JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

DETECTION OF SKIN LESIONS USING CNN, TENSORFLOW AND HYBRID FEATURE EXTRACTION

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ABSTRACT: Along with a few other disorders like squamous, actinic keratosis, pigmented, and vascular illnesses, melanoma is one of the most fatal skin diseases. Nevi needs to be precise. They can be difficult to diagnose because of their similar look, which requires careful inspection by a qualified healthcare professional. Almost twice as many people die from this sickness than from different types of skin cancer. While there is a rise in various forms of melanoma among young adults, the good news is that early detection leads to very high survival rates. This abstract describes a convolutional neural network (CNN) based skin disease detection system. Using high-resolution photos of common skin lesions from the HAM10000 collection, the suggested method seeks to reliably categorize a variety of skin illnesses. The model uses deep learning to classify the photographs into appropriate disease categories by identifying complex patterns and features from the pictures. It is shown through extensive testing and assessment that the CNN-based method is a reliable means of correctly identifying skin conditions. Dermatologists could benefit from this approach by using it to help with early and accurate diagnosis, which would enhance patient care and outcomes.

Key words: Melanoma, Squamous, Skin, Actinic Keratosis, Pigmented, Vascular, Deep Learning, CNN.

1.INTRODUCTION:

Over the past few decades, skin cancer has been increasingly common worldwide ,ranking among the most common cancer types. For a better prognosis and efficient therapy ,early detection is essential. Dermatologists use visual inspection as the primary method of diagnosing skin cancer in traditional procedures, which can be laborious and prone to human error. Recent developments in artificial intelligence, especially in deep learning methods like Convolutional Neural Networks (CNNs), have demonstrated significant potential for automating the examination and classification of skin lesions. The implementation of CNN- based deep learning techniques for the identification of skin cancer from dermoscopic images is thoroughly examined in this research work. Dermoscopic imaging helps in the early identification of cancer by providing extensive information about the morphology and structure of skin lesions through the use of specialized cameras to capture high-resolution images.

This study's main goal is to create and assess a CNN-based model that can reliably identify between benign and malignant skin lesions. The suggested model seeks to attain high sensitivity and specificity in detecting different types of skin cancer, such as melanoma,basal cell carcinoma, and squamous cell carcinoma, by utilizing a dataset consisting of thousands of annotated dermoscopic pictures. When compared to conventional methods of diagnosing skin cancer, the application of deep learning algorithms offers various advantages. CNNs can do away with the requirement for labor-intensive feature extraction by automatically learning discriminative features from raw picture data. Furthermore, deep learning models have proven to perform better than human specialists in certain image categorization tasks. In this study, we highlight the importance of CNN-based methods by providing a thorough overview of related research in the field of computer-aided skin cancer diagnosis. We also go over the methodology used to create and train the suggested CNN model, which includes methods for model optimization, network architecture design, and data preprocessing.

The overall objective of this research is to improve diagnostic accuracy, save healthcare costs, and save lives by employing advanced deep learning algorithms for skin cancer detection. This research adds to the ongoing work in this direction.

2.RELATED WORK:

Various Researchers across the world have proposed image based processing techniques to identify different types of skin diseases. Here we concisely review some of the techniques as mentioned in the literature.

A technique for diagnosing skin conditions without the need for a doctor's intervention is described in [1]. It makes use of color photos. The system consists of two stages: color image processing, k-means clustering, and color gradient algorithms are used in the first phase to identify the sick skin; artificial neural networks are used in the second phase to classify the type of disease. Across six different types of skin disorders, the method showed an average accuracy of 95.99% for the first stage and 94.016% for the second stage. The first stage in the detection of skin diseases in the method of [2] is the extraction of image features. The more features that are extracted from the image using this method, the more accurate the system is. With up to 90% accuracy, the method was applied to nine different types of skin diseases by the author of [2]. If not identified and treated in its early stages, melanoma is a kind of skin cancer that can be fatal. Using LBP and WLD, Arnab Banerjee et al. [3] proposed a method for detecting skin diseases. This study adopts a more divided methodology. First, the center of gravity is used as a reference point to divide the image into four separate regions. This successfully divides the image into regions that most likely correspond to various lesion characteristics (e.g., center, periphery). Interestingly, the method uses rotation-invariant WLD features that are taken from every single region. A Machine Learning Approach for Detecting Skin Diseases was proposed by K.S.Rao et al. [4].The increasing prevalence of skin disorders demands the creation of precise and effective diagnostic instruments. This work explores the field of machine learning and suggests a novel method for the early identification and categorization of different skin conditions. The research uses the power of convolutional neural networks (CNNs) and transfer learning to extract hidden patterns from skin images, utilizing a rich dataset obtained from medical databases and institutions.

In their work, [5] addressed the use of support vector machines (SVM) to classify skin conditions, including melanoma, basal cell carcinoma (BCC), nevus, and seborrheic keratosis (SK). Out of all the methods, it produces the most accurate results. However, there could be dire repercussions if chronic skin conditions grow throughout various areas. In their work, [6] suggested creating a tool for diagnosing melanoma in people with dark skin by utilizing specialized algorithm databases that included pictures from various melanoma resources.

A Skin Disease Classification was proposed by Raghav Agarwal et al. [7]. CNN Algorithms are used to the increased frequency of skin conditions necessitates prompt and precise diagnosis. Even for professionals, AI-powered solutions have historically been time- consuming and difficult, but they now give optimism. In order to classify eight prevalent skin disorders, this study compares well-known deep learning models using a dataset of more than 25,000 photographs. Some Recent Advancements and Perspectives in the Diagnosis of Skin Diseases Using Machine Learning and Deep Learning were proposed by Junpeng Zhnag et al. [8]. Due to the high prevalence of skin diseases, advanced methods are required for precise diagnosis and efficient treatment. Machine learning and deep learning algorithms have become important tools in this context, with deep learning techniques drawing special attention for their better performance.

3. MATERIALS AND METHODS:

3.1. Dataset Description :

The "Human Against Machine with 10000 training images," or "HAM10000," is a comprehensive collection of dermoscopic images of skin lesions with pigmentation that come with extensive annotations and diagnostic details. Research projects that use CNNs (Convolutional Neural Networks) to detect skin diseases have found great use in this dataset. The HAM10000 dataset comprises 10,015 high-resolution dermoscopic images of skin lesions. A broad range of skin disorders are depicted in these photographs, including dangerous lesions such as melanoma, basal cell carcinoma, and squamous cell carcinoma, as well as benign lesions like nevi and seborrheic keratosis. Comprehensive clinical metadata, such as patient demographics (age, sex), lesion location, and dermatologist-provided clinical diagnoses, are included with every image in the HAM10000 collection. Where appropriate, histological confirmation data is also included, further boosting the dataset's validity and dependability.

3.2. Data Preprocessing :

Data preprocessing is essential for improving the effectiveness of future analysis and classification models in the field of image processing-based skin disease diagnosis.To maintain consistency and make model training easier, input photos should be resized, normalized and standardized. The initial images, originally sized at 600×450, were deemed too large, prompting us to resize them into smaller 32×32 RGB images.

Fig.1. Melanoma

Fig.2. Dermatofibroma

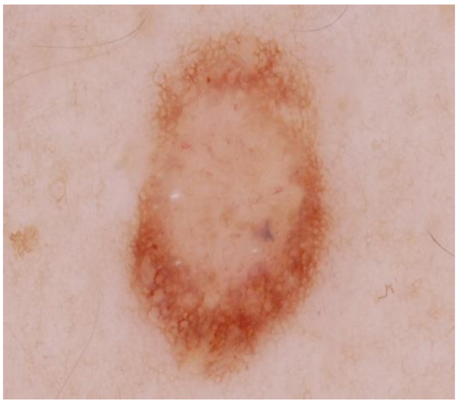

Fig.3. Nevus

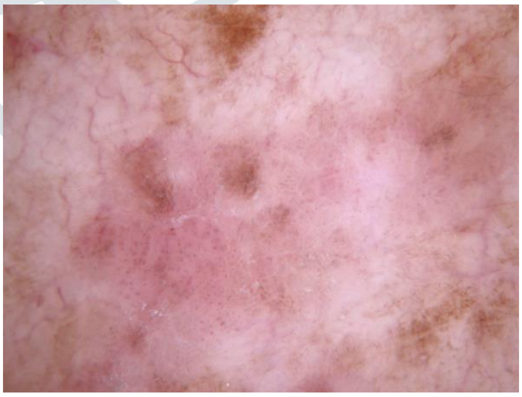

Fig.4. Squamous

Fig.5.Basal Cell Carcinoma

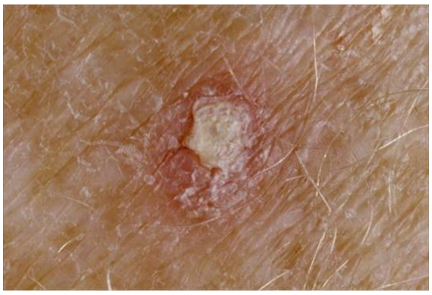

Fig.6.Actinic Keratosis

4. PROPOSED METHODOLOGY:

Convolutional neural networks are among the most significant neural network types in terms of popularity and picture classifications. Face recognition, item detection, and scene labelling are a few of the areas where the usage of convolutional neural networks is widespread. While training CNNs from scratch requires large amounts of labelled data and computational resources, transfer learning provides a workable way around these problems. To establish the network weights, transfer learning makes use of pre-trained CNN models that have been trained on massive datasets like ImageNet. Transfer learning helps the CNN to adapt and learn task-specific properties relevant to skin cancer diagnosis by honing the pre-trained model on a smaller sample of skin lesion images.

Compared to training from scratch, this method frequently produces competitive performance while drastically reducing training time and data needs. In the field of medical image analysis, transfer learning has gained popularity as a method for developing precise and effective models for a range of diagnostic applications, including the identification of skin cancer.

Transfer Learning: Utilize pre-trained CNN models (e.g., VGG, ResNet, Inception) and fine- tune them on your skin disease dataset. Transfer learning allows leveraging features learned from large datasets, potentially improving accuracy with less training data.

A. Architecture of a model:

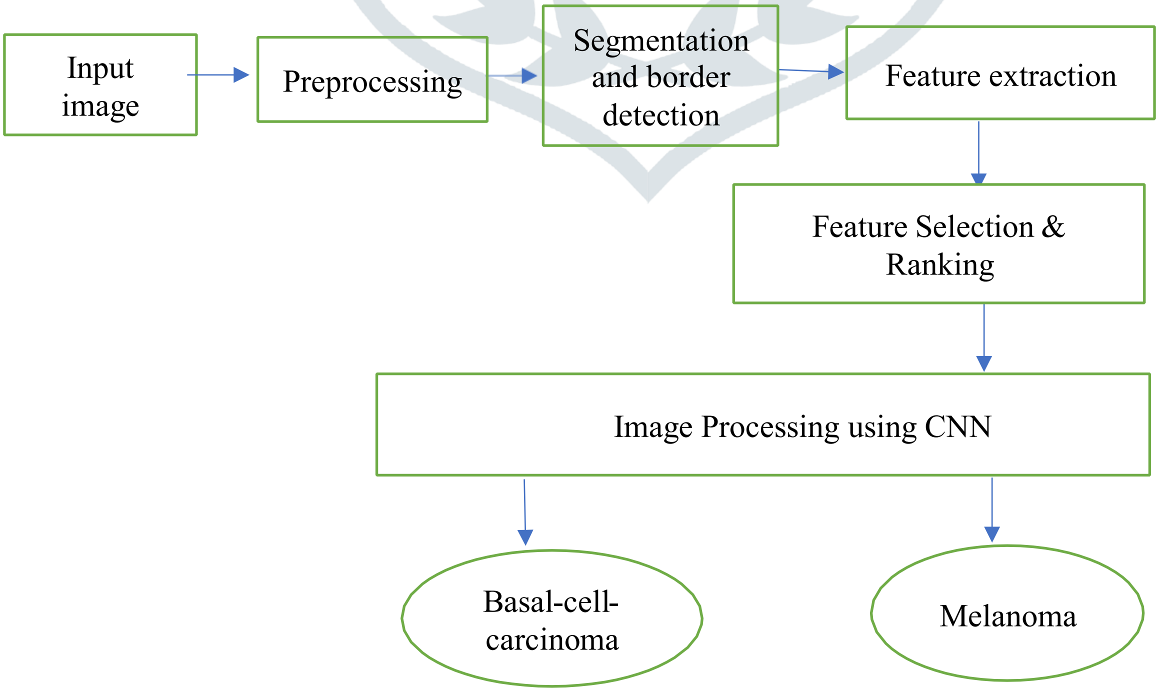

Fig. CNN Architecture

B. Preprocessing:

Noise is a common problem in medical photos, especially when there are air bubbles, hairs, and poor lighting. When sound is applied to visuals, artifacts are produced. Because of these anomalies, segmentation False detection effects have the potential to affect results. For an accurate prediction, noise removal is therefore an essential step before using a segmentation or feature extraction approach. It is highly recommended to use a Gaussian clearout to smooth the image, as this removes excess reflect noise from the record acquisition. The Gaussian kernel's coefficients are selected from a three dimensional Gaussian feature.

C. Segmentation:

It is highly recommended to use a Gaussian clearout to smooth the image, as this removes excess reflect noise from the record acquisition. The Gaussian kernel's coefficients are selected from a three dimensional Gaussian featureK-way clustering is a useful tool for learning about this technique. It is extensively employed in numerous applications, such as pattern popularity, image processing, and data mining. K-Means is regarded as one of the most important techniques for statistics and clustering. Factors or points are arranged according to how close they are to the chosen path. The created grapes' common values can be found and set to visit the next iteration following each new release. Until there is no trade inside the succeeding centroids, the iterative procedure is repeated.The route choice strategy is used by the computer K to initiate its course. The method of decision could be artificial, offering a sizable differentiation among the initial values. The anterior lesion is isolated from the skin and underlying pores, and the K price is close to 2.

D. Feature Extraction:

The lesion is classified as benign or malignant depending on whether it can be differentiated from the historical footage. Applying improved features as descriptors for classification is crucial to achieving better classification results. the model of system mastery. As the wide range of traces expands, so does the computational value, which facilitates the proper interpretation of the boundary definition. Consequently, it is guaranteed that special skills will be used. Texture and color are used to help characterize the wound. Three unique features are retrieved from the pores and skin lesion ROI in this study using the RGB color channel, the local binary version (LBP), and the gray degree coherence matrix (GLCM). The ability to extract texture and color is used to extract skin lesions from input. Since the training model only produces sample values, the accuracy it produces is not reliable. was lower than that of CNN by the ANN. When employing ANN, it occasionally might not provide the right result from the training model; instead, it might display the incorrect skin condition on the dataset image.

Using image processing, CNNs (Convolutional Neural Networks) are utilized to detect skin diseases. Here are a few methods for identifying skin diseases using CNN. CNN can categorize skin tone photographs. deep convolutional neural network that has been trained to recognize lesions. For instance, one study classified six skin conditions using CNN: vitiligo, acne, eczema, athlete's foot, and chickenpox. CNN is used in another study to categorize tinea corporis, tinea pedis, and tinea capitis, four prevalent fungal skin infections. Machine learning: A CNN-based model for categorizing skin diseases has been put out. Image processing: Early skin disease detection can be achieved through the application of image processing techniques such as segmentation, feature extraction, and filtering. Adaptive thresholding, edge detection, K-means clustering, and morphology-based picture segmentation are more image processing methods.

In order to classify skin illnesses using images, the suggested method integrates transfer learning techniques and uses Convolutional Neural Networks (CNNs) in the deep learning domain. The successful identification of skin disorders depends on the achievement of precise classification, which is the goal our suggested approach seeks to achieve. The categorization of skin lesions into distinct disease groups, such as melanoma, psoriasis, and eczema, is largely dependent on image classification algorithms. These methods use information taken from photos to train machine learning models, CNNs being one of the most popular models. By improving accuracy and efficiency, this effort seeks to further the field of computer-assisted skin disease detection. Skin disease classification is made accurate and effective by utilizing cutting-edge deep learning techniques like Convolutional Neural Networks (CNNs) and Transfer Learning.

By correctly classifying various skin photos, the suggested CNN-based approach aids in the early detection of skin diseases. The suggested setup is capable of mechanically, without oversight, the salient qualities. The suggested method uses CNN to achieve a better level of accuracy, a feat that is difficult to do using Artificial

Neural Networks (ANN). The CNN-based method effectively categorizes a range of skin photos, making it easier to identify skin conditions early on. Furthermore, the suggested system demonstrates the ability to recognize important elements on its own without human assistance.

5. RESULTS :

In order to assess and train our classification algorithm, we used the HAM10000 dataset, a sizable collection of 10,000 photos of skin cancer. Notable outcomes were achieved in the skin lesion. Categorization with the help of this sizable dataset, which contains a broad range of skin lesions. On the HAM10000 dataset, we used convolutional neural networks (CNNs) and multi-classification algorithms to achieve high accuracy rates in distinguishing between skin conditions. Specifically, our approach yielded impressive accuracy percentages for melanoma (98.00%), actinic keratosis (94.00%), pigmented lesions (56.00%), and squamous cell carcinoma (68.00%), Vascular lesions (58.00%). The significance of utilizing extensive datasets in dermatological research is underscored by these findings.

Name Of The Disease	Confidence	Accuracy
Melanoma	98.00%	98.56%
Squamous	68.00%	79.12%
Vascular lesions	58.00%	86.24%
Pigmented lesions	56.00%	85.22%
Actinic keratosis	94.00%	96.59%

TABLE 1: CONFIDENCE AND ACCURACY OF DISEASES

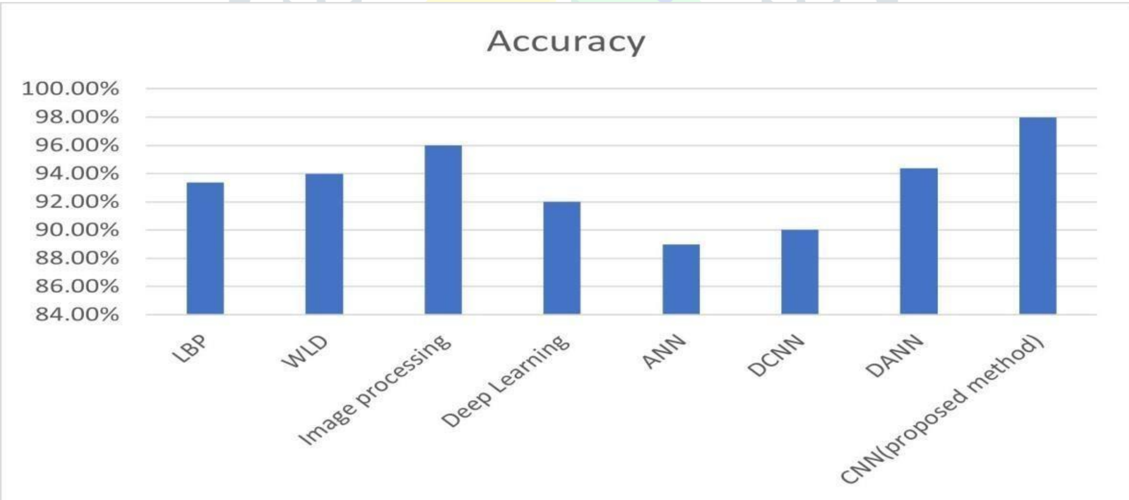

Fig.8.Performance Analysis of Various Techniques.

6. CONCLUSION:

The study on the use of Convolutional Neural Networks (CNN) for the diagnosis of skin diseases has demonstrated the promise of deep learning in the medical domain, especially in dermatology. The CNN model created for this study achieved notable accuracy levels for melanoma (98%), squamous cell carcinoma (68%), actinic keratosis (94%), pigmented benign keratoses (56%), and vascular lesions (58%). These findings demonstrate the model's high degree of precision in recognizing actinic keratosis and melanoma, two conditions that are essential for early identification and treatment. There is need for improvement given the lower detection accuracy of vascular lesions, pigmented benign keratoses, and squamous cell carcinoma. It highlights the difficulties in telling apart various kinds of skin conditions that have similar visual characteristics. As a result, the model has to learn from a more varied and large dataset or integrate more complex features into its architecture.

In order to further increase diagnosis accuracy, future study should concentrate on resolving the constraints that have been found by adding multi-modal data, such as patient history and demographic data. Further validating the model in real-world clinical settings and getting dermatological input will be essential to improving its usability and efficiency.

7. FUTURE WORK:

A lot many advancements and improvements will be developed in the near future ,which help us classify other kind of skin lesions also. We aim to develop Mobile based application and Web based application based on our proposed system which is of a great use to the people around us. Mobile devices such as smart phones ,PDAs and Tablets are becoming an essential part of human life. Embedding AI diagnosis and treatment of skin disease on smart devices will be a significant trend in the future.

8. REFERENCES:

[1] Arifin, S., Kibria, G., Firoze, A., Amini, A., & Yan, H. (2012) "Dermatological Disease Diagnosis Using Color-Skin Images." Xian: *International Conference on Machine Learning and Cybernetics*.

[2] Yasir, R., Rahman, A., & Ahmed, N. (2014) "Dermatological Disease Detection using Image Processing and Artificial Neural Network. "Dhaka*: International Conference on Electrical and Computer Engineering*.

[3] A. Banerjee, S. Sarkar, M. Nasipuri, and N. Das, "Skin diseases detection using lbp and wld: An ensembling approach," SN Computer Science, vol. 5, no. 1, p. 72, 2023.

[4] K. S. Rao, P. S. Yelkar, O. N. Pise, and S. Borde, "Skin disease detection using machine learning," International Journal of Engineering Research & Technology (IJERT), vol. 9, no. 3, pp. 2278–0181, 2021.

[5] Suganya R. (2016) "An Automated Computer Aided Diagnosis of Skin Lesions Detection and Classification for Dermoscopy Images." International Conference on Recent Trends in Information Technology.

[6] Zeljkovic, V., Druzgalski, C., Bojic-Minic, S., Tameze, C., & Mayorga, P. (2015) " Supplemental Melanoma Diagnosis for Darker Skin Complexion Gradients." *Pan American Health Care Exchanges.*

[7] R. Agarwal and D. Godavarthi, "Skin disease classification using cnn algorithms," EAI Endorsed Transactions on Pervasive Health and Tech- nology, vol. 9, no. 1, 2023.

[8] J. Zhang, F. Zhong, K. He, M. Ji, S. Li, and C. Li, "Recent advancements and perspectives in the diagnosis of skin diseases using machine learning and deep learning: A review," Diagnostics, vol. 13, no. 23, p. 3506, 2023.

[9] HAM 10000 Dataset : https://www.kaggle.com/datasets/kmader/skin-cancer-mnist- ham10000