Deep Learning-Based Skin Lesion Detection and Classification: A Review

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Abstract - *Detection and classification of skin lesions are crucial in diagnosing skin cancer and detecting melanoma. Melanoma is a menacing form of skin cancer accountable for taking the lives of numerous people each year. Early identification of melanoma is essential and attainable through visual examination of pigmented lesions on the skin, treated by extirpating the cancerous cells. Standard vision detection of melanoma in skin lesion images might be imprecise. The visual similarity between the benign and malignant types poses hardship in identifying melanoma. To solve the problems in identifying melanoma, automated models are needed to assist dermatologists in the identification task. This paper presents a comprehensive review and analysis of the various deep learning techniques used to diagnose and classify skin lesions.*

Key Words: **Skin cancer, skin lesion detection and classification, deep learning, image processing, Convolution Neural Network, Fuzzy neural network.**

1. INTRODUCTION

Skin lesions are skin portions with an atypical appearance or growth in contrast to the surrounding skin. Skin melanoma is a type of deadly skin cancer. The epidermis is one of the many layers of human skin, producing melanocytes that produce melanin at a high rate. Prolonged exposure to the sun's UV rays produces melanin. The abnormal development of melanocytes leads to melanoma, a cancerous tumour, the deadliest skin cancer. Early diagnosis of melanoma is essential for planning treatment and saving the affected. This is achievable by visual observation of pigmented skin lesions healed by simply removing the cancer cells. Detecting melanoma from images of skin lesions using human vision can be inaccurate. The stark resemblance between benign and malignant types poses hardship in differentiating between them and identifying melanoma. Also, traditional methods like biopsy are time-consuming, painful and expensive. Therefore, an automated computer model that supports specialists in identification tasks is essential. In recent times, deep learning techniques are frequently used skin lesion detection. It is considered a class of machine learning that utilises several layers to extricate complex-level features from the input. Since a considerable amount of research has been done regarding skin lesion detection using deep learning techniques. It's vital to survey and summarise the research findings for future researchers. This paper reviews the different deep learning techniques used, like convolution neural networks and artificial neural networks for skin lesion detection.

2. LITERATURE REVIEW

M. Kahn et al. [1] proposed a fully automated system classifying skin lesions into many classes. They describe segmentation techniques using deep learning and CNN feature optimisation using an enhanced Moth Flame Optimization (IMFO) method as part of the framework. First, the input image is stretched with the Histogram Intensity Value with Local Color Key (LCcHIV). Subsequently, saliency is evaluated using a new deep saliency segmentation technique using a 10-layer convolutional neural network. A pre-trained CNN is used for feature extraction from the segmented colour lesion images. They proposed an improved Moth Flame Optimization (IMFO) algorithm to choose the most discriminating features. The Kernel Extreme Learning Machine (KELM) classifies the features. The limitation of this task is the increase in calculation time. In addition, advanced segmentation techniques are needed to avoid deep model training on irrelevant image features.

P. Dhar et al. [2] put forward a technique for segmentation and detecting skin lesions utilising dermoscopy images. The proposed method is based on fuzzy logic and classification rules using CNN. First, a set of rules is adapted to the dermoscopy image. The output is thresholded. The close operation is used as a morphological tool on threshold images. Area filtering is then performed to generate the desired area. For classification, CNN was used. The dataset under consideration is inadequate and unbalanced. Classification of images without skin lesions gave poor results.

M. Arshad et al. [3] presented a novel automated framework for classifying multiclass skin lesions. The pre-processing involves three operations: 90 rotations, flip left / right and flip-up / down. Next, the deep model is fine-tuned. ResNet50 and ResNet101 are the two selected models, and their layers are updated. In addition, transfer learning is applied, features are extricated, and fusion is performed using an altered series-based method. The final selected feature is categorised using multiple machine learning algorithms. The fusion system's limitations include an increase in computation time. The results demonstrate that the feature selection procedure decreases calculation time and precision.

M.A. Kahn et al. [4] proposed an approach to emphasise segmentation and lesion classification using deep CNN. The proposed Gauss's method is used to improve contrast in the first phase, then RGB to HSV colour space conversion, followed by a prominence map of lesion segmentation. DCNN functionality is retrieved through two distinct levels and combined using a concurrent, decision-driven methodology. Then, the top features are chosen and given to the ANN for categorization. The methodology follows four basic steps: lesion pretreatment, prominent segmentation detection, feature extraction with optimum feature choice, deep learning, and final categorization of neural networks. The drawback of the proposed method is that it relies somewhat on pretreatment steps (contrast stretch). Additional calculations are made when you add pre-processing and segmentation steps. Decreasing the number of predictors will likely reduce performance, especially for complex dermoscopy images.

Nida et al. [5] proposed novel a technique based on Fuzzy C-mean (FCM) clustering and Deep Area-Based Convolutional Neural Network (RCNN) for effective Melanoma region segmentation inside dermoscopic pictures. The method consists of three steps: Skin refinement using morphological closing operation. Detection and localisation of Melanoma using RCNN. Segmentation of Melanoma using Fuzzy C-Means. This proposed system does not consider skin disease classification as it includes only detection.

L Bi et al. [6] A fully convolutional network (FCN) has been suggested that automatically segments skin lesions while recognising objects by hierarchically mixing low-level visual input with high-level semantic information. A novel parallel integration technique obtained final segmentation results with accurate location and clear lesion boundaries. Methodology: Robustness results from multi-level FCNs iteratively learning and inferring complex skin lesions' visual characteristics, always minimising segmentation errors in training and test times. Additionally, the use of parallel integration to incorporate supplementary data from various stages of mFCN has made it possible to constantly recognise complex skin lesions' complex boundaries. One limitation is that this proposed system does not consider the classification of skin diseases.

In this paper, Mohammad Ali Kadanpur et al. [7] utilised a deep learning architecture that is model-driven. This white paper described the DLS tool's features and demonstrated how to use it to create a deep learning model. The method of data preparation employing skin cell pictures and their test application in the DLS model for cancer cell detection were both covered in this research. The DLS model successfully identified cancer cells from cancer cell pictures with an AUC of 99.77 per cent. Methodology: DLS, a model-driven architecture tool, offers components for building neural networks as a drag-and-drop art stack. The essential general procedure sequence included as a research methodology in this document is data preparation, project creation, and loading. Publish datasets, deep learning classifier creation, model tuning, result validation, inference drawing, code access, and models as REST APIs. This paper pointed out the offer to receive. The model's source code is provided for programmers to examine further. The best foundational research this paper observes for future work is the capability to download trained models and create enterprise-level applications. Finally, the objectives outlined in the introduction section have been met by this research.

In this study, G. Reshma et al. [8] have developed a new IMLTDL a deep learning-based automatic skin lesion segmentation model for effective skin lesion segmentation and an intelligent classification model for dermatoscopic imaging. Methodology: The IMLTDT model diagnoses skin lesions using various steps such as pretreatment, Feature extraction, segmentation, and classification. The exhibited IMLTDL model incorporates top hat filters at the base level and repair techniques to preprocess dermoscopy images. The infected skin lesion area in the dermoscopy image is then identified using a multi-level threshold-based segmentation. Effective skin lesion detection is accomplished using feature extraction procedures based on Inception v3 and classification processes based on GBT. The ISIC dataset is used to run the proposed IMLTDL model and analyse some of the experimental findings.

M.Y. Sikkandar et al. [9] proposed a system that is a skin lesion diagnosis segmentation-based classification model that combines the Grab Cut algorithm and the Adaptive NeuroFuzzy classifier (ANFC) model. Top hat filtering is used during the preprocessing stage. The morphological image processing strategy, a top hat filter, is used to extract minute details and elements from the provided photos in order to detect the dense and dark hair present in the image. Segmentation is carried out using the Grab cut algorithm to segment the preprocessed images. GrabCut is a methodology for iterative, semi-automatic picture segmentation where the segmentation of the image can be expressed as a graph. The pixels from the image are represented by the created network nodes. A deep learning-based Inception model is used for the feature extraction process. Convolutional neural network architecture known as Inceptionv4 improves on earlier incarnations of the Inception family by streamlining the design and utilising more Inception modules than Inceptionv3. The dermoscopic pictures are then classified into several classifications using an adaptive neuro-fuzzy classifier (ANFC) method. The ANFC is a hybrid model that combines the advantages of the NN's capacity for self-adaptation and learning with the fuzzy model's capacity for taking into account the present state of uncertainty and the imprecision of real-time models. With the help of the ANFC model, the fuzzy primary system is generated with the help of filtered rules from the I / O data. Then use a neural network to tune the rules of the primary model to generate the final ANFC model. Other optimal techniques can be used in the feature extraction step. In the future, you can improve performance by using other deep learning models in Inception v4.

3. CONCLUSIONS

A detailed review of the different deep learning techniques used in skin lesion detection has been discussed. Each paper has been analysed, and a summary of various methodologies and their limitations have been included for future research. Some models used were fully Convolutional Neural Networks, Artificial Neural Networks, Fuzzy C-Means, and a hybrid model called the Adaptive Neuro-Fuzzy Classifier model. Constraints in these papers were the increase in computational time. Furthermore, extending the segmentation technique is required to prevent deep models from being trained on pointless image characteristics. Additionally, a performance decrease was noted, particularly when complicated dermoscopic pictures were involved. Going forward, more enhanced and optimal segmentation and feature extractions techniques are required. More ensemble and hybrid classification models using deep learning can be used for better results.

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