Kufa Journal of Engineering
Vol. 16, No. 4, October 2025, P.P. 125-133
Article history: Received 28 April 2024, last revised 20 December 2024, accepted 20 December 2024

DETECTION OF HAIR FALL AND SCALP DISORDERS THROUGH ML AND IMAGE PROCESSING

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https://doi.org/10.30572/2018/KJE/160406

ABSTRACT

Hair loss impacts approximately 80 million people in the United States and arises from factors such as aging, genetic predisposition, stress, and medication. In many cases, early signs of scalp and hair disorders remain unnoticed, delaying timely diagnosis and treatment. Neural networks, particularly in image-based diagnostics, have shown great promise across medical domains, including oncology and dermatology. This research investigates the application of deep learning for identifying three major scalp conditions: alopecia, psoriasis, and folliculitis. Major challenges included limited literature, a small dataset, and non-uniform image quality from online sources. To address these, the study compiled 150 scalp images and employed preprocessing techniques such as denoising, histogram equalization, augmentation, and class balancing. A two-dimensional Convolutional Neural Network (CNN) was trained on this dataset, achieving a training accuracy of 96.2% and a validation accuracy of 91.1%, with consistently high precision and recall across all classes. Additionally, a new scalp scan dataset was introduced to support future research, contributing to the development of AI-driven diagnostic tools for hair and scalp health assessment.

KEYWORDS

Pad net algorithm; DenseNet; AlexNet; Confusion matrix; Machine Learning; Scalp Diseases.

1. INTRODUCTION

As hair loss and scalp diseases are affecting individuals' psychological well-being and confidence, many research undergone to diagnose their root cause strategies. Sadick (2018) proposed novel therapeutic approaches for male pattern baldness, while Pratt et al. (2017) and Sterkens et al. (2021) experiminted the etiology and clinical management of alopecia areata. In the same way, Alshahrani et al. (2020) examined the occurrence and features of alopecia in Saudi Arabia, and Simakou et al. (2019) discussed about the autoimmune nature.

Machine learning has turn out to be progressively significant in medical diagnosis owing to its capacity to notice patterns inside complex datasets. Sahli (2020) and Mathiyalagan & Devaraj (2021) emphasized its usefulness in diagnosing diseases for example brain tumors in addition to diabetes. Additionally, Saber et al. (2021) and Yue et al. (2021) confirmed the value of deep learning for cancer detection, together with breast as well as ovarian cancers.

In the background of scalp analysis, Bernardis & Castelo-Soccio (2018) and Kapoor & Mishra (2018) projected computational frameworks for sensing alopecia, although Wang et al. (2018) and Hoffmann (2003) announced image-based tools to examine hair growth patterns. Furthermore, Svanera et al. (2016) technologically advanced *Figaro*, a dataset for hair detection and segmentation. Advances in convolutional neural networks (CNNs), as revealed in the works of Ibrahim et al. (2020) and Rimi et al. (2020), have made it conceivable to analyze dermatological conditions competently and precisely. As a group, these studies form the groundwork for relating artificial intelligence to hair and scalp diagnostics.

2. EXPERIMENTAL OR MATERIALS AND METHODS

2.1. DenseNet

DenseNet helps as a real deep learning framework for identifying scalp and hair-related problems by assimilating machine learning and image processing. Its exclusive architecture eases strong inter-layer connections, permitting efficient gradient flow and feature reuse. When accomplished on extensive image datasets, DenseNet can distinguish between normal scalp situations and disorders such as alopecia or dermatitis by identifying intricate patterns in texture, color, and follicular density.

Outside organization, DenseNet provides insights into underlying causes—such as genetic predisposition or stress—offering provision for personalized recommendations. Its flexibility permits it to join in with diverse imaging systems, refining accessibility and scalability. As illustrated in Fig. 1, DenseNet's layered structure increases diagnostic accuracy and provisions dermatologists with rapid, reliable investigation.

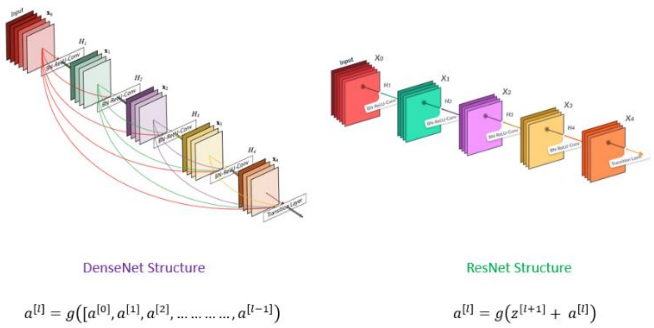

Fig.1 Structure of DenseNet.

2.2. AlexNet

Even though AlexNet signifies an earlier CNN architecture, it ruins operative for medical image analysis when properly adjusted. By leveraging its deep feature extraction abilities, AlexNet can recognize subtle differences in scalp images and benefit differentiate among communal and simple conditions like folliculitis or alopecia.

Its tiered feature learning structure permits precise pattern recognition from raw images, associate dermatological diagnostics. Owing to its computational efficiency and flexibility, AlexNet can be combined with multiple imaging modalities. In spite of being an older model, it residues a robust tool for initial detection and arrangement of scalp and hair disorders when enhanced through transfer learning and modern preprocessing methods.

2.3. Data description

2.3.1. Data collection

Among the key challenges in visual disease prediction, it is obtaining a varied and high-quality dataset. Medical images associated to scalp disorders are frequently unusual and conflictingly labeled. To remedy this, the dataset for this research was curated from several online repositories and through support from healthcare professionals, confirming representative samples across multiple conditions.

2.3.2. Architecture of the Model

DenseNet was tweaked by means of improved hyperparameters found through grid search, comprising learning rate, batch size, and dropout rate. Transfer learning was realistic to adjust the pretrained model for scalp disease detection. The learning rate was attuned to attain stable convergence, while an appropriate dropout value lessened overfitting specified the dataset's size.

The network's dense blocks and growing rates were experienced to balance accuracy with computational efficiency. Preprocessing steps—such as normalization, augmentation, and class weighting—were united to address class imbalance and progress model generalization. Fig.2 illustrates the complete workflow, highlighting the sequential processes of optimization, preprocessing, and training that contribute to the final diagnostic model.

The below is the flowchart of the overall working process of our model.

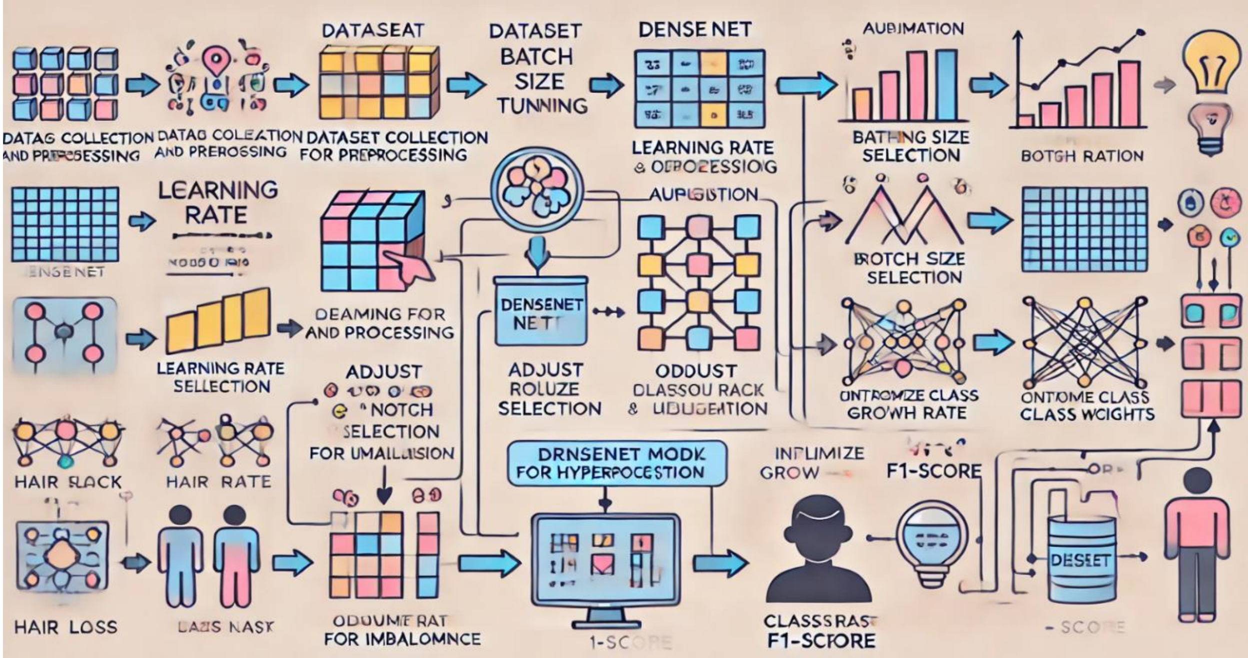

Fig. 2. Flow Chart

2.3.3. Data description

Obtaining sufficient and balanced image samples posed a significant challenge. The dataset included multiple categories representing different scalp conditions—alopecia, folliculitis, and psoriasis—collected from verified sources. Fig.3 visualizes the categorical distribution of these subsets, which were used to train and validate the CNN models.

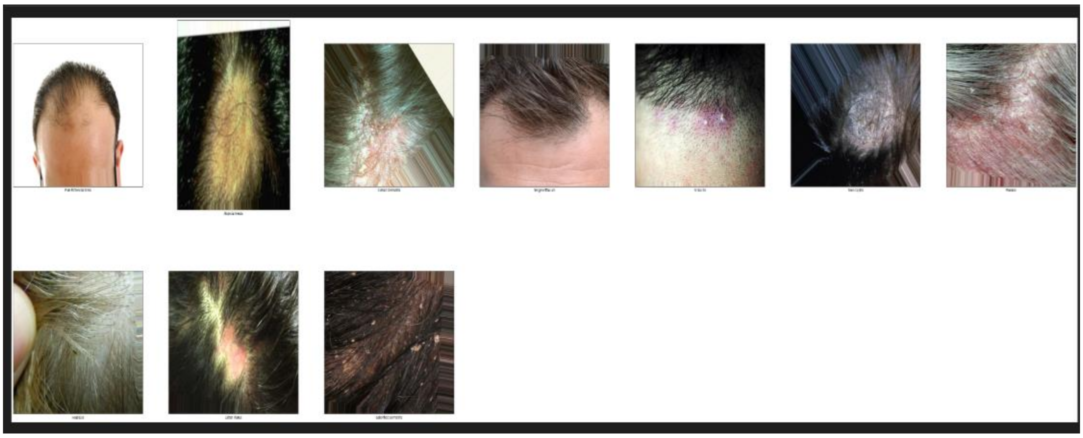

Fig .3. Image subset categories in sub set.

3. RESULTS AND DISCUSSION

The CNN model was trained using optimal parameters derived from grid search. The dataset was split into 70% training and 30% testing subsets. Data preprocessing ensured consistency and reliability by resizing images to uniform dimensions, normalizing pixel values to a [0,1] range, and applying Gaussian blur or median filters to remove noise. Histogram equalization corrected contrast variations, while brightness normalization addressed lighting inconsistencies.

To enhance model robustness, data augmentation—such as random flipping, rotation, and zooming—was applied without compromising realism. Both training and testing data underwent identical preprocessing to maintain uniformity. These methods significantly improved accuracy and reduced overfitting.

After training, the DenseNet model demonstrated higher performance compared to AlexNet. Table 1 summarizes the comparative results in terms of Accuracy, Precision, Recall, and F1 Score.

Table 1. Comparing algorithms for real time data set.

Algorithm Name	Accuracy	Precision	F1 Score	Recall
DenseNet	99.667%	0.99671	0.99667	0.99667
AlexNet	83.917	0.84724	0.83803	0.83917

The performance graphs Fig. 4 and 5 depict the training and validation accuracy as well as loss over epochs. The DenseNet model exhibited steadily increasing accuracy with a corresponding decline in loss, reflecting successful convergence and reduced errors.

The front-end interface of the developed application Fig.6 displays the model's output, enabling real-time detection of scalp diseases from user-uploaded images.

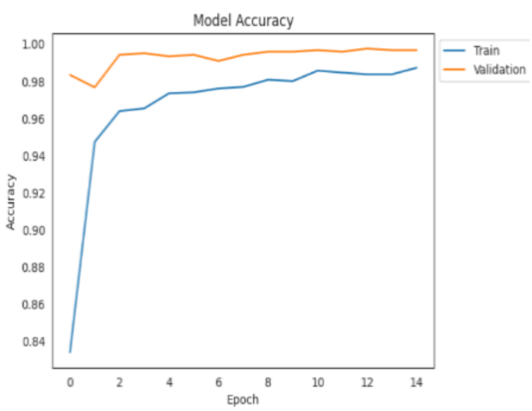

Fig. 4.DenseNet Model Accuracy

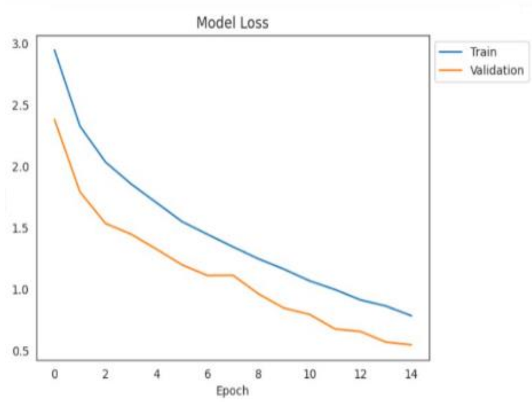

Fig 5. AlexNet Model Loss

Fig. 6. Front end of the model with the output

This below graph Fig. 4 shows the Epoch of the model and its loss in training and validation measures.We could also see that the model loss has been decreased and trained our model in a way that the errors in the model are less and it is more accurate.

3.1. Application to display overall results

Here in the Fig 6 we can see that the total outcome of the project which is hari fall scalp disease detection.

4. CONCLUSION

Hair loss and scalp disorders often remain untreated due to delayed recognition and lack of accessible diagnostic tools. Integrating artificial intelligence into dermatology can significantly reduce this gap by enabling early detection. This study developed a machine learning–based framework utilizing DenseNet for diagnosing common scalp diseases such as psoriasis, folliculitis, and alopecia.

The proposed model achieved high accuracy and reliability after comprehensive preprocessing and optimization. By automating the detection process, it provides valuable assistance to dermatologists and facilitates timely intervention for patients. The inclusion of a new scalp image dataset further supports future advancements in AI-driven dermatological research. Overall, the system demonstrates that deep learning–based diagnostic models can play a crucial role in early disease identification and personalized scalp care solutions.

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