Journal of Harbin Engineering University
ISSN: 1006-7043

Vol 45 No. 7
July 2024

An Innovative Approach for Detecting Skin Diseases using Deep CNN Classifier Model

Faisal Khan[1], Pradheep manisekaran[2]
Department of computer science and Engineering
Chhatrapati Shivaji Maharaj University, Navi Mumbai, India

Abstract
Dermatology is one of the most unpredictable and challenging fields to diagnose, due to the intricacies involved in the process. In the field of dermatology, determining the potential skin problem a patient may be experiencing frequently requires doing thorough tests. Depending on the practitioner, the time may differ. This is also predicated on the individual's experience. Therefore, a system that is capable of diagnosing skin diseases without these limitations is required. We suggest an automated image-based approach that uses machine learning classification to identify skin conditions. This system will process, evaluate, and relegate the picture data according on different aspects of the photos by using computational techniques. Skin visuals are processed to improve the image quality and filtered to eliminate unwanted noise. Using sophisticated methods like Convolutional Neural Networks (CNNs), extract features from the image, categorize it using the Softmax classifier algorithm, and create a diagnosis report. This application will be an effective and reliable technique for the detection of dermatological diseases since it will produce results more quickly and with greater precision than the conventional method. Moreover, dermatology stream medical students can use this as a trustworthy real-time detection tool.

Keywords: Skin, Diseases, Convolutional neural networks, Feature extraction, Machine learning, deep Learning

1. Introduction

Skin conditions impact millions of individuals worldwide, spanning all age groups and socioeconomic backgrounds, making them one of the most common health concerns. Effective management and treatment of skin disorders depends on timely and correct diagnosis. On the other hand, dermatological diagnosis can be difficult and therefore calls for specific knowledge. Recent developments in artificial intelligence, especially in deep learning, have demonstrated encouraging outcomes in automating the diagnosis of a range of illnesses, including skin disorders. Convolutional neural networks, or CNNs, are a potent tool for image recognition applications, which makes them ideal for image analysis in dermatology [1]. Accurate classification of skin lesions and disorders is made possible by CNNs' ability to automatically recognize and extract complex patterns and features from images. Even in situations where access to dermatologists is restricted, using CNNs in a skin disease detection system has the potential to completely transform dermatological diagnosis by offering quick and accurate analyses. Our skin disease detection system seeks to provide a quick and easy way to diagnose a variety of skin disorders by utilizing deep learning and CNN capabilities. In the end, we aim to improve the science of dermatology while also empowering medical practitioners through the automated study and classification of skin lesions.

Since skin cancer patients can die at a rate of up to 75%, according to American Cancer Society illness estimates, and melanoma incidence, which raises the death rate, is still rising at 14%. Skin cancer can occur at any stage of life and is one of the cancer kinds with the highest death rate [2]. Cancer can arise anywhere in the trillions of cells that comprise the human body. When someone has cancer, their cells divide unchecked and spread throughout the surrounding tissues. Human cells normally divide and multiply to make new ones in response to the body's demands. The World Health Organization (WHO) projects that skin cancer accounts for a significant portion of all cancer diagnoses worldwide. Dermatologists assess clinical information about the patient, look for signs of skin cancer, and categorize lesions according to their experience. Cancer can result in two different types of tumors: benign and malignant. Tumors classified as malignant have a high concentration of cancerous cells. A cell's potential to infiltrate or spread to neighbouring tissues is indicated by its malignancy. A benign tumour cannot grow back once it has been removed, but a malignant tumour may do so even after surgery. While benign tumors in many human organs are typically not deadly, benign tumors in the brain can pose a threat to life. The 5-year survival percentage for a circumscribed, early-stage malignant skin tumour is 99%; however, if the tumour spreads to other body parts, the survival rate falls to 20%. Occasionally, it comes in a range of dark colours [3]. Furthermore, it could show up in the skin as royal purple, rose pink, azure, or even be colourless. It spreads more quickly, making it more harmful and deadly. Although it usually appears on the back of the lower limb, melanoma can occur anywhere on the human body. Early detection of skin cancer can lower genetic risk factors associated with skin. A number of radar systems have been developed for use in therapeutic settings, such as the detection of glucose levels, precise breathing measurements, blood pressure computation, and breast cancer diagnosis. Mm-wave radars detect skin cancer by comparing the electrical properties of melanomas with those of healthy skin tissues. This paper addresses the complex permittivity of skin at micrometre frequencies through theoretical modelling and experimental findings. It is true that two non-invasive in-package reflectometry devices operating at 42 GHz and 70 GHz have been utilized to identify problems in tissue samples, including slightly earlier skin cancers [4].

Multiple imaging techniques are used more efficiently for skin cancer detection, and deep learning algorithms dramatically increase skin cancer detection performance. Not many of the more popular technologies that have been proposed as substitutes for the automatic procedures and visual examination of the disease have materialized. Dermoscopy images seem to be particularly difficult to use to actively monitor melanoma because of the numerous interfering factors, including keratin on the uppermost layer of skin, compounds that make skin lesions more evident, and distinctive disks used for extra identification. The goal of dermoscopy techniques is to provide a clear image of the skin lesion; to enhance the visual effect, reflection is removed. However, due to artefacts, skin colour, low contrast, hairs, veins, and similar appearances of melanoma and non-melanoma, automatic skin lesion recognition may be difficult [5]. Nowadays, with colour features containing high-level visual information, there is an increasing need for colour feature surveys. Dermoscopy uses incident light and a polarized magnifying glass to locate features on the skin's surface. This approach has a higher disease detection rate than unassisted observations. However, the dermatologist's expertise is the only thing that affects how accurate the detection is. The rising demand for computer-aided diagnostic (CAD) systems for malignancy is a result of its high prevalence and dearth of professionals. Recent advances in deep neural networks (DNNs) have made it possible for medical image analysis to automatically classify various types of skin diseases. Nowadays, with colour features containing high-level visual information, there is an increasing need for colour feature surveys.

Following are the objectives of the research:

- There are numerous studies on the detection of skin cancer, however there are still issues with increasing accuracy and reducing on computation time. The main goal of this research is to use deep CNN classifier cancer to accurately predict skin cancer in less time and with lower latency.
- A fine adjustment improved the classifier's robustness and convergence, enabling it to identify skin cancer in a shorter amount of time.
- This analysis makes it possible to demonstrate CNN's superiority over other current techniques, followed by comparison techniques included in the study.

2. Literature Work

Following a survey of the numerous literature studies on skin cancer, the following interpretations of the observations are made: Pacheco and Krohling used a meta block to help in the effect classification of skin cancer to tackle the challenges related to image composition and metadata feature extraction. Because metadata was enabled, performance increased and higher statistical test results and balanced accuracy were obtained. Although the approach increased stability, more model improvement is required to produce findings that are more.

Authors in [6] used a lightweight network, where the CNN is efficiently used to extract the features, to detect the lesions in the dermoscopy pictures. To extract the discriminative lesions that contribute to improved performance, a fusion technique was used. Both the segmentation accuracy and precision of the approach were enhanced. The extraction of the discriminative features is hampered by the limitations in the data. Authors in [7] used a unique system that relied on transfer learning to detect skin cancer. The approach was primarily focused on melanoma because of the high death rate from melanoma-related cancer. By turning on the augmentation approaches, the system was also able to prevent data imbalance problems while successfully identifying the normal and melanoma-affected regions. When the ROI was specified, this method produced the best results; however, the metrics values were noticeably low when the entire image was used. After [8] identified the type of skin lesion in the pictures, localization and segmentation were completed. After the binary images are fused with the 16-layered CNN model's layers, a contrast transform model is employed to carry out the segmentation process. The down-sampling removed the redundant data from the model. For increased efficiency, the method's time consumption for lesions recognition might be decreased.

In [9], authors used a deep learning system to identify cancer and distinguish between different types of moles. Even in cases of heterogeneity, the approach performed well and could identify from the retrained images. This technique reduced false negatives while improving detection performance. Although the approach used less computing power, it created challenges in addressing the interclass variation problems. [10] used deep CNN to identify and categorize skin cancer while allowing for the use of several augmentation methods. The technique reduced the noise and significantly increased the image's resolution. The best training period and image enhancement allowed for an accurate illness classification. The training that was given to the classifier is not fully interpreted by the research.

The authors of [11] used an optimized CNN to diagnose skin cancer and turned on whale optimization to improve the classifier's performance. Gradient descent and multilayer perception modeling helped to reduce the discrepancy between the network's actual response and the desired value. Although the strategy produced improved results, there is still room for improvement in terms of comprehensibility. Writers in [12] An early-stage skin cancer detection probe was created. The technique that can extract the proper impacted photos can make advantage of the dielectric substrate that was utilized in the probe to give accurate matching on the skin. Because of its low cost and potential for mass production, this technology is widely available. There is additional computational complexity in this strategy. The second approach employed a classifier called bag-of-features, which used color and texture cues to classify the skin lesions once they were identified using global methods. When the color feature was employed exclusively, this strategy produced better results. The identification of the epidermal area was crucial for the detection of skin cancer. This was accomplished by [13] utilizing watershed segmentation, and feature extraction was carried out using GLCM and ABCD rules from the segmented picture. The SVM classifier was then used to classify the retrieved characteristics. Because the SVM is non-parametric and non-linear, its operation is low.

Partial-difference equations (PDEs) were utilized by the authors in [14] to identify the boundaries of skin lesions from digital photographs. Anisotropic diffusion and contrast enhancement were both employed in the preprocessing stage, and the PDE-filter was utilized to eliminate any hair that was visible in the images. A limited region can be covered by this strategy. By applying the color histogram approach to dermoscopy images, [15] was able to identify the skin lesion from several locations. One of the features of this approach was its ability to identify the internal lesion locations. Jaisakthi, et al.'s skin lesion identification process includes two steps. The segmentation method known as the GrabCut algorithm is used to eliminate the lighting, hair, and rulers. When K-means clustering is combined with colour features, border segmentation is enhanced and the dice coefficient value is low. A system for separating skin into malignant and non-cancerous categories was created in [15]. Fuzzy C-means clustering is used to distinguish the skin patches that are comparable. The LBP and GLCM preprocessing methods enhanced the picture attribution.

There are issues in efficiently optimizing the classifier and selecting the appropriate solution in the allotted period. It is a difficult challenge to diagnose skin cancer in less time than the specified period with lower latency in the investigation. Correct diagnosis is challenging and requires adequate training and competence, even though dermoscopy is a non-invasive diagnostic technique that uses optic magnification to permit the viewing of morphologic features that are invisible to the unaided eye. An important issue that can lead to biased learning and negatively impact performance is data imbalance. The complex combination of lesion features and background makes it challenging to automatically identify lesions in dermoscopy images. Future algorithmic applications may encounter challenges due to the larger model size, though, as it is imperative to resolve overfitting issues as they directly affect the accuracy of detecting malignant melanoma. The classifier's computational complexity may rise while training large amounts of data; this should be kept to a minimum to ensure the classifier is appropriate for real-world situations.

With about 9500 new cases identified each day, skin cancer is an emerging illness that is spreading more quickly. It ranks 13th among all cancers in men and 15th among all cancers in women. The consequences of this skin cancer include serious financial losses as well as a life-threatening risk. If the illness is discovered early on, these effects may be substantially mitigated. The enormous dimensionality of the data, the need for substantial memory resources for processing, the asymmetry of the data, the interclass variance, the absence of information regarding classifier training, and other issues made the previous methods quite challenging. Therefore, the creation of a unique framework is required to increase efficiency even further. A schematic representation of the basic methods established for skin cancer diagnosis is shown in Figure 1.

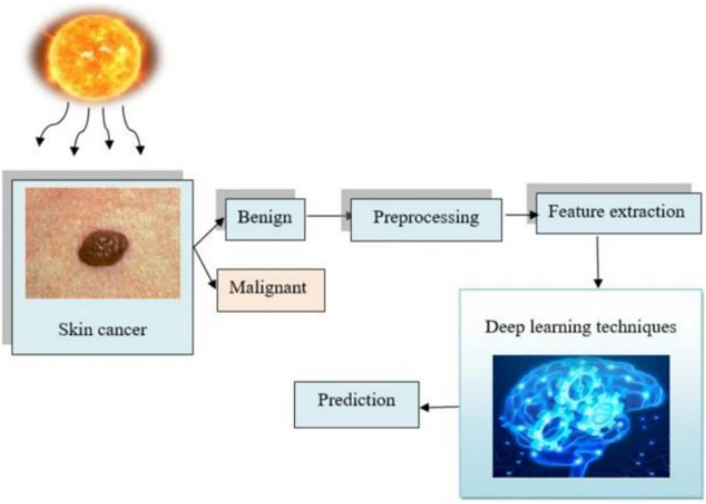


Figure 1: Framework for Skin Cancer Detection

3. Materials and Methodology

Recent advancements in computer-aided diagnosis through picture analysis have elevated the method to a sophisticated level in the medical and technological domains. Because it decreases the image dimension without losing any features, the proposed deep CNN is frequently employed. One of the diseases with a high death rate is skin cancer, and correctly classifying skin lesions from photographs is challenging because to the fine-grained variation in how skin lesions form. Information about various patients is gathered by attaching IoT nodes to patients, and this information is then collected and stored in the standard repository. The gathered data will be kept on cloud storage for further use.

- **Dataset Used**
  This set consists of 2357 images of malignant and benign oncological diseases, which were formed from The International Skin Imaging Collaboration (ISIC). All images were sorted according to the classification taken with ISIC, and all subsets were divided into the same number of images, with the exception of melanomas and moles, whose images are slightly dominant [16].

- **Data Pre-Processing**
  The development of the dataset is predicated upon two groups, namely benign and malignant. First, the necessary libraries are imported. Next, the photos are loaded. Next, the dictionary of images is labeled. Finally, the labels are categorized. After the training and testing sets of data are divided and the normalization function is activated, cross-validation is carried out.

- **Data Augmentation**
  The process of removing over-fitting issues, resizing, cropping, and reshaping the data makes the new data fully prepared for the experiment. The new data is retrieved from the existing training data.

- **CNN**
  CNNs are neural networks with a specific architecture that have been shown to be very powerful in areas such as image recognition and classification. CNNs have been demonstrated to identify faces, objects, and traffic signs better than humans and therefore can be found in robots and self-driving cars. CNNs are a supervised learning method and are therefore trained using data labeled with the respective classes. Essentially, CNNs learn the relationship between the input objects and the class labels and comprise two components: the hidden layers in which the features are extracted and, at the end of the processing, the fully connected layers that are used for the actual classification task. Unlike regular neural networks, the hidden layers of a CNN have a specific architecture. In regular neural networks, each layer is formed by a set of neurons and one neuron of a layer is connected to each neuron of the preceding layer. The architecture of hidden layers in a CNN is slightly different. The neurons in a layer are not connected to all neurons of the preceding layer; rather, they are connected to only a small number of neurons. This restriction to local connections and additional pooling layers summarizing local neuron outputs into one value results in translation-invariant features. This results in a simpler training procedure and a lower model complexity.

In this section, the individual CNN methods used to classify skin lesions are presented. CNNs can be used to classify skin lesions in two fundamentally different ways. On the one hand, a CNN pre-trained on another large dataset, such as ImageNet, can be applied as a feature extractor. In this case, classification is performed by another classifier, such as k-nearest neighbors, support vector machines, or artificial neural networks. On the other hand, a CNN can directly learn the relationship between the raw pixel data and the class labels through end-to-end learning. In contrast with the classical workflow typically applied in machine learning, feature extraction becomes an integral part of classification and is no longer considered as a separate, independent processing step. If the CNN is trained by end-to-end learning, the research can be additionally divided into two different approaches: learning the model from scratch or transfer learning.

4. System Design and Architecture

One of the diseases with a high death rate is skin cancer, and correctly classifying skin lesions from photographs is challenging because to the fine-grained variation in how skin lesions form. Using a modified deep boosted deep CNN classifier that is equipped with a skin cancer detection dataset, the primary goal of this research is to detect skin cancer. The base station acts as the central hub of the network, sending data to its destination from a variety of sources. The massive amount of collected data from the base station is distilled for in-depth examination using a data aggregation technique. Once acquired, the aggregated data is subjected to preprocessing. Skin cancer disease detection characteristics are extracted using feature extraction, and image quality is enhanced

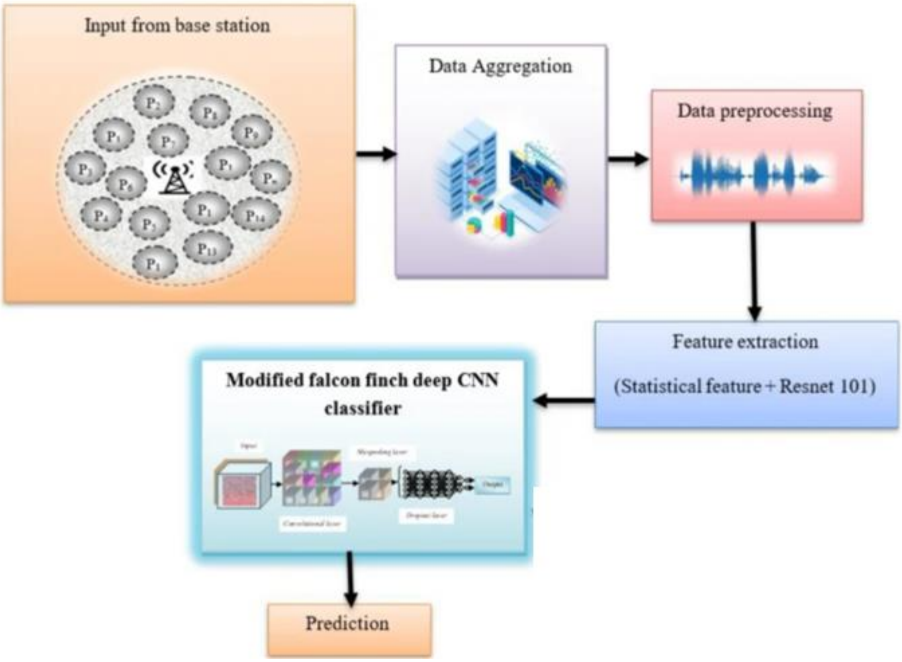


Figure 2: System Design of the Proposed Work

through preprocessing, which eliminates unnecessary noise. A systematic illustration of the suggested skin cancer diagnosis paradigm is shown in Figure 2. The process of feature extraction involves the extraction of features, statistical features, and other relevant information. These elements are then input into a modified version of the deep CNN classifier, which effectively predicts the existence of skin disease.

Data Collection

The input image needed for skin cancer identification is gathered from the standard skin cancer detection dataset repository. The dataset is obtained from the International Skin Image Collaboration Archive, and information is collected from a range of patients and kept in the base station, which facilitates communication. There are 2357 images in total in the dataset; there are 1800 images of benign moles and 1497 images of malignant categorized moles. Every image has been scaled to 224 × 224 × 3 RGB low resolution. When appropriate access is granted, users can retrieve data from the base station at any time. The research's input data is expressed mathematically as follows:

$$S = \{S_1,\ S_2,\ S_3 \ldots\ldots\ldots S_m\}$$

here, S designates the skin cancer detection dataset and the number of images in the dataset is depicted by m.

Data Pre-Processing

Through the process of data aggregation, a large amount of data is condensed to enable in-depth analysis. At its most basic level, it involves collecting data from a range of designated patients, arranging it into a more user-friendly and easy model, and then representing the aggregated data. Quick NL Averages In this study, de-noising preprocessing is applied to reduce noise, resize, and reshape the image during the preprocessing phase, all of which contribute to enhancing the image's actual quality as indicated by

$$S = \sum Pre\left(S_m^*\right)$$

This stage is also responsible to carry out the process labeling the data and resizing the obtained images using OpenCv. In the next stage, the process of binarization also takes place; wherein the output is binarized as either 0 or 1. This step enhances the overall prediction mechanism of the research.

EDA

An essential component of machine learning is data visualization, which helps analysts comprehend and interpret patterns, connections, and trends in data. Data visualization is an essential part of machine learning because it makes insights and patterns in data easily analyzed and presented. The figure below illustrates visualization of the dataset thus obtained.

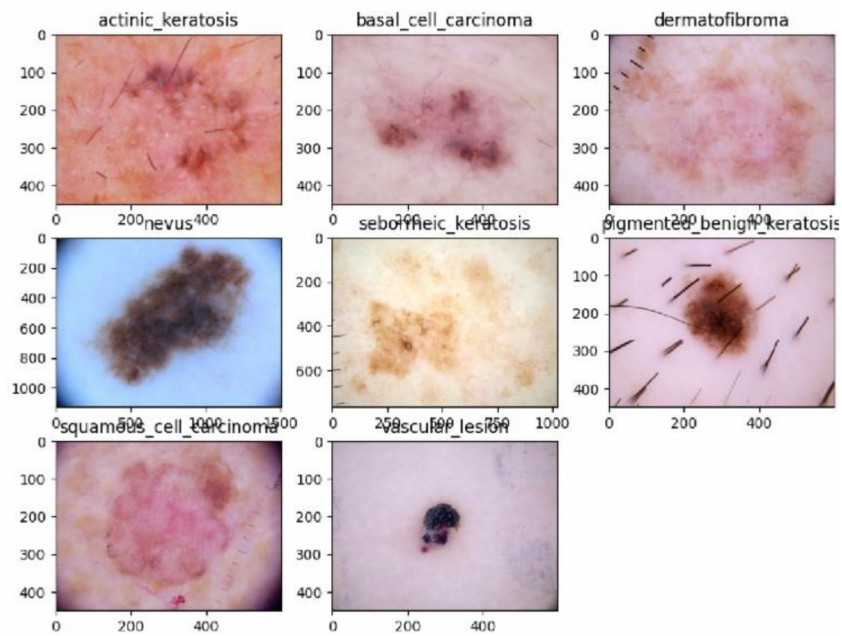


Figure 3: EDA of the dataset

Data Balancing

When it comes to binary classification tasks, machine learning researchers are frequently faced with imbalanced datasets. Practical commercial applications such as spam filtering, hardware malfunction detection, fraud detection, and unusual disease diagnosis routinely encounter this situation. One well-liked method for resolving this problem is the Synthetic Minority Oversampling Technique (SMOTE). SMOTE creates artificial samples for the minority class with the express purpose of addressing imbalanced datasets. The importance of SMOTE in addressing class imbalance is examined in this paper, with an emphasis on how it can be used to enhance classifier model performance. SMOTE improves model performance and accuracy by reducing bias and capturing significant characteristics of the minority class.

Model Evaluation The study's sensitivity, specificity, and accuracy are tested to show how effective the model is. On a Windows 10 PC with 8 GB of RAM, the PYTHON program is used for the research. The network's hyperparameters include a batch size of 32, 100 epochs, Adam as the default optimizer and relu and softmax as the

Figure 4: Accuracy VS Loss graph

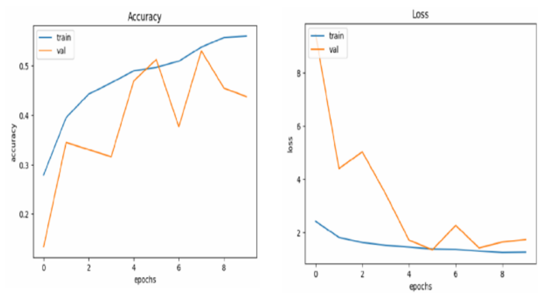
activation functions. The metrics used for measuring the improvement are measured concerning the k-fold and the training percentage and are described as follows,

Accuracy: The measure of how accurately the modified falcon finch deep CNN identified the skin cancer is measured using this metrics and is given by,

$$Acc = \frac{P_t + N_t}{P_t + N_t + P_f + N_f}$$

5. Results and Analysis

In the test dataset, the model showed excellent efficiency and accuracy in recognizing a range of dermatological diseases. Evaluation measures such as F1-score, precision, and recall consistently showed strong



performance in a variety of skin conditions.

The figure above depicts the increase in accuracy and a decrease in loss with the number of epochs thus taken. The table below depicts the classification table of the same:

Table 1: Classification Report

	precision	recall	f1-score	support
0	0.36	0.27	0.31	48
1	0.21	0.08	0.12	48
2	0.37	0.69	0.48	48
3	0.61	0.65	0.63	48
4	0.46	0.62	0.53	47
5	0.88	0.48	0.62	48
6	0.00	0.00	0.00	48
7	0.48	0.94	0.63	48
accuracy			0.46	383
macro avg	0.42	0.47	0.41	383
weighted avg	0.42	0.46	0.41	383

The efficacy of the model in automating the diagnostic process was demonstrated by its precise localization and classification of lesions. The system's capacity to recognize skin conditions that were not experienced during the training phase further demonstrated the system's real-world applicability and highlighted its generalization skills. The system's versatility and ability to assist dermatologists in complete diagnostics were enhanced by the incorporation of a diverse range of datasets.

6. Conclusions

This study performs skin cancer detection using deep CNN. These methods are mostly suitable for on-the-spot medical applications, especially in dermatology. In this work, deep CNN is used to diagnose the condition more accurately. The updated CNN classifier allowed for error-free analysis of the data relevant to skin cancer. Because the method offered the feeding and perching traits required for effective parameter tuning, its incorporation in the deep CNN classifier was significant. This modification allows the classifier to identify skin cancer faster while maintaining stronger and better convergence.

References

[1] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118

[2] Haenssle, H. A., Fink, C., Schneiderbauer, R., Toberer, F., Buhl, T., Blum, A., ... & Enk, A. (2018). 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), 1836-1842

[3] Tschandl, P., Rosendahl, C., & Kittler, H. (2017). The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. Scientific data, 4(1), 1-8

[4] Menegola, A., Tavares, J., & Fornaciali, M. (2017). Deep learning for skin lesion classification. In International Conference on Computational Science (pp. 302-311). Springer, Cham

[5] Brinker, T. J., Hekler, A., Enk, A. H., Klode, J., Hauschild, A., Berking, C., ... & Schadendorf, D. (2019). Deep learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task. European Journal of Cancer, 113, 47-54

[6] Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., & Torralba, A. (2016). Learning deep features for discriminative localization. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2921-2929)

[7] He, K., Gkioxari, G., Dollar, P., & Girshick, R. (2017). Mask R-CNN. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2980-2988

[8] Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologistlevel classification of skin cancer with deep neural networks. Nature, 542(7639), 115-118
[9] Shen, D., Wu, G., & Suk, H. I. (2017). Deep Learning in Medical Image Analysis. Annual Review of Biomedical Engineering, 19, 221-248
[10] Girshick, R. (2015). Fast R-CNN. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), 1440-1448
[11] Ronneberger, O., Fischer, P., & Brox, T. (2015). U-Net: Convolutional Networks for Biomedical Image Segmentation. In International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI), 234-241
[12] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., & Reed, S. (2016). SSD: Single Shot MultiBox Detector. In European Conference on Computer Vision (ECCV), 21-37
[13] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You Only Look Once: Unified, Real-Time Object Detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 779-788
[14] Argenziano G, Soyer HP. Dermoscopy of pigmented skin lesions: A valuable tool for early diagnosis of melanoma. Lancet Oncol 2001 Jul;2(7):443-449
[15] Kittler H, Pehamberger H, Wolff K, Binder M. Diagnostic accuracy of dermoscopy. Lancet Oncol 2002 Mar;3(3):159-165
[16] https://challenge2018.isic-archive.com/