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Review Article

Deep Learning Based Detection Approaches on Skin Cancer Detection: A Review

Su Myat Thwin[1*]

[1]Dept. of Computer Science and Engineering, Ewha Womans University, Seoul 03760, Republic of Korea

**Corresponding Author: sumyatthwin@ewhain.net*

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Abstract: Skin cancer, one of the most common malignancies worldwide, necessitates early detection for better patient outcomes and efficient treatment. Recent advancements in deep learning have shown significant promise in enhancing the accuracy and efficiency of skin cancer diagnosis. This review comprehensively examines the current state of deep learning-based approaches for skin cancer detection, highlighting key methodologies, datasets, and performance metrics. We explore the integration of Convolutional Neural Networks (CNNs), Transfer Learning, and Attention Mechanisms in dermatological imaging analysis. Additionally, we discuss the impact of modified attention mechanisms, such as spatial and channel attention, in improving model performance by focusing on critical features of skin lesions. The review also addresses challenges related to data quality, class imbalance, and model interpretability. By synthesizing findings from recent studies, this review aims to provide a detailed understanding of how deep learning technologies are transforming skin cancer detection and to identify future research directions that could further enhance diagnostic accuracy and clinical applicability.

Keywords: Deep Learning, Machine Learning, Convolutional Neural Network, Transfer Learning, Attention Mechanism, Skin Cancer Detection

1. Introduction

Skin cancer is among the most prevalent forms of cancer, affecting millions of people globally each year. Early and accurate detection is crucial for effective treatment and improved survival rates. Traditional methods of skin cancer diagnosis, such as visual examination by dermatologists followed by biopsy, are time-consuming and subject to inter-observer variability. This emphasizes how important it is to have automated, trustworthy, and effective diagnostic tools. Computer science research is focused on developing algorithms and models that can recognize skin abnormalities in photos and reliably identify skin cancer [1]. Dermatologists manually scrutinize and analyze skin samples using traditional methods for the identification of skin cancer, which can be laborious and subjective.

Skin cancer is the most prevalent type of cancer worldwide. The World Health Organization (WHO) estimates that skin cancer accounts for one in three cancer diagnoses [2]. Over the past few decades, there has been a fairly steady increase in the frequency of skin cancer diagnoses in nations such as Australia, the USA, and Canada [3, 4, 5]. The deadliest type of skin cancer is melanoma, and patients who are diagnosed with it early have considerably better prognoses [6]. However, there are insufficient medical re-sources and trained personnel to support the populace, particularly in developing nations and rural areas [7, 8]. Over the past few decades, a number of computer-aided diagnosis (CAD) systems have been introduced to address the problem of skin cancer detection. These systems generally use traditional computer vision techniques to ex-tract various aspects, like shape, color, and texture, and feed them into a classifier. [10, 11, 12, 13].

Recently, machine learning approaches have become more and more popular as a remedy for this problem. In this field, CNNs, a kind of deep learning model, have demonstrated remarkable performance. Yu et al. developed a number of learning algorithms using minimal training data and a very advanced CNN [14]. Esteva et al. [15] trained over 120 thousand pictures using a pre-trained CNN model, yielding a diagnosis that was on par with a dermatologist's. When compared to dermatologists, CNN models by Haenssle et al. [16] and Brinker et al. [17] have shown competitive or even better performance. Deep learning has been used in previous attempts to detect skin cancer, such as feature aggregation of several models [20], ensemble of models [18, 19], and others [21, 22, 23].

The progress in deep learning techniques has brought about a substantial change in the development of deep learning applied models for the diagnosis of skin cancer. These models use CNN to automatically extract information from the input pictures and predict the presence or absence of skin cancer [24]. In recent years, a number of studies have been carried out to compare the effectiveness of deep learning-based and conventional approaches for the identification of skin cancer [25]. These results show that deep learning-based models outperform conventional techniques in terms of speed and accuracy.

Nevertheless, there are still certain difficulties in applying deep learning-based models to the diagnosis of skin cancer [26]. Getting patients and dermatologists to believe the models depends on their interpretability and explain ability, which presents another difficulty. In general, computer science research on skin cancer detection is crucial and has the potential to greatly enhance skin cancer treatment and early diagnosis. Computer scientists and dermatologists will need to collaborate and conduct ongoing research in order to develop accurate and trustworthy skin cancer detection algorithms.

Deep learning has become a very effective method in medical imaging in recent years, providing notable improvements in efficiency and accuracy. A type of deep learning model called CNN has demonstrated impressive performance in image classification tasks, including the detection of skin cancer. CNNs are highly accurate in differentiating between benign and malignant tumors by automatically learning and extracting information from dermoscopic images. This paper aims to provide an extensive overview of deep learning-based techniques for skin cancer detection. This study explores multiple approaches, emphasizing the application of transfer learning, CNNs, and attention mechanisms in dermatological imaging. The significance of altered attention mechanisms, like spatial and channel attention, in improving model performance by concentrating on the most important characteristics of skin lesions is emphasized in particular.

We also address the challenges inherent in developing and deploying these models, including issues related to data quality, class imbalance, and model interpretability. By synthesizing findings from recent studies, this review aims to provide information about the state of the field today and suggest possible lines of inquiry for further study. Ultimately, this review aims to shed light on how deep learning technologies are trans-forming skin cancer detection, offering promising avenues for more accurate, efficient, and accessible diagnostic solutions.

2. Methods and Material for Skin Detection

Detecting skin cancer involves a combination of visual inspection, imaging technologies, and advanced computational methods. In this section the materials and applied methods of the skin cancer detection are presented as following.

2.1 Clinical Examination

Dermoscopic Analysis: Dermatologists use a dermatoscope to examine skin lesions. Dermatoscopy can reveal patterns and colors not visible to the naked eye, aiding in the differentiation between benign and malignant lesions. In patient history, Collect detailed information about the patient's personal and family history of skin cancer. This includes any history of melanoma, basal cell carcinoma, squamous cell carcinoma, or atypical moles. Assess risk factors such as fair skin, a history of sunburns, use of tanning beds, a large number of moles, immunosuppression, and prolonged exposure to ultraviolet (UV) radiation.

Assemble comprehensive data regarding the patient's personal and familial history of skin cancer. Any history of melanoma, squamous cell carcinoma, basal cell carcinoma, or atypical moles falls under this category. Assess risk factors such as fair skin, a history of sunburns, use of tanning beds, a large number of moles, immunosuppression, and prolonged exposure to ultraviolet (UV) radiation. Record any history of previous skin lesions or treatments and monitor any changes or new developments. Record any history of previous skin lesions or treatments and monitor any changes or new developments.

High-frequency ultrasound imaging is a powerful technique for the detection and assessment of skin cancer. When combined with advanced deep learning algorithms, it offers a non-invasive, real-time diagnostic tool that enhances the accuracy and efficiency of skin cancer detection. Future research should focus on overcoming existing challenges and integrating these technologies into routine clinical practice to improve patient outcomes.

2.2 Imaging Techniques

Effective skin cancer detection relies on various imaging techniques that capture detailed visual information about skin lesions. In this sections, new up loaded using image techniques such as Optical Coherence Tomography (OCT) and Ultrasound Imaging. OCT uses light waves to take cross-section images of the skin, allowing for the visualization of skin structure and potential abnormalities.

Low-coherence interferometry is used by OCT to produce cross-sectional skin pictures, similar to ultrasound imaging but using light instead of sound. OCT images can be integrated in-to multimodal analysis for more comprehensive lesion assessment. High-frequency sound waves are employed in ultrasound imaging to produce images of the skin and underlying tissues. High-frequency ultrasound in particular has become an important diagnostic and assessment tool for skin cancer.

This non-invasive imaging method provides vital information about the location and extent of skin lesions by creating comprehensive images of the skin and underlying tissues using high-frequency sound waves.

2.3 Computer-Aided Diagnosis (CAD)

Computer-Aided Diagnosis (CAD) systems have become an essential tool in modern dermatology, leveraging advancements in image processing, using deep learning and machine learning can increase the precision and effectiveness of skin cancer detection. CAD systems assist dermatologists by providing objective, reproducible analyses of skin lesions, thereby enhancing diagnostic confidence and potentially improving patient outcomes. CAD systems utilize various imaging modalities, digital photography, confocal laser scanning microscopy, and high-frequency ultrasound to capture de-tailed images of skin lesions. Dermoscopic images are highly detailed and commonly used in CAD systems.

A CAD system that integrates ultrasound imaging with machine learning to assess the depth and extent of skin lesions. CAD systems are transforming skin cancer detection by combining advanced imaging techniques with powerful machine learning and deep learning algorithms. These systems enhance diagnostic accuracy, reduce observer variability, and provide valuable decision support to dermatologists. Continued research and development in this field, coupled with improvements in data quality and model interpretability, will further advance the capabilities and clinical adoption of CAD systems for skin cancer detection. CAD systems have been developed, leveraging advancements in imaging technologies, machine learning, and deep learning. Using image processing algorithms, CAD systems examine digital pictures of skin lesions to look for characteristics that could be signs of skin cancer, like asymmetry, uneven borders, color fluctuation, diameter, and evolution (ABCDE criteria). In order to automatically detect and classify skin lesions, powerful computational models such as CNNs are trained on massive datasets of skin pictures in machine learning and deep learning models. This review offers a thorough analysis of CAD systems for the diagnosis of skin cancer, including their approaches, efficacy, and drawbacks.

3. Literature Review

Melanoma is the deadliest type of skin cancer, which is among the most prevalent in the world. Better patient outcomes and successful treatment depend on early identification. Clinical examination and histological investigation are two traditional methods of diagnosis, however they are often subject to subjective interpretation and call for specialist knowledge.

Skin cancer detection may now be automated and its accuracy increased thanks to recent breakthroughs in deep learning. This review summarizes the current state of research on deep learning based detection approaches for skin-cancer, highlighting key methodologies, datasets, performance metrics, and challenges. In this section, related works of the previous research on skin cancer detection based on the deep learning techniques (CNN, Transfer Learning and Attention Mechanism).

3.1 Reviews on Convolutional Neural Network

Because deep learning techniques, in particular CNNs, can automatically extract features from unprocessed picture data, they are extensively employed in the diagnosis of skin cancer. Deep learning models in particular, CNNs are frequently seen as "black boxes," which makes it challenging to decipher their forecasts and win over clinicians. Deep learning-based techniques have demonstrated some promise in the identification of skin cancer, and they may greatly enhance patient outcomes and early diagnosis. The application of CNNs has led to models that perform comparably to experienced dermatologists. However, challenges related to data quality, class imbalance, model interpretability, and clinical integration need to be addressed to fully realize the potential of these technologies. Future research should focus on creating larger and more diverse datasets, developing methods to interpret deep learning models, and ensuring seamless integration into clinical practice.

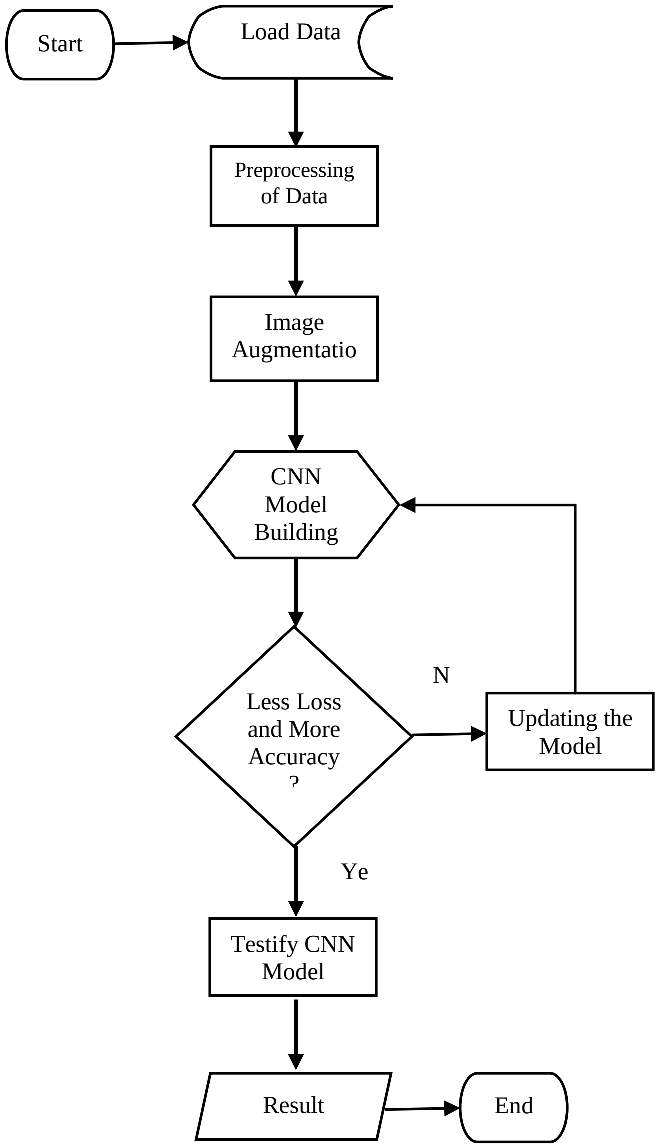

Figure 1. Steps for skin cancer detection using CNN

In the realm of medical image processing, CNNs have become indispensable, especially for the diagnosis of skin cancer. With the use of their inherent capacity to learn and extract features from unprocessed picture data, CNNs have shown great promise in the accurate diagnosis of skin cancer.

The CNN is an extension of the current neural network. In digital imaging applications, CNNs outperform fully

connected feedforward neural layers because to the weight sharing characteristics of picture pixels and spark connection. Other mathematical learning techniques, like as regularization methods, learning algorithms, and back propagation algorithms, can also be applied to CNNs, nonlinear pooling, and fully linked network layers make up CNN's hidden layer.
Convolution layers in CNN are stacked one after the other after several completely connected layers. Convolution, pooling, and full-connected layers are the three fundamental layers in the construction of a CNN. In CNN, the input size ratio is reduced by pooling layers, which lowers a set of weights that the convolution layer controls to produce output. The fully connected layer uses and receives the output from the pooling layer after the convolutional layer. The convolutional layer, a crucial part of CNN, has various weights for various applications, including photo segmentation and arithmetic 2D matrices that shown in figure 1.

This review section summarizes the current state of research on CNNs for skin cancer detection, focusing on key findings, methodologies, datasets, performance metrics, and challenges.

In [15], Esteva and et al. developed a CNN model trained on a dataset of over 129,000 clinical images representing more than 2,000 different diseases. They employed a standard CNN architecture, fine-tuned for the task of skin cancer classification. The CNN achieved performance comparable to that of board-certified dermatologists, demonstrating its potential for clinical application. Their work highlighted the feasibility of using CNNs for automated skin cancer detection and paved the way for further research in the field.

In [27], Codella et al. conducted a comprehensive analysis of many deep learning techniques for melanoma identification as a component of the ISIC (International Skin Imaging Collaboration) competition. The authors coupled ensemble learning strategies with a variety of CNN architectures, such as ResNet and Inception. The best-performing models achieved high accuracy, sensitivity, and specificity, demonstrating the effectiveness of CNNs for melanoma detection. Their work provided a benchmark for future research and highlighted the importance of large, well-annotated datasets for training robust models.

In [28], Tschandl et al. explored the collaboration between human experts and CNN models for skin cancer detection. They trained a CNN on the ISIC archive and compared its performance with that of dermatologists. Their study found that combining the CNN's predictions with those of dermatologists resulted in improved diagnostic accuracy compared to either the CNN or the dermatologists alone. This work emphasized the potential of human-AI collaboration in enhancing diagnostic performance and reducing errors.

In [29], Yunendah Nur Fu'adah et al. presented a study in which a CNN was used to develop a system that can distinguish between benign skin diseases and skin cancer. With random regulators, the CNN approach yielded an accuracy of 97.49% in this experiment. Numerous skin lesions, such as nevus lesions, carcinoma, and melanoma, can be identified using it. The augmentation data from the ISIC dataset is used in this work. This information is utilized to distinguish benign cancerous tumors from cutaneous cancerous ones. The output channel and three hidden layers make up the suggested model. The mod-el also makes use of a variety of optimizers, such as Adam, SGD, RMSprop, Nadam, and others. The CNN model using the Adam optimizer achieves the greatest results in dataset categorization, with a 99% accuracy rate.

In [30], Hasan et al. suggested conducting a study that uses automatic skin cancer detection. Images of cancer were classified as benign or malignant using CNNs. In this study, the features of skin cells affected by cancer are extracted using feature extraction approaches. The extracted characteristics are sorted in the next step using CNNs. This approach achieves 89.5% accuracy and 93.7% training accuracy using the publicly available data set. Based on the experimental and assessment portions, the procedure can be considered a standard for the diagnosis of skin cancer.

In [31], Brinker et al. conducted the first comprehensive analysis of the most re-cent studies on the use of CNN for the classification of skin cancer lesions. Whether CNN is utilized for end-to-end learning or as a feature extractor helps to classify the study's methodology. The sources of the data used in this investigation were Web of Science, ScienceDir ect, PubMed, Medline, and Google Scholar. Thirteen publications demonstrated the use of CNN to identify skin cancer lesions. CNNs have demonstrated exceptional performance as the cutting-edge skin lesion classification system. Differentiating between the different categorization strategies is challenging, though, be-cause some research employ private datasets for testing.

In [32], a study was proposed by Seung Seog Han et al. with the goal of determining whether an algorithm can automatically identify a skin lesion that may be cancerous or not. In order to extract benign lesions from photos, this study used region-based CNNs to create 924,538 potential lesions. The next action is to annotate these lesions, either automatically or manually. 1,106,886 photos were used to teach CNN to identify the area of skin cancer. In this study, a data collection of benign and normal photos is created using R-CNN technology. By using the acquired dataset to train the illness classifier and fine-image selection, malignant melanoma on the face was successfully identified. For doctors who do not specialize in dermatology, the study's diagnosis ac-curacy was greater.

In [33], Raja Subramanian et al. classified and identified skin cancer using CNN. This study makes use of clinical imaging historical data. The study's main objective is to develop a CNN model with more than 80% accuracy, more than 80% precision, and fewer than 10% false negative rate. The investigation used the HAM10000 data set, which consists of dermatoscopic images of skin lesions. There were 10,015 colored photos in the dataset overall, with the majority having a resolution of 600 by 450. A number of research articles and techniques were examined and tested. Using the HAM10000 dataset, an accuracy of at least 80% was attained. The ultimate outcome demonstrated that the most effective method for detecting skin cancer is standard CNN.

In [34], The authors highlighted a recent study that employs image processing techniques to identify skin cancer early on. The study employs whale optimization and optimal CNNs. The whale optimization algorithm is used to optimize CNN. The optimization approach employed in the network results in the best possible choice of weights and biases. Zhang et al. This is done in an attempt to reduce anticipated out-put error and network error. Digital datasets from Dermquest and DermIS were used in the study. The findings of the study were compared with those from other methods, including as the spot mole tool, conventional CNN, AlexNet VGG-16, LIN, Inception, and ResNet, as well as the semi-supervised approach. The end results show that the study offers the greatest result for skin cancer detection.

In [35], Pham et al.'s study proposal included two key additions. Using CNNs and data augmentation, a classification model was presented to improve the performance of skin cancer classification. Their second contribution was a demonstration of how to employ picture augmentation to get around the problem of limited data.

Additionally, the impact of varying numbers of enhanced samples on the performance of different classifiers was investigated through the use of picture augmentation. The largest public dataset, comprising 6,162 training and 600 testing photos, is used in this study. Furthermore, the impact of every image enhancement on three different classes was investigated. Additionally, it was noted that each classified ID's behavior and ability changed differently with each augmentation and produced more encouraging out-comes when compared to conventional approaches.

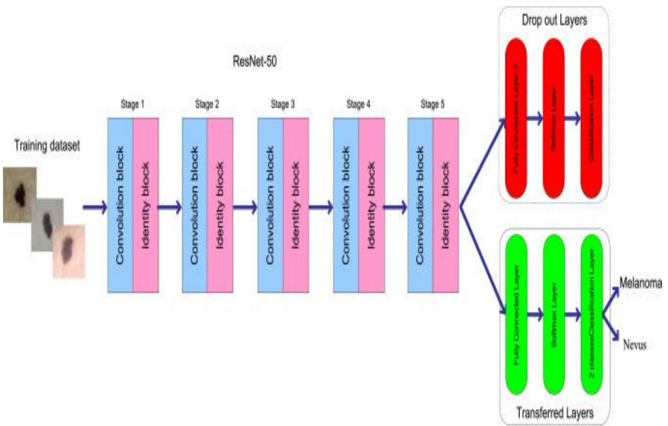

Figure 2. CNN Architecture for Skin Cancer Detection [64]

The figure 2 shows for the CNN based skin cancer detection architecture and figure 3 presents the SVM architecture for skin cancer detection.

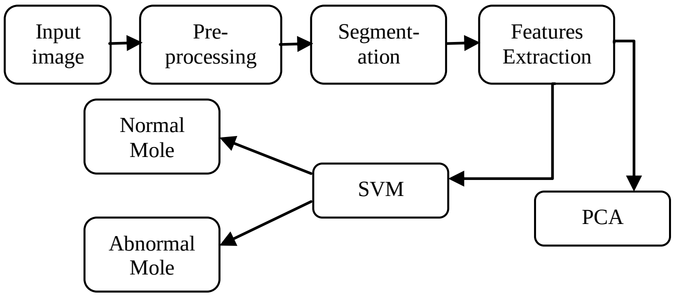

Figure 3. SVM Architecture for Skin Cancer Detection [65]

4. Discussion

The application of CNNs in skin cancer detection has shown remarkable promise, with numerous studies demonstrating their potential to match or exceed the diagnostic performance of dermatologists.

Table 1. Performance Accuracy Analysis based on CNN based Skin Cancer Detection

[Reference]	Author	Algorithm	Dataset	Accuracy
[35]	Brinker et al.	CNN	ISIC	96%
[36]	Munir et al.	CNN	ISIC	81.7%
[37]	Saba et al.	SVN & CNN	ISIC, PH2	98.4%
[38]	Goyal et al	CNN, Hybrids	ISIC, PH2	95.67%
[39]	Brinker et al.	CNN	HAM10000, ISIC	93.8%
[40]	Mahbod et al.	CNN, Hybrids	ISIC	96.3%
[41]	Hekler et al.	CNN	Own Dataset	68%
[42]	Adegun and Viriri	CNN, Hybrids	ISIC	99.2%
[43]	Zhang et al.	CNN	Own Dataset	97%
[44]	Albahar	CNN	ISIC	97.49%
[45]	Khan et al.	SVM, CNN, Hybrids	Own Dataset	96.5%
[46]	Öztürk et al.	CNN	ISIC, PH2	96.92%
[47]	Gu et al.	CNN	HAM10000	82.9%
[48]	Kaymak et al.	CNN	ISIC	94.81%
[49]	Khan et al.	SVM, CNN	PH2	97.74%
[50]	Anand et al.	CNN, Hybrids	HAM10000	97.96%
[51]	Okur and Turkan	CNN	ISIC	94%
[52]	Rahman et al.	CNN, Hybrids	ISIC, PH2	88%
[53]	Alizadeh and Mahloojifar	SVM, CNN, Hybrids	ISIC, PH2	97.5%
[54]	Shetty et al	CNN	HAM10000	95.18%
[55]	Abunadi and Senan	CNN	ISIC, PH2	97.91%

Continued advancements in data collection, model development, and integration with clinical workflows will further enhance the capabilities and adoption of these systems, ultimately improving patient outcomes. Table 1 shows the performance accuracy analysis on the previous research work of CNN based skin cancer detection.

This section provides a thorough overview based on the reported and implemented algorithms, which were created using CNNs, SVMs, and other hybrid techniques. The application of CNN algorithms has become increasingly common in this context, leading to the creation of innovative techniques such as fully CNNs (FCN) architectures [56], data augmentation methods in conjunction with "k-fold" cross-validation techniques [58], two methods for automatically detecting skin lesions are the three-step cascade design [37], and the Kaymak aggregation of new thick pooling layers for segmenting lesion regions in skin pictures [59].

The works that have been evaluated indicate that CNNs are the most widely employed algorithms in this field of study. Convolutional layers, which combine several kernels to create feature maps, are the general characteristics of CNNs. These layers are in charge of extracting the main features. Furthermore, as the pooling layers progressively shrink the image, the unique properties that will be utilized to train the model become more accurate. Applying these layers in a sequential manner begins with the initial input image in the network's first layer. A CNN's architecture can have different numbers of convolutional or pooling layers in addition to fully connected (FC) levels. FC layers' process previous features for classification before the data are available for the final output and categorization. This initiates the categorization phase, which could be repeated in layers that follow [60,61].

When CNNs are employed in conjunction with pretrained models to identify skin cancer, especially melanoma, better accuracy results have been produced. A few of the predefined algorithms that were looked at in the studies were ResNeXt, SeResNeXt, DenseNet, Xception, AlexNet, ResNet, SVMs, and random forests [62,45,60]. Moreover, it is important to highlight that there is a dearth of comprehensive documentation in-formation in the reviewed literature regarding the software libraries that were used to implement the algorithms—a point that needs to be looked into more in future re-search projects. TensorFlow and PyTorch, on the other hand, were found to be the most popular libraries for neural network building and training within the purview of the examined studies. The following graph shows how the algorithms discussed are pre-sent in the research articles that are either a general reference in the conceptual framework that is offered or part of the proposed experimental [63].

5. Conclusion

The review of deep learning-based detection approaches for skin cancer highlights significant advancements and challenges in the field. The application of convolutional neural networks (CNNs) and other deep learning models has shown promising results in the early and accurate detection of skin cancer, potentially surpassing traditional diagnostic methods. Deep learning methods, particularly CNNs, have demonstrated high accuracy in classifying skin lesions and detecting skin cancer. These models leverage large datasets and advanced image processing techniques to identify patterns that are often imperceptible to the human eye. The success of deep learning models heavily depends on the quality and quantity of the training data. High-resolution images with precise annotations are crucial for training robust models. Publicly available datasets like ISIC have played a vital role in advancing research in this area. To address the challenge of limited data, techniques such as data augmentation, synthetic data generation, and advanced preprocessing methods have been employed. These techniques help in enhancing the model's ability to generalize and perform well on unseen data. Future research should focus on creating more diverse and representative datasets, improving model interpretability, and developing standardized evaluation metrics. Collaboration between researchers, clinicians, and policymakers is essential to address these challenges and ensure the safe and effective deployment of deep learning-based skin cancer detection tools in clinical practice.

In conclusion, deep learning-based approaches have shown tremendous potential in revolutionizing skin cancer detection, offering the possibility of early diagnosis and improved patient outcomes. However, continued research and development are needed to overcome current limitations and fully realize the benefits of these advanced technologies in healthcare settings.

References

[1] X. Jin, J. Ma, Y. Wang, and Z. Li, "Melanoma recognition in dermoscopy images via skin lesion segmentation and multi-scale deep feature learning," Pattern Recognition, Vol.**104**, pp.**107316, 2020.**

[2] World Health Organization (WHO). How common is the skin cancer?, **2019**.

[3] Cancer Council Australia. "Understanding skin cancer - a guide for people with cancer, their families and friends", **2018.**

[4] Canadian Cancer Society's Advisory Committee on Cancer Statistics. Canadian cancer statistics 2014 - special topic: Skin cancers, **2014.**

[5] L. Rebecca, Siegel, D. M. Kimberly and A. Jemal. "Cancer statistics", 2019. CA: a cancer journal for clinicians, Vol.**69**, Issue.**1**, pp.**7–34, 2019.**

[6] F. Anthony, J., Jennifer, T. Johnson, C. D. Sheridan, and T.J. Caffrey "Early detection and treatment of skin cancer". American family physician, Vol.**62**, Issue.**2**, **2000**.

[7] H. Feng, J. Berk-Krauss, P. W. Feng, and J. A. Stein. "Comparison of dermatologist density between urban and rural counties in the united states". JAMA dermatology, Vol.154, Issue.11, pp.**1265–1271, 2018.**

[8] M. S. Richard, X. L. Jenny, Y. Kinfu, and R. Mario Dal Poz. "Forecasting the global shortage of physicians: an economic-and needs-based approach". Bulletin of the World Health Organization, 86:516–523B, **2008.**

[9] F. Ercal, A. Chawla, W. V. Stoecker, H. C. Lee, and R. H. Moss. "Neural network diagnosis of malignant melanoma from color images". IEEE Transactions on Biomedical Engineering, Vol.**41**, Issue.**9**, pp.**837–845, 1994.**

[10] M. Emre Celebi, Hassan A. Kingravi, Bakhtiyar Uddin, Hitoshi Iyatomi, Y. Alp Aslandogan,William V. Stoecker, and Randy H. Moss. "A methodological approach to the classification of dermoscopy images", Computerized Medical Imaging and

Graphics, Vol.**31**, Issue.**6**, pp.**362–373, 2007.**

[11] P. Wighton, T. K. Lee, H. Lui, David I. McLean, and M. Stella Atkins. “Generalizing common tasks in automated skin lesion diagnosis”, IEEE Transactions on Information Technology in Biomedicine, Vol.**15**, Issue.**4**, pp.**622–629, 2011.**

[12] I. Maglogiannis and K. K. Delibasis. “Enhancing classification accuracy utilizing globules and dots features in digital dermoscopy”. Computer Methods and Programs in Biomedicine, Vol.**118**, Issue.**2**, pp.**124–133, 2015.**

[13] C. Barata, M. E. Celebi, and J. S. Marques. “Improving dermoscopy image classification using color constancy”. IEEE Journal of Biomedical and Health Informatics, Vol.**19**, Issue.**3**, pp.**1146–1152, 2014.**

[14] L. Yu, Hao Chen, Q. Dou, J. Qin, and P.A. Heng. “Automated melanoma recognition in dermoscopy images via very deep residual networks”. IEEE Transactions on Medical Imaging, Vol.**36,** Issue.**4**, pp.**994–1004, 2017.**

[15] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun. “Dermatologist-level classification of skin cancer with deep neural networks”. Nature, 542(7639):115, **2017.**

[16] H. A. Haenssle, C. Fink, R. Schneiderbauer, F. Toberer, T. Buhl, A. Blum, A. Kalloo, A. B. H. Hassen, L. Thomas, A. Enk, et al. “Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists”. Annals of Oncology, 29(8):pp.**1836–1842**, **2018.**

[17] T. J. Brinker, A. Hekler, A. H. Enk, J. Klode, A. Hauschild, C. Berking, B. Schilling, S. Haferkamp, D. Schadendorf, T. Holland-Letz, et al. “Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task”. European Journal of Cancer, 113: pp.**47–54, 2019.**

[18] N. Codella, Q. Bao Nguyen, S. Pankanti, D. Gutman, B. Helba, A. Halpern, and J. Smith. “Deep learning ensembles for melanoma recognition in dermoscopy images”. IBM Journal of Research and Development, 61(4): pp.**5–1, 2017.**

[19] B. Harangi. “Skin lesion classification with ensembles of deep convolutional neural networks”. Journal of Biomedical Informatics, 86: pp.**25–32, 2018.**

[20] Z. Yu, X. Jiang, F. Zhou, J. Qin, D. Ni, S. Chen, B. Lei, and T. Wang. “Melanoma recognition in dermoscopy images via aggregated deep convolutional features”. IEEE Transactions on Biomedical Engineering, 66(4): pp.**1006–1016, 2019.**

[21] S. S. Han, M. S. Kim, W. Lim, G. H. Park, I. Park, and S. E. Chang. “Classification of the clinical images for benign and malignant cutaneous tumors using a deep learning algorithm”. Journal of Investigative Dermatology, 138(7): pp.**1529– 1538, 2018.**

[22] M. Attia, M. Hossny, S. Nahavandi, and A. Yazdabadi. “Skin melanoma segmentation using recurrent and convolutional neural networks”. IEEE 14th International Symposium on Biomedical Imaging, pp.**292–296, 2017.**

[23] N. Nida, A. Irtaza, A. Javed, M. H. Yousaf, and M. T. Mahmood. “Melanoma lesion detection and segmentation using deep region based convolutional neural network and fuzzy c-means clustering”. International journal of medical informatics, 124: pp.**37–48, 2019.**

[24] A. Bissoto, "Exploring the Impact of Data Augmentation and Transfer Learning for Skin Lesion Classification," in IEEE Journal of Biomedical and Health Informatics, Vol.**24**, No.**12**, pp.**3412-3422, 2020.**

[25] J. Yap, "Skin Cancer Detection Using Deep Learning-Based Convolutional Neural Network with Multi-Modal Transfer Learning," in Sensors, Vol.**21**, No.**2**, pp.**433**, **2021.**

[26] [26] D. Arora, S. Sood, and S. Bhargava, "Skin Cancer Detection Using Deep Learning: A Comparative Study," in Biocybernetics and Biomedical Engineering, Vol.**42**, No.**1**, pp.**219-231, 2022.**

[27] Codella, N. C. F., Rotemberg, V., Tschandl, P., Celebi, M. E., Dusza, S., Gutman, and Halpern, A. (2018). “Skin Lesion Analysis Toward Melanoma Detection: A Challenge at the ISIC”. IEEE Journal of Biomedical and Health Informatics, Vol.**23,** Issue.**2**, pp.**501-512, 2017.**

[28] Tschandl, P., Rinner, C., Apalla, Z., Argenziano, G., Codella, N., Halpern, A., ... & Kittler, H., Human–computer collaboration for skin cancer recognition. Nature Medicine, Vol.**26**, Issue.**8**, pp.**1229-1234, 2019.**

[29] Fu’adah YN, Pratiwi NC, Pramudito MA, Ibrahim N. Convolutional Neural Network (CNN) for automatic skin cancer classification system. In: IOP Conference Series: Materials Science and Engineering. Vol 982. IOP Publishing Ltd; **2020**. doi:10.1088/1757-899X/982/1/012005).

[30] Hasan M, Barman S das, Islam S, Reza AW. Skin cancer detection using convolutional neural network. In: ACM international conference proceeding A. Shah, M. Shah, A. Pandya et al. Clinical eHealth 6 (2023) 76–84 83 series. Association for Computing Machinery; pp.**254-258, 2019**. doi:10.1145/ 3330482.3330525.

[31] Brinker TJ, Hekler A, Utikal JS, et al. “Skin cancer classification using convolutional neural networks: Systematic review. “J Med Internet Res.; 20(10), **2018**. https://doi.org/10.2196/11936.

[32] Han SS, Moon IJ, Lim W, et al. “Keratinocytic skin cancer detection on the face using region-based convolutional neural network”. JAMA Dermatol, Vol.**156**, Issue.**1**, pp.29–37, **2020.**

[33] Raja Subramanian R, Achuth D, Shiridi Kumar P, kumar Reddy KN, Amara S, Chowdary AS. “Skin cancer classification using Convolutional neural networks”. In: Proceedings of the Confluence 2021: 11th International Conference on Cloud Computing, Data Science and Engineering. Institute of Electrical and Electronics Engineers Inc.; pp.**13-19, 2021.**

[34] Zhang N, Cai YX, Wang YY, Tian YT, Wang XL, Badami B. “Skin cancer diagnosis based on optimized convolutional neural network”. Artif Intell Med.;102, **2020.** https://doi.org/10.1016/j.artmed.2019.101756.

[35] Brinker, T.J.; Hekler, A.; Enk, A.H.; Klode, J.; Hauschild, A.; Berking, C.; Schilling, B.; Haferkamp, S.; Schadendorf, D.; HollandLetz, T.; et al. “Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task.” Eur. J. Cancer, 113, pp.**47–54, 2019.**

[36] Munir, K.; Elahi, H.; Ayub, A.; Frezza, F.; Rizzi, “A. Cancer diagnosis using deep learning: A bibliographic review.” Cancers, 11, 1235, **2019.**

[37] Saba, T.; Khan, M.A.; Rehman, A.; Marie-Sainte, S.L. Region Extraction and Classification of Skin Cancer: A Heterogeneous framework of Deep CNN Features Fusion and Reduction. J. Med. Syst., 43, 289, **2019.**

[38] Goyal, M.; Oakley, A.; Bansal, P.; Dancey, D.; Yap, M.H. “Skin Lesion Segmentation in Dermoscopic Images with Ensemble Deep Learning Methods”. IEEE Access, 8, pp.**4171–4181, 2020.**

[39] Brinker, T.J.; Hekler, A.; Enk, A.H.; Klode, J.; Hauschild, A.; Berking, C.; Schilling, B.; Haferkamp, S.; Schadendorf, D.; Fröhling, S.; et al. “A convolutional neural network trained with dermoscopic images performed on par with 145 dermatologists in a clinical melanoma image classification task”. Eur. J. Cancer, 111, pp.**148–154, 2019.**

[40] Mahbod, A.; Schaefer, G.; Wang, C.; Dorffner, G.; Ecker, R.; Ellinger, I. “Transfer learning using a multi-scale and multi-network ensemble for skin lesion classification.” Comput. Methods Programs Biomed., 193, 105475, **2020.**

[41] Hekler, A.; Utikal, J.S.; Enk, A.H.; Solass, W.; Schmitt, M.; Klode, J.; Schadendorf, D.; Sondermann, W.; Franklin, C.; Bestvater, F.; et al. “Deep learning outperformed 11 pathologists in the classification of histopathological melanoma images.” Eur. J. Cancer, 118, pp.**91–96, 2019.**

[42] Adegun, A.; Viriri, S. “Deep learning techniques for skin lesion analysis and melanoma cancer detection: A survey of state-of-theart.” Artif. Intell. Rev., 54, pp.**811–841, 2021.**

[43] Zhang, N.; Cai, Y.X.; Wang, Y.Y.; Tian, Y.T.; Wang, X.L.; Badami, B. “Skin cancer diagnosis based on optimized convolutional neural network.” Artif. Intell. Med., 102, 101756, **2020.**

[44] Albahar, M.A. “Skin Lesion Classification Using Convolutional Neural Network with Novel Regularizer”. IEEE Access, 7,

pp.**38306–38313, 2019.**
[45] Khan, M.A.; Sharif, M.I.; Raza, M.; Anjum, A.; Saba, T.; Shad, S.A. “Skin lesion segmentation and classification: A unified framework of deep neural network features fusion and selection.” Expert Syst., 39, e12497, **2022.**
[46] Öztürk, ¸S.; Özkaya, U. Skin Lesion Segmentation with Improved Convolutional Neural Network. J. Digit. Imaging, 33, pp.**958–970, 2020.**
[47] Gu, Y.; Ge, Z.; Bonnington, C.P.; Zhou, J. “Progressive Transfer Learning and Adversarial Domain Adaptation for Cross-Domain Skin Disease Classification.” IEEE J. Biomed. Health Inform., 24, pp.**1379–1393, 2020.**
[48] Kaymak, R.; Kaymak, C.; Ucar, A. “Skin lesion segmentation using fully convolutional networks: A comparative experimental study”. Expert Syst. Appl., 161, 113742, **2020.**
[49] Khan, M.A.; Akram, T.; Sharif, M.; Javed, K.; Rashid, M.; Bukhari, S.A.C. “An integrated framework of skin lesion detection and recognition through saliency method and optimal deep neural network features selection.” Neural Comput. Appl., 32, pp.**15929–15948, 2020.**
[50] Anand, V.; Gupta, S.; Koundal, D.; Singh, K. “Fusion of U-Net and CNN model for segmentation and classification of skin lesion from dermoscopy images.” Expert Syst. Appl., 213, 119230, **2023.**
[51] Okur, E.; Turkan, M. “A survey on automated melanoma detection”. Eng. Appl. Artif. Intell., 73, pp.**50–67, 2018.**
[52] Rahman, Z.; Hossain, M.S.; Islam, M.R.; Hasan, M.M.; Hridhee, R.A. “An approach for multiclass skin lesion classification based on ensemble learning.” Inform. Med. Unlocked, 25, 100659, **2021.**
[53] Alizadeh, S.M.; Mahloojifar, A. Automatic skin cancer detection in dermoscopy images by combining convolutional neural networks and texture features. Int. J. Imaging Syst. Technol., 31, pp.**695–707, 2021.**
[54] Shetty, B.; Fernandes, R.; Rodrigues, A.P.; Chengoden, R.; Bhattacharya, S.; Lakshmanna, K. “Skin lesion classification of dermoscopic images using machine learning and convolutional neural network.” Sci. Rep., 12, 18134, **2022.**
[55] Abunadi, I.; Senan, E.M. “Deep learning and machine learning techniques of diagnosis dermoscopy images for early detection of skin diseases.” Electronics, 10, 3158, **2021.**
[56] Oskal, K.R.; Risdal, M.; Janssen, E.A.; Undersrud, E.S.; Gulsrud, T.O. “A U-net based approach to epidermal tissue segmentation in whole slide histopathological images.” SN Appl. Sci., 1, 672, **2019.**
[57] Shetty, B.; Fernandes, R.; Rodrigues, A.P.; Chengoden, R.; Bhattacharya, S.; Lakshmanna, K. “Skin lesion classification of dermoscopic images using machine learning and convolutional neural network.” Sci. Rep., 12, 18134, **2022.**
[58] Nasr-Esfahani, E.; Rafiei, S.; Jafari, M.H.; Karimi, N.; Wrobel, J.S.; Samavi, S.; Soroushmehr, S.M.R. “Dense pooling layers in fully convolutional network for skin lesion segmentation.” Comput. Med. Imaging Graph., 78, 101658, **2019.**
[59] Amin, J.; Sharif, A.; Gul, N.; Anjum, M.A.; Nisar, M.W.; Azam, F.; Bukhari, S.A.C. “Integrated design of deep features fusion for localization and classification of skin cancer.” Pattern Recognit. Lett., 131, pp.**63–70, 2020.**
[60] Spyridonos, P.; Gaitanis, G.; Likas, A.; Bassukas, I.D. A convolutional neural network based system for detection of actinic keratosis in clinical images of cutaneous field cancerization. Biomed. Signal Process. Control, 79, 104059, **2023.**
[61] Iqbal, S.; Qureshi, A.N.; Mustafa, G. Hybridization of CNN with LBP for Classification of Melanoma Images. Comput. Mater. Contin., 71, pp.**4915–4939, 2022.**
[62] Al-masni, M.A.; Kim, D.H.; Kim, T.S. Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification. Comput. Methods Programs Biomed., 190, 105351, **2020.**
[63] Mahbod, A.; Schaefer, G.; Ellinger, I.; Ecker, R.; Pitiot, A.; Wang, C. Fusing fine-tuned deep features for skin lesion classification. Comput. Med. Imaging Graph., 71, pp.**19–29, 2019.**
[64] Sara Medhat, Hala Abdel-Galil, Amal Elsayed Aboutabl, Hassan Saleh, “Skin cancer diagnosis using convolutional neural networks for smartphone images: A comparative study”, Journal of Radiation Research and Applied Sciences, pp.**262–267, 2022.**
[65] S. Mane, S. Shinde, “Different Techniques for Skin Cancer Detection Using Dermoscopy Images”, Published 31 December **2017.** DOI:10.26438/IJCSE/V5I12.159163.