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Proactive Cancer Screening Through Convolution Neural Networks

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ABSTRACT

Melanoma represent one of the most perilous types of skin cancer due to their rapid progression and the challenges associated with diagnosis. This research used the HAM10000 dataset to demonstrate Convolutional Neural Networks (CNNs), the most sophisticated deep learning model for classifying skin cancer lesions. During this investigation, we gathered 10,015 dermatoscopic images and classified them into seven separate kinds of skin lesions. The model performs feature extraction and classification hierarchically using fully connected, pooling, and convolutional layers. This endeavor has resulted in an impressive 98.57% training accuracy and 93.34% validation accuracy, representing a substantial improvement over the previously used approach. Essential performance metrics, such as accuracy, recall, and F1-score, demonstrate the model's efficacy in detecting different types of skin cancer. We obtained high accuracy, an F1 score, and sub-optimal recall. The evidence indicates that CNN-based approaches may facilitate early diagnosis, improve treatment results, and reduce dermatologists' workloads. This study's results contribute to the advancement of skin cancer research.

Keywords: *Computer vision in healthcare, Image classification, CNN, Dermatology, HAM10000*

1. INTRODUCTION

People widely recognize the epidermis as the most essential organ of the animal organism. Consequently, it regulates our body temperature and protects us from potentially hazardous substances, including sunlight and elevated temperatures [12–15]. In addition, this molecule can absorb water and lipids. Excessive ultraviolet radiation can compromise skin cells, ultimately leading to the development of skin cancer [4, 2016–18]. Skin cancer is a significant concern due to the potential for infection, pollution, and illness to contribute to its development. The cells that comprise the epidermis, which is located on the skin, are the source of skin cancer. The generation of new cells is a consequence of the capacity of epidermal cells to divide and proliferate simultaneously. As time progresses, the younger cells gradually replace the elder ones [5, 6]. This process occurs on a daily basis due to the natural process of ageing and the loss of epidermis cells. Despite precise implementation, this procedure may not always succeed. The epidermis initiates the production of new cells and the elimination of the old ones in conditions that are not essential. The development of a tumour is the result of the accumulation of these surplus cells, which subsequently proliferate and form a tissue mass. Melanomas are the most prevalent and lethal form of skin cancer, and they have the second-highest mortality rate among all skin cancer sub types. Melanoma is one of the most prevalent and frequently occurring types of skin cancer. Various factors influence the trajectory of the illness, even though the precise origin of the disease remains obscure. There are numerous variables that contribute to the situation, such as the transmission of the illness from parents to children and exposure to UV radiation. Despite the fact that patients have a reasonable chance of recuperating from their condition, the illness's incidence remains a significant issue [19–23]. Although the lymphatic system is the main route of melanoma development, it can also form in the circulatory system. Melanoma progresses to other regions of the body during its later phases [24–25]. Despite the fact that experienced professionals frequently fail to identify melanoma in its early stages, there is evidence to suggest that early detection may reduce the risk of mortality. Unfortunately, this endeavor will prove challenging for even the most accomplished individuals. It would be advantageous to implement a strategy that automates the diagnostic process and minimizes the number of errors associated with human labor. Recent research unequivocally demonstrates the rapid dissemination of computer vision technologies and

digital image processing across a diverse array of industries, including healthcare. Additionally, these techniques have demonstrated their significant utility. Consequently, the utilization of these methodologies may simultaneously enhance the rate of diagnosis and decrease the incidence of human errors. Over the past few years, a variety of industries, including computer vision, digital image processing, and photo categorization tools, have extensively employed a specific artificial intelligence methodology. Artificial neural networks (ANNs) are a technique that has revolutionized the field. The intricate architecture of the human brain, comprising numerous neuronal layers and perceptrons, inspired the development of artificial neural networks. The potential to achieve astonishing results for applications that are both fundamental and sophisticated is present in the implementation of convolutional neural networks (CNNs), which are an enhancement to artificial neural networks. For example, the classification of objects, their identification, and the processing of images are among the applications. Twenty-one board-certified dermatologists effectively demonstrated the efficacy of the process by using clinically validated photographs verified through histology. Numerous medical imaging modalities employ Convolutional neural networks (CNNs) due to their efficiency and efficacy. The number is nine. This field encompasses applications such as exhaustive analysis, lesion classification, magnetic resonance image fusion, breast cancer diagnosis, and tumour detection. CNN-based approaches [10] apply the operator to each individual super pixel at a later stage, following the initial phase of dividing the pictures into small super-pixels. We will continue with this procedure once we have acquired photographs that are free of any defects. The aforementioned corpus of research has demonstrated that the use of CNN models enhances the operational efficiency of the clinical diagnostic system. The second section of the investigation examines the proposed approach. The third section of the report addresses the conclusions and comments. The conclusion and references are located in the fourth section of the book.

2. PROPOSED METHOD

The classification of cutaneous cancer has shown significant potential in recent years, with convolutional neural networks validating this capability. Deep learning algorithms have shown significant potential in this domain. The HAM1000 collection has around 10,015 dermatoscopic images. In our categorization method, each image represents a distinct kind of cutaneous lesion. We developed a skin cancer classification system using CNN architectures, which facilitated the automated extraction of hierarchical information from images. We perform a preprocessing procedure on the dataset before its use to ensure consistency. This approach employs scaling, normalization, and picture augmentation to enhance the model's applicability across many scenarios. The CNN model employs several convolutional layers within its design to extract essential visual information. These layers are preceded by pooling layers, which serve to reduce the dimensionality of the model. A fully connected layer at the conclusion of the network facilitates the classification of lesions into pertinent categories. The model uses a cross-entropy loss function and an Adam optimizer to expedite the convergence process during training. To evaluate the model's effectiveness, we use several evaluation metrics. The assessment components include calculations for precision, recall, accuracy, and F1-score. This instrument aids medical practitioners in the early identification of skin cancer due to its high efficiency and accuracy in distinguishing between benign and malignant lesions. The CNN-based method for skin cancer categorization is an effective tool that aids in the categorization of skin cancer. Figure 1 depicts an example of the proposed strategy.

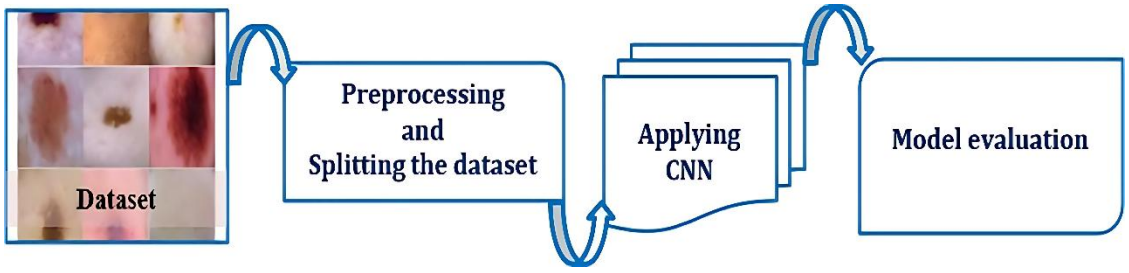

Fig 1: Proposed System Architecture Workflow

2.1 Data Set:

The HAM10000 collection includes multiple images of various types of skin samples. A substantial number of research initiatives used test pictures. The training of deep neural networks for the development of automated machine learning models aimed at classifying and detecting skin cancer samples is hindered by the restricted dataset, lack of diversity, and absence of critical information. This course aims to create models for skin cancer diagnosis. Harvard Data Verse released the "Human Against Machine with 10,000 Training Images," also known as the HAM10000 dataset, to efficiently address this problem. We collected several skin samples from various sites, processed them, and then underwent a series of diagnostic evaluations. The whole collection comprises one hundred and fifteen photographs of skin. Furthermore, a wide range of computer vision applications may use each of these images, and deep learning systems often use them as training data. This collection encompasses many notable kinds of skin cancer. Examples of vascular lesions include basal cell carcinoma (BCC), dermatofibroma (DF), melanoma (MEL), melanocytic nevi (NV), and actinic keratosis. Twenty-five percent of the samples

have undergone histological verification, and examinations are now in progress for the other samples. The HAM10000 dataset's "lesion id" attribute makes it easier to identify lesions across a wide range of photos. The collection contains a substantial number of pictures depicting lesions. Figure 2 illustrates the many classes that constitute the image collection, offering a comprehensive overview of it.

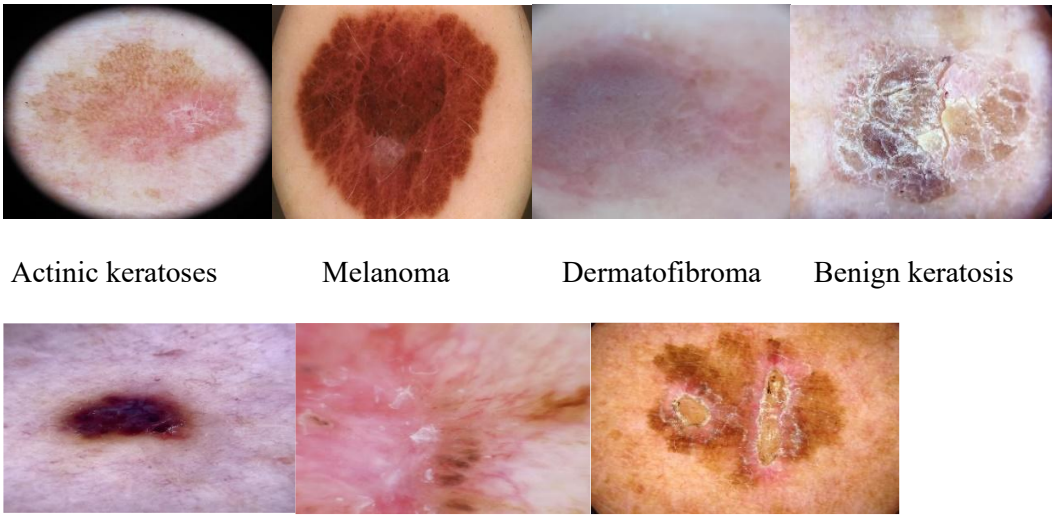

Fig 2: Representative Samples of HAM10000 Cancer Categories

2.2 *Dataset Splitting*

In order to evaluate the effectiveness of our model, we divided the HAM10000 dataset into three subsets for this study: training, testing, and subsequent validation. We used 30% of the data for testing and validation and 70% for training the model.

2.3 Convolutional Neural Networks

Traditional neural network typologies have evolved into contemporary convolutional neural networks. Yann LeCun and his associates initially introduced Convolutional Neural Networks (CNNs), demonstrating their effectiveness in digital image processing applications following their introduction. Their supremacy stems from their proficiency in weight-sharing attributes and pixel interconnections. One can adapt Convolutional Neural Networks (CNNs) to incorporate various mathematical learning techniques, including back propagation, learning algorithms, and regularization methods, among others. The three essential components of a conventional CNN are the convolutional layer, the pooling layer, and the fully connected layer. Neural networks have greater performance in addressing complex challenges such as computer vision and picture segmentation. Conversely, CNNs, similar to other neural networks, have the drawback of a propensity to converge to local optimum solutions, complicating the identification of the global optimal solution. This issue often impacts multi-layerperceptrons and other models reliant on gradient descent and optimization techniques to minimize the discrepancy between expected and actual outputs. Convolutional neural networks (CNNs) are very successful for challenging problem-solving tasks. The convolution layer uses a set of weights after input processing to reduce the layer's dimensionality. The pooling layers provide further weight reduction. This process results in a decrease in the overall weights the network holds. The fully connected layers then receive the outputs from the pooling layer for further processing. The convolution layer is a crucial element of CNNs, especially beneficial for processing 2D matrices and image segmentation. The learning process uses weighted matrices to enhance performance, whereas these layers employ a diverse array of weights to provide features beneficial for certain tasks. The backpropagation method, which employs the chain rule, can mitigate network errors. Activation functions, such as sigmoid and ReLU, are very beneficial throughout the scaling phase for each layer. The rectified linear unit (ReLU) activation function produces a result that is either greater than the input or zero, while the sigmoid activation function constrains outputs to a range between 0 and 1 with appropriate scaling. Here's a list of the parameters that comprise this model:

The total parameters	652,615
The total trainable parameters	652,615
The total non-trainable parameters	0

Table 1. provides a basic summary of CNN layered design.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 62, 62, 32)	896
max_pooling2d (MaxPooling2D)	(None, 31, 31, 32)	0
conv2d_1 (Conv2D)	(None, 29, 29, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 6, 6, 128)	0
conv2d_3 (Conv2D)	(None, 4, 4, 256)	295,168
max_pooling2d_3 (MaxPooling2D)	(None, 2, 2, 256)	0
flatten (Flatten)	(None, 1024)	0
dense (Dense)	(None, 256)	262,400
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 7)	1,799

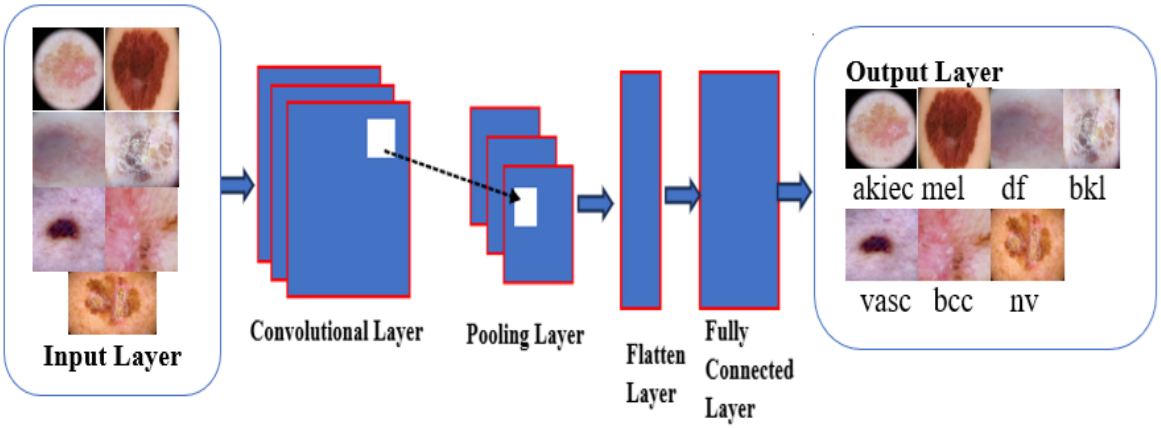

Fig 3: The Architecture of CNN

3. EXPERIMENTAL RESULTS AND DISCUSSION

We evaluated the proposed model using the HAM10000 dataset, which included F1 scores, recall, accuracy, and precision, among other common classification metrics. We examined the performance of the model using these criteria. While Figure 2 shows a thorough analysis of accuracy, recall, and F1 scores for every category, Table 1 shows CNN's effectiveness. The table demonstrates the amazing capacity of the model to correctly detect a wide range of skin conditions. Among the skin conditions are actinic keratosis, melanoma, dermatofibroma, benign keratosis-like lesions, vascular lesions, basal cell carcinoma, and melanocytic nevi. Figure 4 shows the class distribution within the sample.

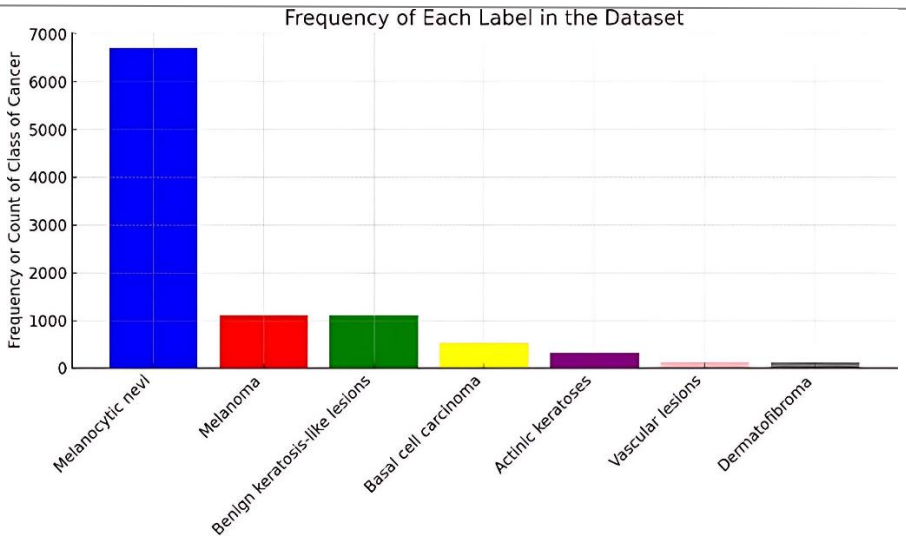

Fig 4: Class Distribution in Data Set

Table 2: Evaluation Results of the CNN Model

Algorithms	Accuracy	Loss	Validation Accuracy	Validation Loss	Time
CNN	98.57%	0.0505	93.34%	0.8181	523ms/step

The CNN model demonstrated satisfactory performance, as evidenced by its accuracy of 98.57% and minimum loss value of 0.0505, as indicated in Table 1. This implies that the model was capable of making accurate predictions, in addition to reducing the frequency of errors during the training phase. The model demonstrated a robust capacity to generalize to instances not previously observed, with a validation loss of 0.8181 and a validity accuracy of 93.34%. Nevertheless, there was a modest reduction in efficacy when contrasted with the training data previously employed. The method was relatively effective, as each stage of the training procedure required 523 milliseconds.

Table 3: Algorithms classification Report performance

Models	Classes	Precision	Recall	F1-score	Support
CNN	Vascular lesions	0.98	0.99	0.98	806
	Melanocytic nevi	0.94	0.90	0.92	827
	Melanoma	0.87	0.87	0.87	439
	Dermatofibroma	0.98	0.99	0.98	688
	Benign keratosis-like lesions	0.89	0.90	0.90	881
	Basal cell carcinoma	0.94	0.96	0.95	805
	Actinic keratoses	0.94	0.94	0.94	688

Table 2 shows that the CNN model performs very well in a variety of skin conditions. For example, dermatofibroma and vascular lesions had an F1 score of 0.98 and 0.99, respectively, indicating great accuracy and recall. This suggests that the model has a low rate of false positives or missed cases and is very good at identifying certain situations. Melanoma, with an F1-score of 0.87, exhibits somewhat lower metrics, including an accuracy of 0.87 and a recall of 0.87. This persists despite the ongoing positive results. This suggests that melanoma classification presents more difficulties for the model than other diseases. Furthermore, other diseases, such as benign keratosis-like lesions and melanocytic nevi, perform well, with F1-scores of 0.90 and 0.92, respectively.

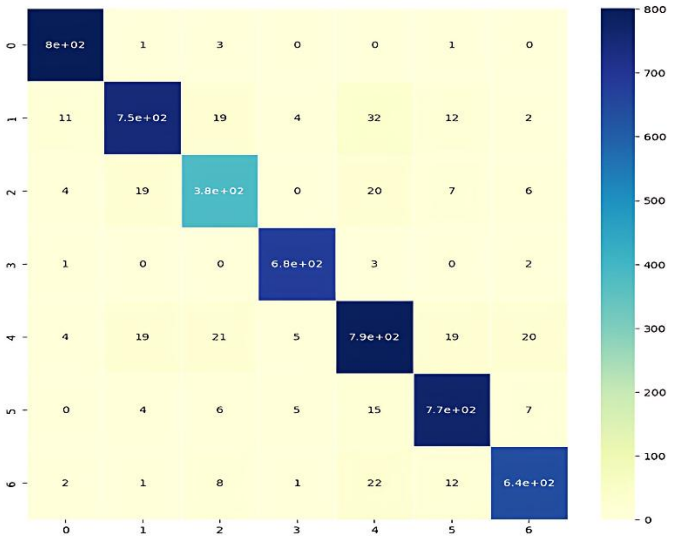

Fig 5: Visualizing CNN Model Efficacy with a Confusion Matrix

Figure 5 illustrates that Class 0 made 800 accurate predictions, mistakenly classifying three cases as Class 1 and one as Class 2. Out of the 750 predictions, the first class incorrectly classified 11 as Class 0 and 19 as Class 3. Class 2 produced 380 correct predictions, whereas Class 3 produced 40 incorrect classifications, and Class 4 produced 20. Class 3 made 680 correct predictions, whereas the other classes 1 and 4 misclassified 19 and 20 times, respectively. Class 4 correctly predicted 790 incidents, despite misclassified 13 cases as Class 5 and 19 as Class 3. There are 770 correct predictions in Class 5, 17 incorrect Class 3 classifications, and 13 incorrect Class 4 classifications. Class 6 accurately predicted 640 cases, but incorrectly classified 22 cases as Class 5.

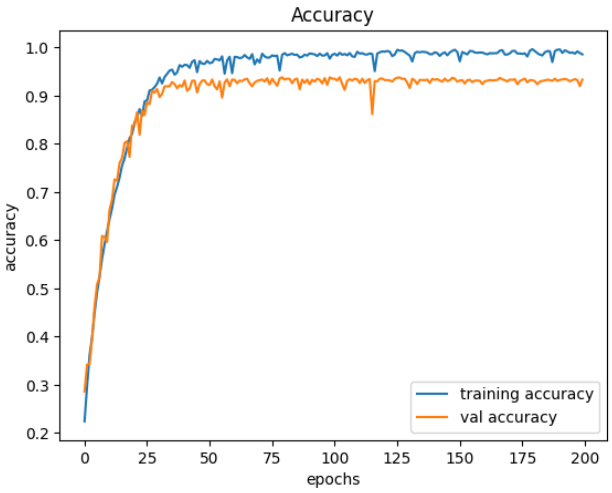

Fig 6: Train and Validation accuracy

Figure 6 illustrates the model's accuracy throughout 200 epochs during both the training and validation phases. Initially, there is a pronounced increase in accuracy, with validation accuracy leveling out at 93.34% and training accuracy stabilizing at 98.57%.

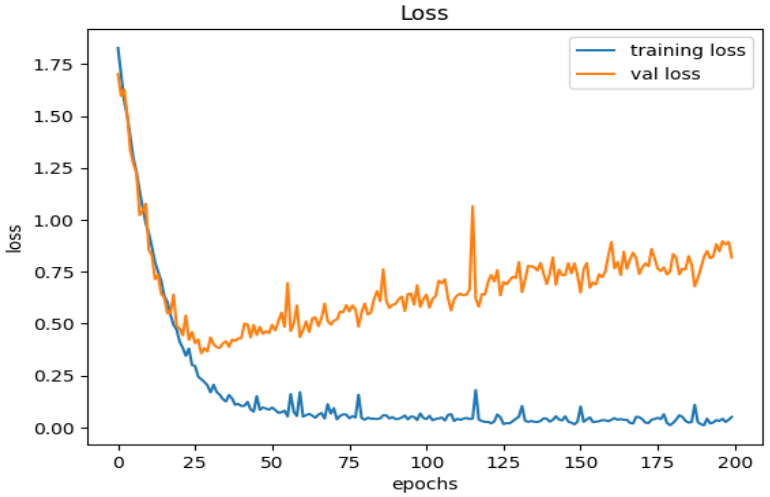

Fig 7: Train Loss and Validation Loss

Figure 7 illustrates the model's loss throughout 200 epochs during the training and validation phases. Initially, there was a considerable decrease in losses, with the validation loss level ling out at 0.8181 and the training loss stabilizing at 0.0505.

Table 4: Comparison of the results for proposed algorithms for UCI dataset

Paper	**Methods**	**Dataset**	**Accuracy**
Subramania, R. et. al [1]	CNN	HAM10000 dataset	83.11%
Rezaoana, N. et.al [2]	CNN, VGG-16 and VGG19	HAM10000 dataset	79.45%
Nugroho, A. A et.al [3]	CNN	HAM10000 dataset	80.00%
Proposed Method	**CNN**	**HAM10000 dataset**	**98.57%**

Table 3 shows the performance of several CNN-based techniques for classifying skin lesions on the HAM10000 dataset. Subramanian et al. [1] reported an accuracy of 83.11% using CNN, Rezaoana et al. [2] reported 79.45% using CNN models (VGG-16 and VGG-19), and Nugroho et al. [3] reported an accuracy of 80% using a CNN model. With an accuracy of 98.57% on the same dataset, our proposed strategy fared better than the current approaches.

4. CONCLUSION

This study aimed to develop a technique able to detect skin cancer lesions in dermatoscopic pictures by means of CNNs and deep learning. Under testing on the HAM10000 dataset, the model achieved 98.57% classification accuracy. This indicates that the model can identify melanoma and many other forms of skin cancer. Overall, the model produced impressive results, demonstrating remarkable accuracy, recall, and F1-score values. Against all the difficulties, we effectively classified the melanoma. One effective approach for skin cancer detection is the design of the convolutional neural network (CNN), which uses many layers for feature extraction and classification. The research results indicate that automated, efficient, and reliable methods, enabled by artificial intelligence and convolutional neural networks (CNNs), have the potential to completely transform medical diagnostics. Dermatologists can evaluate patients more quickly and precisely with this technology. Future research might concentrate on improving the generalizability of the model to different data types and investigating alternative deep learning methods to boost performance.

REFERENCES

[1] Subramanian, R. R., Achuth, D., Kumar, P. S., Kumar Reddy, K. N., Amara, S., & Chowdary, A. S. (2021, January). Skin cancer classification using Convolutional neural networks. In 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 13-19). IEEE.

[2] Rezaoana, N., Hossain, M. S., & Andersson, K. (2020, December). Detection and classification of skin cancer by using a parallel CNN model. In *2020 IEEE international women in engineering (WIE) conference on electrical and computer engineering (WIECON-ECE)* (pp. 380-386). IEEE.

[3] Nugroho, A. A., Slamet, I., & Sugiyanto, S. (2019, December). Skins cancer identification system of HAMl0000 skin cancer dataset using convolutional neural network. In *AIP conference proceedings* (Vol. 2202, No. 1). AIP Publishing.

[4] CCA, Under Standing Skin Cancer - A Guide for People with Cancer, their Families and Friends, Cancer Council Australia, 2018,https://www.cancer.org.au/.

[5] R.L. Siegel, K.D. Miller, A. Jemal, Cancer. statistics, Cancer statistics 2019, CA Cancer J. Clint. 69 (1) (2019) 7–34.

[6] WHO, World Health Organization (WHO), 2019, https://www.who.int/news-room/questions-and-answers/item/radiation-ultraviolet-(uv)-radiation-and-skin-cancer.

[7] Yu, L., Chen, H., Dou, Q., Qin, J., & Heng, P. A. (2016). Automated melanoma recognition in dermoscopy images via very deep residual networks. *IEEE transactions on medical imaging*, *36*(4), 994-1004.

[8] Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical image analysis*, *42*, 60-88.

[9] Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., ... & Summers, R. M. (2016). Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. *IEEE transactions on medical imaging*, *35*(5), 1285-1298.

[10] Tajbakhsh, N., Shin, J. Y., Gurudu, S. R., Hurst, R. T., Kendall, C. B., Gotway, M. B., & Liang, J. (2016). Convolutional neural networks for medical image analysis: Full training or fine tuning?. *IEEE transactions on medical imaging*, *35*(5), 1299-1312.

[11] Schadendorf, D., Fisher, D. E., Garbe, C., Gershenwald, J. E., Grob, J. J., Halpern, A., ... & Hauschild, A. (2015). Melanoma. *Nature reviews Disease primers*, *1*(1), 1-20.

[12] Romanovsky, A. A. (2014). Skin temperature: its role in thermoregulation. *Acta physiologica*, *210*(3), 498-507.

[13] Jablonski, N. G. (2004). The evolution of human skin and skin color. *Annu. Rev. Anthropol.*, *33*(1), 585-623.

[14] Yousef, H., Alhajj, M., & Sharma, S. (2017). Anatomy, skin (integument), epidermis.

[15] Montagna, W. (2012). The structure and function of skin. Elsevier.

[16] Panich, U., Sittithumcharee, G., Rathviboon, N., & Jirawatnotai, S. (2016). Ultraviolet radiation-induced skin aging: the role of DNA damage and oxidative stress in epidermal stem cell damage mediated skin aging. *Stem cells international*, *2016*(1), 7370642.

[17] Saraiya, M., Glanz, K., Briss, P. A., Nichols, P., White, C., Das, D., ... & Rochester, P. (2004). Interventions to prevent skin cancer by reducing exposure to ultraviolet radiation: a systematic review. *American journal of preventive medicine*, *27*(5), 422-466.

[18] Wei, Q., Matanoski, G. M., Farmer, E. R., Hedayati, M. A., & Grossrnan, L. (1995). DNA repair capacity for ultraviolet light-induced damage is reduced in peripheral lymphocytes from patients with basal cell carcinoma. *Journal of investigative dermatology*, *104*(6), 933-936.

[19] Emmett, E. A., & Epstein, J. H. (1973). Ultraviolet radiation as a cause of skin tumors. *CRC critical reviews in toxicology*, *2*(2), 211-255.

[20] Meyle, K. D., & Guldberg, P. (2009). Genetic risk factors for melanoma. *Human genetics*, *126*, 499-510.

[21] Bouzouki, P. (2005). Non-melanoma skin cancer: what drives tumor development and progression?. *Carcinogenesis*, *26*(10), 1657-1667.

[22] Chin, L., Garraway, L. A., & Fisher, D. E. (2006). Malignant melanoma: genetics and therapeutics in the genomic era. *Genes & development*, *20*(16), 2149-2182.

[23] Davis, L. E., Shalin, S. C., & Tackett, A. J. (2019). Current state of melanoma diagnosis and treatment. *Cancer biology & therapy*, *20*(11), 1366-1379.

[24] Damsky Jr, W. E., Rosenbaum, L. E., & Bosenberg, M. (2010). Decoding melanoma metastasis. *Cancers*, *3*(1), 126-163.

[25] Dadras, S. S., Lange-Asschenfeldt, B., Muzikansky, A., Mihm, M. C., & Detmar, M. (2005). Tumor lymphangiogenesis predicts melanoma metastasis to sentinel lymph nodes. *Journal of Cutaneous Pathology*, *32*(1), 84-84.

[26] Kittler, H., Pehamberger, H., Wolff, K., & Binder, M. J. T. I. O. (2002). Diagnostic accuracy of dermoscopy. The lancet oncology, 3(3), 159-165.