 cases reported of melanoma and 10,130 deaths. This results in the death of more than one person every hour in the United States. As a result, the incidence of melanoma is growing globally Early identification and diagnosis may entirely cure melanoma. The primary risk factor for melanoma, as well as all other types of skin malignant development, is exposure to both natural and counterfeit ultraviolet (UV) light. Skin diseases can be caused by tanning or it might be inherited. The phenomenon of melanoma metastasis stands as the predominant etiology behind mortality arising from this form of cancer. The visual representation depicted in Figure 1 clarifies the presence of melanoma cells that exhibit a proclivity for infiltrating the epidermis and penetrating the underlying dermal layers.

Images of lesions are thoroughly examined. To begin, pigmented and non-pigmented lesions must be distinguished. Then, if the lesion is pigmented, it is necessary to determine if it is melanocytic or non-melanocytic. Additionally, if the lesion is considered to be melanocytic, determine whether it is benign or malignant. If the physician

Figure 1. **Melanoma Skin Disease**

determines that the skin lesion is melanoma, the practitioner should initiate melanoma diagnosis immediately, as it is the leading cause of mortality. The phase of melanoma is critical for diagnosing melanoma patients. Cancer diagnosis during surgical therapy is primarily determined by the cancer's stage or thickness. The stage and size of the tumour are key diagnostic factors. Breslow indexing and Clark scale are the ways to determine the depth and thickness of a tumour during pathological examination. These techniques should only be employed following excisional or incisional surgery for a questionable lesion. Clark scale is used to determine the depth of melanoma development and the afflicted skin levels. There are 5 levels of categorization with severity increasing with each level. The Breslow index consists of five levels. This enables the width of surgical margins of excision to be determined. There are three categories of melanoma development:

- **Stage 0 (Melanoma in situ)**: The melanoma is restricted to the epidermis, the outermost layer of skin.
- **Stage I:** Stage I describes primary melanoma with a small risk of metastasis. After this point, surgical intervention is usually successful in preventing further progression. Particular features are observed that can be used to predict a greater likelihood of recurrence, while a lack of dissemination is found.
- **Stage II**: Melanoma is characterized by the presence of metastasis in the adjacent skin or lymph nodes.
- **Stage III:** Melanoma is characterized by the dissemination of cancer cells to distant skin, lymph nodes, or internal tissues.

It can originate in stupid skin tissue, such as a mole or pigmentation, and may unfold to greater pigmented pores and skin in addition to non-pigmented skin. Male zits typically start off evolved first on the head, neck, or between the shoulders and hips of the person who is suffering from it. Ladies are more at risk of getting it on the legs and arms than men. Also, feasible places encompass the palm of your hand, the underneath of your foot, beneath this type of fingernail or toenail, physiological fluid linings (consisting of the linings of your mouth, vagina, or buttocks), or even the whites of your eyes. Melanoma isn't always a difficult sickness to treat and is normally curable if caught and handled early. As a result, it progresses more quick than other styles of pores and skin most cancers, and it has the ability to spread past the pores and skin to other regions of the frame, consisting of as the bones and the cerebral cortex. It is tough to deal with and there may be no manner to cast off it at that factor.

Melanoma that has been diagnosed earlier can be treated with the aid of medications and surgery. Melanoma, a variant of skin malignancy, possesses the capacity to infiltrate the dermal layers and establish intricate connections with various internal organs. Melanoma incidence seems to be rising, particularly among women under the age of 40. In order to diagnose and treat skin cancer before it has spread, it is important to be aware of the early warning indications. If melanoma is caught in its early stages, it may be effectively treated. An invasive melanoma is one that has spread to lymph nodes or blood arteries within the body and is now difficult to operate on. The diagnosis and treatment of melanoma are simplified by early detection made possible by technology developments like machine learning.

In recent times, there has been a remarkable surge in the favorability of deep learning systems owing to their capacity to mechanize procedures and deliver discernible enhancements in performance when juxtaposed with more traditional machine learning-based approaches. Medical image analysis has been revolutionized by deep learning, which has produced notable results in several areas. These encompass a range of medical applications, such as the identification of gastrointestinal ailments, the detection of diabetic retinopathy, the analysis of microscopic and histological elements, the imaging of cardiac structures, the identification of tumors, the detection of Parkinson's and Alzheimer's diseases, and the categorization of skin lesions [34]. Convolutional neural networks, the most prevalent kind of deep neural architecture, have seen a lot of success in recent years. Although CNNs have been studied for decades, AlexNet's victory in the ImageNet 2012 competition helped propel the technology into the mainstream. By redesigning the architecture, the error rate was cut in half, from 26% to 15%. VGGNet, GoogleNet, ResNet, and many more innovative CNN designs have been released since then. Since these designs are so popular and productive, the sector is developing swiftly and effectively.

II. RELATED WORK

In 2021, V Patil, A et.al [1] examined computer vision images of melanoma and analyzed using ML algorithms to determine if a mole or spot is melanoma or not. Color, form, size, and elevation above the skin are all investigated as features that can be recorded using computer vision. This early detection aids in the treatment of melanoma. Analyzing the optimal algorithm and grasping its underlying formula; tailoring one's approach to ensure accuracy, efficiency, and the fine-tuning of processing parameters within a specific dataset, while considering the intricacies of model complexity. In order to effectively predict the onset of melanoma skin cancer during its growing phases, researchers can employ CNNs.

In 2021, Tanna & Sharma [2] present two approaches for the detection of skin cancers, focusing on melanoma malignant cells using image data. One employs three-layer CNNs, while the other employs a simple SVM model with default RBF kernel. After performing image processing on the image, the recovered feature variables are utilised to identify it as malignant or benign. The accuracy, AUC, confusion matrix, and ROC curve are all calculated metrics. Classification accuracy of 79.39 percent and AUC of 0.81 were obtained with the SVM classifier. The CNN is calculated for 100 epochs and achieves an accuracy of 84.39 percent. With the assistance of Streamlit, the CNN model is brought to life as a web application.

In 2021, Ramachandro, M., et.al [3] discuss four different forms of skin cancers: Basal Cell Carcinoma (BCC), Actinic Keratoses (AK), Melanoma, and Dermatofibroma. Late detection of cancer results in the spread of the disease to other organs. CNNs have the capability to effectively detect and classify instances of skin cancer within image datasets. This method would make use of the ISIC image database and the HAM10000 database. Transfer learning enhances the model's performance in CNNs. To extract characteristics, pre-trained models are employed, which are then used to classify different forms of skin cancer. RF, CNN, SVM, and Dense net are the ML and DL algorithms employed in this approach.

In 2021, Murugan, A., et.al [4] identifies melanoma based on scans of the skin. The skin undergoes initial filtration through the application of the median filter, followed by segmentation employing mean shift segmentation. The input for the feature extraction procedure consists of segmented images. The present research study employs the extraction of Moment Invariants, GLCM, and GLRLM features. Various methods for classification, including RF, SVM, probabilistic NNs, as well as combined SVM+RF classifiers, are employed to classify the retrieved characteristics. In this particular instance, the integrated SVM combined with RF classifier exhibited superior performance compared to alternative classifiers.

In 2021, Yu, Z., et.al [5] proposed the development of a framework aimed at automating the early detection of melanoma through the analysis of successive dermoscopic images. As such, the methodology is built in three stages by the researchers. The authors first propose a spatio-temp network to capture dermoscopic changes from aligned lesion images and the corresponding difference images, which are obtained by first aligning sequential dermoscopic images of skin lesions using estimated Euclidean transformations and subsequently, the process of delineating the region of lesion growth is accomplished through the utilization of computational algorithms that analyze the disparities in image characteristics between successive images. In the end, researchers devise an early diagnostic module to calculate malignancy risk ratings for lesion pictures.

In 2021, Wang, X., et.al [6] presents a novel knowledge-aware deep framework for the detection of melanoma, a malignant skin cancer. This framework utilizes collaborative learning techniques to effectively perform both melanoma identification and skin lesion segmentation. Notably, it achieves this by incorporating a limited amount of clinical information, thereby enhancing the overall accuracy and reliability of the detection process. To fully leverage the understanding of morphological manifestations within the lesion area as well as its surrounding periphery. The authors' initial proposition pertains to the advancement of a spatiotemporal methodology for the identification of melanoma. The methodology described herein encompasses the integration of a shape extraction technique known as LPSE, alongside a pooling scheme centered around lesions. This amalgamation serves to enable the transfer of structural information obtained through the segmentation of skin lesions, with the ultimate aim of enhancing the identification of melanoma.

In 2020, Daghrir, J., et.al [7] proposed a hybrid methodology for the identification of skin cancer caused by melanoma that can be utilized on any potentially malignant skin lesion. The proposed scheme is founded upon the ability to predict three distinct methodologies: Three classifiers were trained in this study: two conventional ML classifiers and a CNN. The training data included information that described the texture, borders, and color of a skin lesion. Then, via majority vote, these strategies are integrated to increase their performance. Experiments have demonstrated that combining the three strategies results in the highest possible accuracy.

In 2020, Roslin, S. E. et.al [8] presented a comparison study utilizing supervised ML techniques for categorizing the melanoma group. The utilization of dermoscopic data for the categorization of melanoma is proposed as a means to facilitate the practical implementation of the dermatoscopy imaging method for the purpose of categorizing skin lesions. An unsharp masking and anisotropic diffusion filter were used to enhance the images. A versatile k-means clustering conduct was employed to isolate the melanoma from the surrounding context. This process involved dividing the data into two clusters. Additionally, feature extraction techniques were applied to the segmented data, focusing on texture characteristics and intensity. The resulting features were then used to train and test a classifier utilizing dermoscopic information that had not been previously recognized. The k-NN, SVM, multi-layer perceptron, RF, and RF classifiers were all used. The area underneath the ROC is used to evaluate the classifiers' performance. The RF technique is found to reach 93 percent accuracy and performs much better than other classifiers for classifying melanoma.

In 2020, Saba, T. [9] assess, review, categories, and discuss current breakthroughs in the detection of human body cancers utilizing ML approaches for brain, breast, lung, skin, liver, and leukemia. The study demonstrates how ML approaches such as unsupervised, supervised, and deep learning can aid in the detection and treatment of cancer. Numerous state-of-the-art approaches are clustered together and their results on benchmark datasets are compared on the basis of false-positive metrics, accuracy, specificity, sensitivity.

In 2020, Albert, B. A. [10] shows how to train ensembles to perform effectively with little data by use of a unique technique known as Predict-Evaluate-Correct K-fold (PECK). Using 153 pictures of non-dermatoscopic lesions as training data, the PECK algorithm trains a deep ensemble that considerably outperforms earlier publications and state-of-the-art algorithms trained and assessed on the same dataset. The PECK technique achieves introspective learning by fusing deep convolutional neural networks with support vector machines and random forest classifiers. If the ensemble is structured in a hierarchy, then the deeper layers will get not just additional training folds, but also the predictions of the higher levels. The next layer of classifiers then trains on the original data with the inserted predictions for new data folds in an effort to learn and rectify the mistakes made by the preceding layer.

Research gaps

- Previous research neglected the skin's patchy-based characteristics.
- Previous research using machine learning approaches with manual features has increased feature overlap. Nonlinear feature mapping was not used in previous studies.
- Previous research ignores overlapping classes because deep learning improves feature mapping while increasing classification error.
- Previous research has shown that removing residual and overlapping characteristics increases the false positive rate.

III. PROPOSED SYSTEM

Fundamental to all deep learning methods are neural networks [47]. A neural network is comprised of an initial layer for input, intermediate layers for hidden computations, and a final layer for output, comparable to the structure of a multilayer perceptron. Activation function, biases, and weights, (b,W) are all parts of it. One possible representation of the output at each node is as follows:

$$a = f(W^T x + b) \quad \text{..........................} (1.1)$$

The non-linearity function is denoted by f(.). Sigmoid, hyperbolic, and RELU (Rectified Linear Unit) functions are examples of common non-linear functions used in practice [50]. RELU offers two primary benefits over the more common sigmoid: sparsity and lower vanishing gradient probabilities. The acquisition of intricate functions, devoid of dependence on manually designed attributes, is made feasible through the utilization of deep learning, an advanced methodology for hierarchical feature acquisition. The utilization of the backpropagation technique [49] involves the utilization of gradient descent optimization in order to reduce the amount lost at the output by continually modifying the weights within the feed-forward procedure. In order to ensure that the resulting outputs maintain their probabilistic nature, the SoftMax function [49] is employed as an activation function at the output stage. The softmax function, an alternative manifestation of the logistic function, effectively transforms a collection of real-valued scores into a series of numerical values ranging from zero to one, wherein their cumulative sum amounts to unity [50]. In the context of probabilistic multi-class categorization, the SVM is utilized as a discerning cost function for the purpose of distinguishing between various classes.

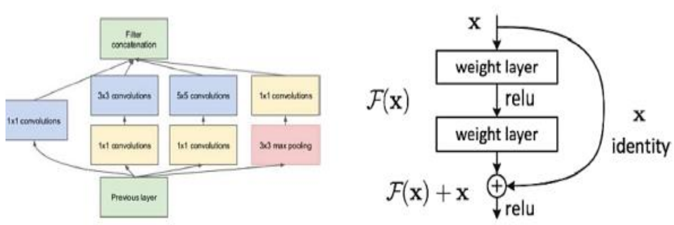
A. Convolutional Neural Networks

Convolutional networks exhibit remarkable proficiency in effectively processing data that is structured as well as unstructured [47], while multi-layer NNs solely accept input in the vectorized format. Image categorization and object identification are two areas where CNN has shown to be very effective. In the ImageNet test, the number of top-5 errors has gone down from 5% in 2012 to 3.6% in 2018. When given a raw pixel-level representation of an image, CNN was able to discern visual patterns with just minimum further processing. This saves us the time and effort of extracting characteristics by manually, which is problematic and sometimes requires expert knowledge in the relevant topic. A CNN is made up of a subsampling layer (average or max pooling), a convolutional layer, and a fully connected layer (FCL). The equation denoted by [47] defines the representation of the output at the convolution layer. It clarifies that said output is contingent upon the activation output derived from the preceding layer, the kernel weights originating from the i-th feature map of the aforementioned layer, and the j-th feature map of the layer (l 1). Additionally, an additional bias parameter is taken into account.

$$A_j^l = f\left(\sum_{i=1}^{M^{l-1}} A_i^{l-1} * \omega_{ij}^l + b_j^l\right) \quad \text{..........................} (1.2)$$

The feature map generated by the preceding convolutional layer is down sampled by the pooling layer (max pooling or average pooling). An extra bias term and non-linearity function are introduced either before or after the subsampling layer. To discover the tunable parameters, the gradient descent with back propagation technique is used. CNNs improve speed by reducing the amount of memory needed to store individual weights and by using the same filter weights for all receptive fields in a given convolutional layer.

In this case, the convolution and pooling layers are not all placed one on top of the other sequentially. They used 1x1 convolution operations before the 3x3 and 5x5 layers. Dimensionality reduction and nonlinearity enhancement were both addressed by this 1x1-convolution technique. As a result of its structure, the model can now recover both granular, local characteristics with smaller convolutions and broad, abstract features with bigger convolutions. Every single one of the convolutional filters is a 3x3 matrix.



(a) (b)

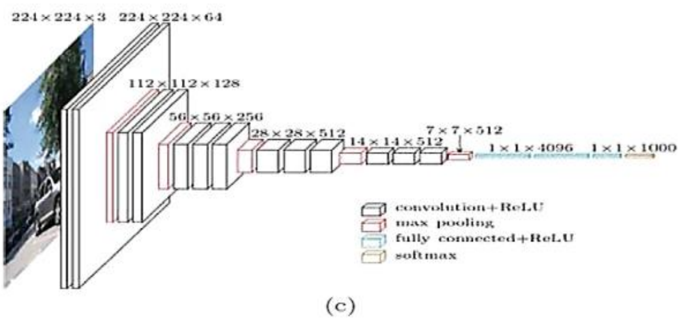


Figure 2. **CNN Architecture [4]**

They claimed that the receptive field of three 3x3 filters is comparable to that of a 7x7 filter, and that of two 3x3 filters, to that of a 5x5. In this way, they were able to minimize the number of trainable characteristics by using a narrower filter.

Algorithm 1

Input: Skin cancer Dataset
Output: Classified in Benning and malignant
Start
1. N <- Skin Cancer Dataset Images
2. WHILE (N>0)
3. Begin
4. Segmented Image (s) <- K-mean (N)
   4.1 S = C_i
   4.2 S^* =initial Solution
   4.3 Repeat step 3 and 4
   4.4 Find the solution S and neighbour S(i+1)
   4.5 IF F (S) > F(S^*)
   4.6 S= S(i+1)
   4.7 Update List
   4.8 When converge list
   4.9 Output Segmented
   4.10 Features (F) <- Residual Network (s)
5. END
6. fea <- F
7. M <- RF-Train(fea,Class)
8. Analysis Parameters <- M(Fea)
9. Stop

In the aforementioned scheme, the input consists of dataset images encompassing two distinct classes, namely benign and malignant. The initial stages of the process involve the implementation of preprocessing techniques and the subsequent application of K-mean segmentation, which are carried out within the framework of steps 1-6.

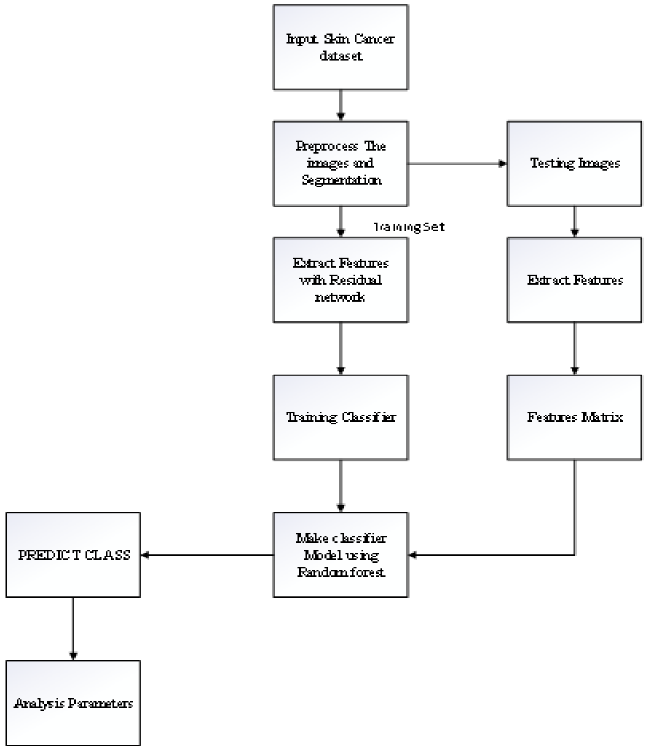


Figure 3. **Flowchart [4]**

After the process of segmentation, the resulting image is subsequently employed in the Residual network's steps 7-8 to facilitate the mapping of distinctive features. Following a series of 8-10 iterations of feature mapping, the random forest (RF) algorithm is employed for the purpose of acquiring knowledge. The assessment and analysis of model performance encompass various parameters of intellectual significance, including but not limited to Recall, Precision, Accuracy, and f-Score.

Step1: The input dataset was melanoma, which was downloaded from https://www.kaggle.com/competitions/siim-isic-melanoma-classification/data

Step2: Preprocess and segment the photos to extract useful features. The entire dataset was separated into two parts: training (80%) and testing (20%).

Step3: Residual network with five blocks and sigmoid activation function is used to map features.

Step4: The mapped features Random Forest-based ensemble learner and classifier model construction.

Step5: Analyze the performance measures and compare them to the existing strategy.

Table 1 Approaches based on accuracy, precision, recall, and F-score.

Approaches	Accuracy	Precision	Recall	F-score
SVM	78.21	76.34	76.33	76.23
CNN	80.23	75.22	76	75.23
RESNET-Random Forest	82.34	78.344	80.233	81.222

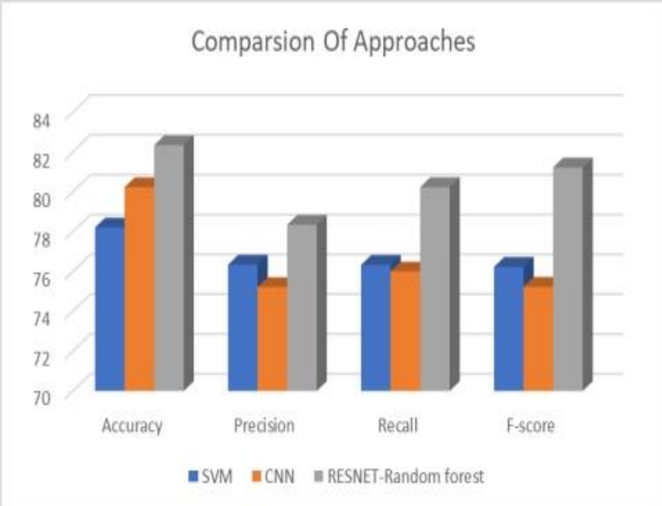


Figure 4. **Comparison of approaches [4]**

Table 1 and Figure 4 represents the comparison of different approaches in terms of accuracy, precision, recall, and F-score. SVM has an accuracy of 78.21, precision of 76.34, recall of 76.33, and F-score of 76.23. An accuracy of 80.23, followed by a precision of 75.22, a recall of 76.0, and an F-score for CNN (75.23). RESNET-Random Forest, on the other hand, has the best accuracy of 82.34, followed by F-score (81.222), recall (80.233), and precision (78.344).

Table 2 Classes based on recall, precision, and f-score.

Class	Precision	Recall	F-score
Benign	79.34	80.23	80.23
Malignant	80.23	82.33	81.23

Figure 5. **Comparison of classes [4]**

Table 2 and Figure 5 compare Benign and Malignant class precision, recall, and F-score. The benign class's precision is 79.34, while its recall and F-score are also 80.23. With a malignant class, recall of 82.33 is obtained followed by F-score (81.23), and Precision (80.23)

IV. CONCLUSION

The increasing number of people diagnosed with melanoma and the number of people who pass away from the disease, in addition to the expanding availability of databases containing dermoscopic pictures, has led to a rise in the interest in technologies that automatically classify skin lesions. The selection and development of classification models call for adequate knowledge of the most applicable learning strategies and algorithms, as well as an understanding of the statistical validity of the results of these analyses. Because of the poor quality of the training data that is currently available, this activity must be completed immediately; the picture annotation step is particularly demanding. The implementation of techniques of the type Multiple Instance Learning is finding a lot of success since they are able to tackle this problem by enabling the management of pictures using just a single global label. It is important to not understate the imbalance that exists between the different types of training datasets. The risk lies within the potentiality of compromising the efficacy of the models in relation to their classification capabilities. This may lead to overfitting, which results in a loss of generalization. It is not always simple to determine which categorization strategy would be most suited for a certain research endeavor. Every possible approach to categorization comes with its own set of benefits. It is feasible to acquire varied categorization results based on a variety of criteria; however, this is contingent upon the problems that are associated with the picture capture and pre-processing procedures being resolved.

Future Scope

In the upcoming scenario, this work will be improved in two areas: first segmentation and second feature mapping. In different deep learning, improve the classification patches by ensemble learner and feature mapping by attention mechanism in segmentation.

REFERENCES

1. V Patil, A. (2021). Detection of Melanoma Through Machine Learning with High Precision for Accuracy. *Detection of Melanoma Through Machine Learning with High Precision for Accuracy (July 11, 2021)*.
2. Tanna, R., & Sharma, T. (2021, September). Binary Classification of Melanoma Skin Cancer using SVM and CNN. In *2021 International Conference on Artificial Intelligence and Machine Vision (AIMV)* (pp. 1-4). IEEE.
3. Ramachandro, M., Daniya, T., & Saritha, B. (2021, November). Skin Cancer Detection Using Machine Learning Algorithms. In *2021*

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Innovations in Power and Advanced Computing Technologies (i-PACT) (pp. 1-7). IEEE.

4. Murugan, A., Nair, S. A. H., Preethi, A. A. P., & Kumar, K. S. (2021). Diagnosis of skin cancer using machine learning techniques. *Microprocessors and Microsystems*, *81*, 103727.
5. Yu, Z., Nguyen, J., Nguyen, T. D., Kelly, J., Mclean, C., Bonnington, P., ... & Ge, Z. (2021). Early Melanoma Diagnosis with Sequential Dermoscopic Images. *IEEE Transactions on Medical Imaging*, *41*(3), 633-646.
6. Wang, X., Jiang, X., Ding, H., Zhao, Y., & Liu, J. (2021). Knowledge-aware deep framework for collaborative skin lesion segmentation and melanoma recognition. *Pattern Recognition*, *120*, 108075.
7. Daghrir, J., Tlig, L., Bouchouicha, M., & Sayadi, M. (2020, September). Melanoma skin cancer detection using deep learning and classical machine learning techniques: A hybrid approach. In *2020 5th international conference on advanced technologies for signal and image processing (ATSIP)* (pp. 1-5). IEEE.
8. Roslin, S. E. (2020). Classification of melanoma from Dermoscopic data using machine learning techniques. *Multimedia tools and applications*, *79*(5), 3713-3728.
9. Saba, T. (2020). Recent advancement in cancer detection using machine learning: Systematic survey of decades, comparisons and challenges. *Journal of Infection and Public Health*, *13*(9), 1274-1289.
10. Albert, B. A. (2020). Deep learning from limited training data: Novel segmentation and ensemble algorithms applied to automatic melanoma diagnosis. *IEEE Access*, *8*, 31254-31269.
11. Zhou, Q., Shi, Y., Xu, Z., Qu, R., & Xu, G. (2020). Classifying melanoma skin lesions using convolutional spiking neural networks with unsupervised stdp learning rule. *IEEE Access*, *8*, 101309-101319.
12. Almaraz-Damian, J. A., Ponomaryov, V., Sadovnychiy, S., & Castillejos-Fernandez, H. (2020). Melanoma and nevus skin lesion classification using handcraft and deep learning feature fusion via mutual information measures. *Entropy*, *22*(4), 484.
13. González-Cruz, C., Jofre, M. A., Podlipnik, S., Combalia, M., Gareau, D., Gamboa, M., ... & Puig, S. (2020). Machine learning in melanoma diagnosis. Limitations about to be overcome. *Actas Dermo-Sifiliográficas (English Edition)*, *111*(4), 313-316.
14. Ameri, A. (2020). Melanoma detection with a deep learning model. *Tehran University Medical Journal TUMS Publications*, *78*(3), 150-154.
15. Alpaydin, E. (2020). *Introduction to machine learning*. MIT press.
16. Vocaturo, E., Perna, D., & Zumpano, E. (2019, November). Machine learning techniques for automated melanoma detection. In *2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)* (pp. 2310-2317). IEEE.
17. Vijayalakshmi, M. M. (2019). Melanoma skin cancer detection using image processing and machine learning. *International Journal of Trend in Scientific Research and Development (IJTSRD)*, *3*(4), 780-784.
18. Kassani, S. H., & Kassani, P. H. (2019). A comparative study of deep learning architectures on melanoma detection. *Tissue and Cell*, *58*, 76-83.
19. Giri, K. C., Patel, M., Sinhal, A., & Gautam, D. (2019, April). A novel paradigm of melanoma diagnosis using machine learning and information theory. In *2019 International Conference on Advances in Computing and Communication Engineering (ICACCE)* (pp. 1-7). IEEE.