

Improved deep learning architecture for skin cancer classification

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ABSTRACT

A leading cause of mortality globally, skin cancer is deadly. Early skin cancer diagnosis reduces mortality. Visual inspection is the main skin cancer diagnosis tool; however, it is imprecise. Researchers propose deep-learning techniques to assist physicians identify skin tumors fast and correctly. Deep convolutional neural networks (CNNs) can identify distinct objects in complex tasks. We train a CNN on photos with merely pixels and illness labels to classify skin lesions. We train on HAM-10000 using a CNN. On the HAM10000 dataset, the suggested model scored 95.23% efficiency, 95.30% sensitivity, and 95.91% specificity.

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1. INTRODUCTION

According to the World Health Organization (WHO), skin cancer is among the most common types of cancer [1]. Of the many cancers identified today, this one ranks among the most prevalent, accounting for 33% of the total [2]. The ozone layer's deteriorating protection from ultraviolet (UV) radiation [3] leads to aberrant skin cell growth, the primary cause of skin cancer. The four most common forms of skin cancer are basal cell carcinoma (BCC), melanoma (Mel), actinic keratosis (SCC), and solar keratosis (Actinic keratosis) [4]. 75% of skin cancer deaths are caused by Mel, the most perilous kind of illness. Skin cancer is among the common cancer type, based on the WHO [1]. It is one of most prevalent cancers in the modern era and makes about 33% of all cancers [2]. The ozone layer's deteriorating protection from UV radiation leads to aberrant multiplication of skin cells, the primary cause of skin cancer. The four most common forms of skin cancer are BCC, Mel, SCC, and Actinic keratosis [4]. Mel, the worst form of skin cancer, accounts for 75% of all skin cancer-related deaths. Those with fair skin, a family history of sunburns, or a habit of tanning beds or extensive sun exposure are at a higher risk of developing this malignancy. The key to successfully managing skin cancer is early and precise detection. Mel grows and spreads via the skin, ultimately reaching higher levels and merging with lymphatic and blood arteries if detected later. As a result, giving the patient the right

treatment requires early detection. If diagnosed late, the predicted five-year survival rate for individuals with diagnosis is 15%; if discovered early, it is over 97%. Skin cancer treatment relies on early detection. When diagnosing skin cancer, oncologists frequently do biopsies. If you suspect that a skin lesion is malignant, a biopsy is the only way to find out. A considerable amount of time and energy is required to diagnose the disease. The symptoms of skin cancer can be more quickly, easily, and cheaply detected with the use of a computer. It is possible to research skin cancer symptoms and identify Mel using a variety of noninvasive methods, including dataset access, dataset preparation, segmentation application, extracting features, and classifying data. Several machine-learning algorithms can detect different types of cancer. In order to detect skin irregularities and categories skin cancer, convolutional neural networks (CNNs) are commonly used by researchers. When it comes to correctly classifying skin malignancies, CNN models have even beaten highly trained medical experts. Immediate skin cancer classification relies on manually extracted information from skin cancer images, which include, among other things, form, texture, and geometry [5]. The field of healthcare imaging has experienced a sea change since the introduction of deep artificial intelligence (DAI). Skin cancer diagnosis in healthcare imaging analysis is a great fit for CNNs, which are famously used widely and have remarkable accuracy. Scientists in the field of artificial intelligence have come up with sophisticated methods for better skin cancer detection, all because to technical advancements. We presented CNN models for skin disease classification in our study. Research using the well-known HAM-10000 dataset has validated the proposed technique, demonstrating improved accuracy, sensitivity, and specificity. To classify datasets with multiple skin diseases, we built a CNN model. We improved the illness area image using various data preparation approaches. In addition, we used the famous HAM-10000 dataset to confirm that our model was accurate. No more details were given. Improved precision, sensitivity, and specificity are hallmarks of the experimental findings. Here is the structure of the paper's sections: in section 2, "Related Work," we review the several models and their outcomes that pertain to skin cancer classification and diagnosis. In section 3, we see a detailed description of the research methodology and approach that were employed in this study. The results and an analysis of them will be presented in section 4. A brief synopsis and review of potential areas for further study make up section 5. Here is the structure of the paper's sections: In section 2, "Related Work," we review the several models and their outcomes that pertain to skin cancer classification and diagnosis. In section 3, we get a detailed description of the research methodology that was employed for this study. The results and an analysis of them will be presented in section 4. A brief synopsis and review of potential areas for further study make up section 5.

2. RELATED WORK

To fully understand deep learning (DL) designs, how they work, and the outcomes they produce, this part reviews the literature on skin tumour diagnosis. A deep CNN and many learning frameworks were built by Yu *et al.* [6] using a small quantity of training data. The study by Ko *et al.* [7] used more than 120,000 photos and a pre-trained CNN technique to get a dermatologist-level diagnosis. A CNN model introduced by Haenssle *et al.* [8] exceeded expectations in terms of test performance. An advanced technique that utilises DL is the ensemble approach. It combines the attributes of many models to detect skin cancer. In order to better diagnose skin cancer, this study [9] looked at using a pre-trained Google Inception-V3CNN model. The dataset used in the study included 129,450 shots of clinical skin cancer; 3,374 of the photos were dermoscopy images. Using the ISCI 2016 challenge dataset, the model was able to obtain a skin cancer classification accuracy of $72.1\% \pm 0.9$, according to the study. A fifty-layer CNN was built in 2016 to classify skin cancers of the malignant Mel variety. A maximum classification accuracy of 85.5% was reached by the competitors. In order to categorise clinical images linked to 12 types of skin illnesses, the researchers employed a deep CNN [7]. The results they produced were 96% accurate. Rather of relying on healthcare workers, as is the case with the typical approach, the authors of the study in reference [10] proposed a machine-learning method for dermatological disease identification using imaging of lesions. There were three phases to the development of the proposed model: data collection and enhancement, model building, and prediction. The research improved the structure using technologies for image processing and a number of AI algorithms, one of which was the artificial neural network (ANN), and achieved an accuracy rate of 89%. To give you a full picture of what DL models can do and how they've been used in skin cancer assessment, this part reviews the literature.

3. METHOD

The methodology section elucidates the systematic steps undertaken to address the research questions and hypotheses posed in this study. It provides a detailed account of the data collection methods, analysis techniques, and theoretical frameworks employed to ensure rigor and validity in our findings. The

proposed model in Figure 1 integrates these methodological approaches into a coherent structure, highlighting the flow of information and processes within the research framework. This model not only guides the implementation phase but also serves as a basis for discussing the implications and contributions of our research in the broader academic and practical contexts.

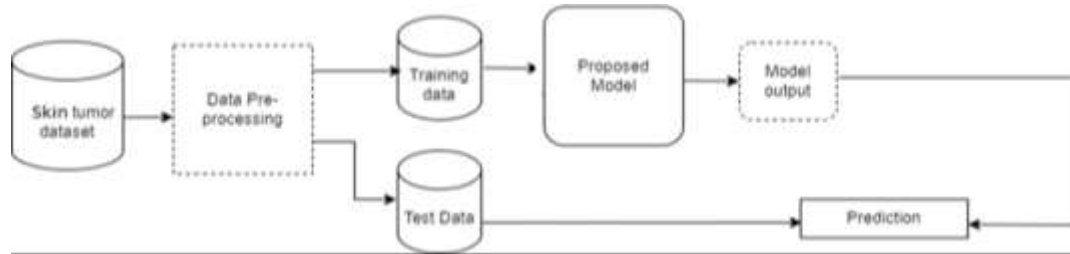


Figure 1. The system layout of the suggested paradigm

3.1. Description of the dataset

The 2018 HAM-10000 picture collection was made public by the International Skin Image Collaboration (ISIC) [11]. There are seven distinct kinds of dermoscopic skin tumour images in the HAM-10000 collection, representing several research organisations and their own approaches. The collection is diverse since it contains several images of a lesion shot under different lighting situations and at different times. The Dermatology Department of the Medical University of Vienna and Cliff Rosendahl's Queensland firm collaborated to generate the HAM-10000 dataset. Twenty years of dogged research yielded these results [12].

3.2. Image processing and transfer learning

Areas created by skin hair are absent in multiple photos in the skin cancer dataset. Preprocessing the skin pictures to remove any artefacts is crucial before moving further with extra processing or enquiry. To get rid of hair on skin, we employed morphological filtration. We cropped the image to remove the extraneous section. The image was downsized to 28×28 pixels in size. Then training new information by utilising current expertise is a common use case for CNN models. Training complex models may need less time and resources if transfer learning is effective. Using data from an already-trained model, transfer learning has the potential to improve the efficiency and accuracy of newly-created models, allowing for faster and more accurate results. We trained all of the layers of our models using a transfer learning-based fine-tuning strategy.

3.3. The proposed model

The CNN model structure is seen in Figure 2. CNNs are preferred over conventional approaches in some cases. By using weight sharing in convolutional layers, the number of parameters is reduced and the identification of distinct characteristics such as edges and corners is made simpler.

The given text is incomplete and does not provide enough information to rewrite it in a straightforward and precise manner. By including a pooling layer, the issue of sensitivity between the output feature map and the original features' position may be resolved. This ensures that the extracted features remain invariant to changes in position and location. The batch normalisation layer is used to improve the resilience of deep network training by reducing internal covariate shift and enhancing stability. The model consists of a series of sequential steps:

The first input layer has an image with dimensions of $28 \times 28 \times 3$ and connects to the first convolutional layer, which comprises 32 filters with a size of 3×3 . Afterwards, the data passes via a max-pooling layer, then undergoes a rectified linear unit (ReLU) activation function and batch normalisation. Hence, the second convolutional layer receives the output of the previous layer as its input. The input is passed via a ReLU non-linearity function, then batch normalisation is used, and lastly a max-pooling layer is used. The third convolutional layer consists of 128 feature maps and is then applied using a ReLU activation function and batch normalisation. Convolutional layers 1 to 3 used 3×3 kernels with a stride of 1. The max-pooling layers used a filter size of 2×2 and a stride of 2. Subsequently, the ReLU non-linearity function, batch normalisation, and an additional max-pooling layer were implemented. When the ReLU activation function is used, the output of the convolutional layer is transformed into a flat shape. This is done using a densely connected layer that has 128 feature mappings. Afterwards, it is joined to a fully connected layer consisting of 64 units. Reconnected to a fully connected layer consisting of 32 units. The SoftMax layer serves as the last layer of the neural network, and its number of units matches the number of classes included in the dataset.

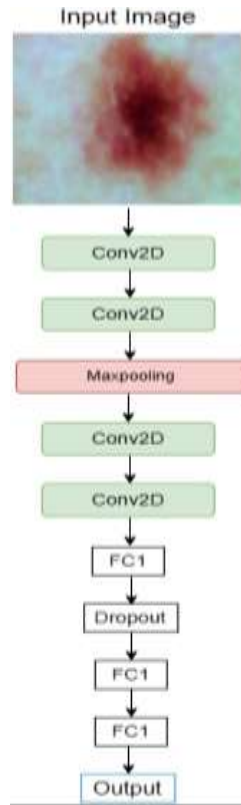


Figure 2. Structure of our CNN model

4. RESULTS AND DISCUSSION

4.1. Techniques of evaluation

When testing the efficacy of a model on problems with more than one class, a confusion matrix can be a lifesaver. True positive (TP) and false positive (FP) values are shown in the confusion matrix. Put the wrong data into the false negative (FN) category while appropriately putting the right data into the true negative (TN) category [13]. The confusion matrix is used to calculate performance metrics such as accuracy, Sn, and Sp [14]–[18] to evaluate the model's effectiveness. A precise evaluation of the suggested model's effectiveness is achieved by calculating the metrics using equations based on the confusion matrix.

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

$$Sensitivity = TP/(TP + FN) \quad (2)$$

$$Specificity = TN/(TN + FP) \quad (3)$$

4.2. Experimental settings

A methodical strategy was used to divide the image data into separate training and testing subsets [19]–[24] in order to solve the multi-class skin disease problem. To be more precise 10% of the original dataset, made up the test data. Underwent thorough data processing procedures. Similar processing techniques, including the addition of augmented photos, were also applied to the training and contained the remaining images, respectively.

4.3. Proposed model result with other models

Skin cancer diagnosis is a significant concern due to its exposure to environmental factors and high susceptibility to disease. Accurate and prompt illness identification is crucial in controlling skin cancer since it often leads to the implementation of beneficial preventive measures after a correct diagnosis. Various ways have been suggested, created, and implemented to identify and diagnose skin cancer problems. Most of these tools cannot accurately identify and diagnose diseases on planets. The study proposed, executed, evaluated,

and contrasted an independent approach for identifying and diagnosing first-line skin cancer conditions. A deep-CNN powers the system.

As shown in Table 1, the results showed that the proposed method is efficient in identifying and diagnosing early skin cancer conditions. Most methods discussed in the literature achieve classification accuracy between 50% and 91%. When more instances of skin cancer are included, these methods may not function as effectively. The preceding test outcomes show that our proposed skin lesion detector is more effective than current methodologies, as shown in Table 1. The research models produced considerable findings; however, they failed to detect microscopic skin lesions that were not visible. Furthermore, our suggested model achieved 95.5% detection accuracy. We believe that the suggested feature extraction approach, which uses ML and DL-based algorithms, will allow us to extract the most representative features from skin lesions. We employed an Adam optimizer to alter the learning rate, which improved the training phase of the suggested classifier. Thus, our suggested model is an effective skin lesion detector with 95.5% precision, 95.80% recall, and a 98% F-score as shown in Table 1. The suggested system detects skin lesions with high accuracy and outperforms current skin lesion detection methods. To test images for this purpose, a visualization approach is used as shown in Figure 3.

Table 1. Accuracy comparison of existing and proposed model based on HAM10000 dataset

Reference	Research method	Accuracy (%)	Sensitivity (%)	Specificity (%)
[25]	CNN+OVA	92.90	-	-
[26]	MobileNet+LSTM	85.34	88.24	92.00
[27]	Modified MobileNetV2	91.86	91.09	92.66
[28]	DenseNet169-two classes	91.10	82.49	95.66
This paper	Proposed model	95.23	95.30	95.91

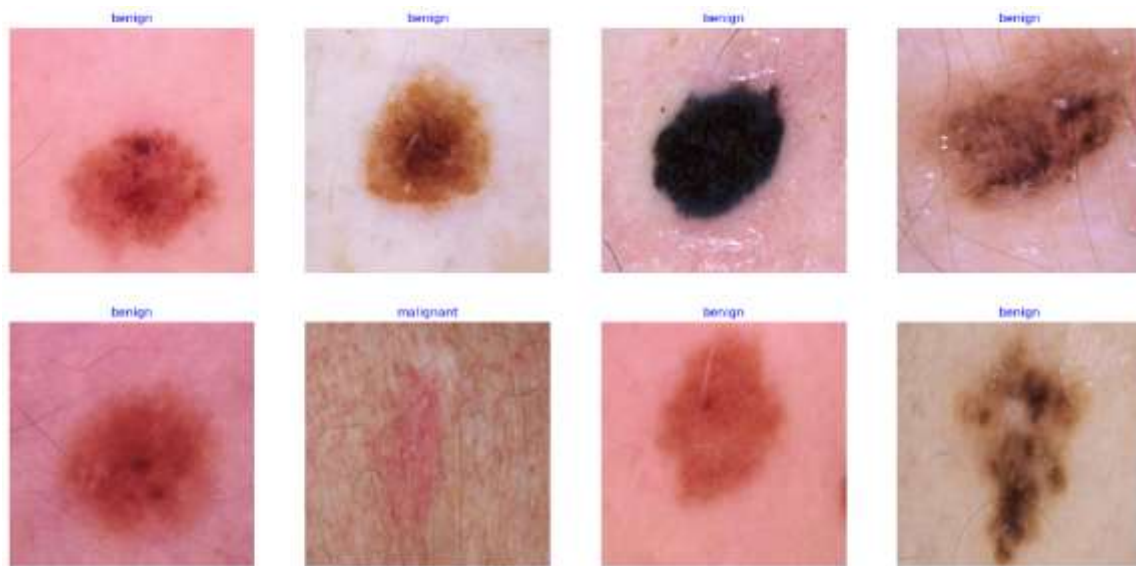


Figure 3. The output images visualization of our proposed model

5. CONCLUSION

This work has introduced a comprehensive method for classifying multiclass skin disease photos in order to diagnose skin cancer. Experiments showed that the suggested strategy outperformed the state-of-the-art models in terms of accuracy and significantly reduced loss, indicating that it is a better fit than the conventional approaches. We made use of the picture dataset HAM-10000, which includes pictures of seven different kinds of skin cancer. Data preprocessing techniques were incorporated to enhance image quality and eliminate undesired portions of the image. On the test set, the suggested model obtained a 95.23% accuracy score, as well as a 95.30% sensitivity score and a 95.91% specificity score. The future research for this study may involve generalizing it to other skin types and races.





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


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