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Revolutionizing Hair Fall Analysis: The Advanced Precipitation U-Net Model

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ABSTRACT

Around the world, long and thick hair is considered a sign of youth, while thick hair in humans is a symbol of youth and vitality. Approximately 80 trillion people suffer from hair fall due to aging, stress, medication, or genetic makeup globally. Hair and scalp-related diseases often go unnoticed in the beginning. Sometimes, a patient cannot differentiate between hair fall and regular hair fall. Diagnosis of hair-related diseases is time-consuming as it requires professional dermatologists to perform visual and medical tests. Machine learning and deep learning studies become a complex overlap between hair loss and psychological issues, making accurate detection difficult. Because of this, the overall diagnosis gets delayed, further increasing the severity of the disease. This study leverages the image-processing capability such as neural network-based applications used in various fields, especially healthcare and health informatics, to predict malignant diseases such as cancer and tumors. This study uses the U-Net to 92% accurately segment even small or thin structures, such as individual hair strands, which is a major challenge in hair fall detection. By producing precise segmentation masks, U-Net helps doctors and researchers identify areas of hair fall more reliably and early, overcoming the difficulties of gradual thinning and subtle changes that are hard to spot with the naked eye.

Keywords: *Hair fall prediction, Machine learning, Deep learning, U-Net, Comparative analysis.*

1. INTRODUCTION

In today's era, everyone wants to get a better look, for which hairstyle plays a major role, which makes a person look attractive. Many people spend a lot of money to maintain their hair because it has both physical and psychological importance in people's lives [1]. It is an asset that makes a person beautiful, intuitive, protects from the sun's ultraviolet rays, and serves as a biological signal [2]. Therefore, it is not surprising that people with excessive hair fall often seek medical help. There are many diseases related to hair, about which people are generally unaware [3]. Due to these diseases, people's hair starts falling out and they lose their beauty [4]. Identifying hair fall is crucial because early detection can significantly improve the chances of successful treatment and prevent further fall [5]. Hair fall can be a symptom of underlying health conditions such as hormonal imbalances, nutritional deficiencies, or autoimmune disorders. Moreover, it can have a profound psychological impact, leading to decreased self-esteem, anxiety, and even depression. For many, hair is closely tied to personal identity and social confidence, making the management of hair health a priority [6].

However, accurately identifying hair fall presents several challenges. Hair fall can occur gradually, making it difficult for individuals to notice changes until significant thinning has occurred. Differentiating between normal shedding and pathological hair fall requires careful observation and sometimes specialized diagnostic tools [7]. The causes of hair fall are multifactorial, ranging from genetics and stress to environmental factors and improper hair care practices. Additionally, cultural perceptions and stigma around hair fall may discourage individuals from seeking timely help [3]. These complexities highlight the need for increased awareness, education, and access to professional evaluation to ensure that hair fall is recognized and addressed effectively.

Hair, composed of keratin protein, is often associated with beauty and masculinity. In general, a healthy human body contains approximately 5 million hair follicles [8]. Scalp hair plays a crucial role in regulating body temperature and shielding the brain from external heat. The typical hair growth cycle lasts between 2 to 7 years, as noted in studies [9] and [10]. An average healthy individual has around 100,000 hairs on their scalp, with a daily loss of 50 to 100 strands considered normal as illustrated in the Figure 1. Traditional machine learning methods, such as Support Vector Machines (SVM) and Random Forests, have been utilized to tackle hair fall [11]. However, their effectiveness is often limited by the variability and complexity of image data, as well as their inability to extract meaningful features [12]. This study utilizes the U-Net [13], a powerful deep learning model designed for semantic image segmentation leading to machine learning and deep learning by labeling every pixel in an image with a specific class, such as hair, skin, or background. This is especially useful in applications like medical imaging, clothes segmentation, flood mapping, and self-driving cars, where knowing the exact shape and location of objects is crucial. This design allows U-Net to accurately segment even small or thin structures, such as individual hair strands, which is a major challenge in hair fall detection [14]. By producing precise segmentation masks, U-Net helps doctors and researchers identify areas of hair fall more reliably and early, overcoming the difficulties of gradual thinning and subtle changes that are hard to spot with the naked eye.

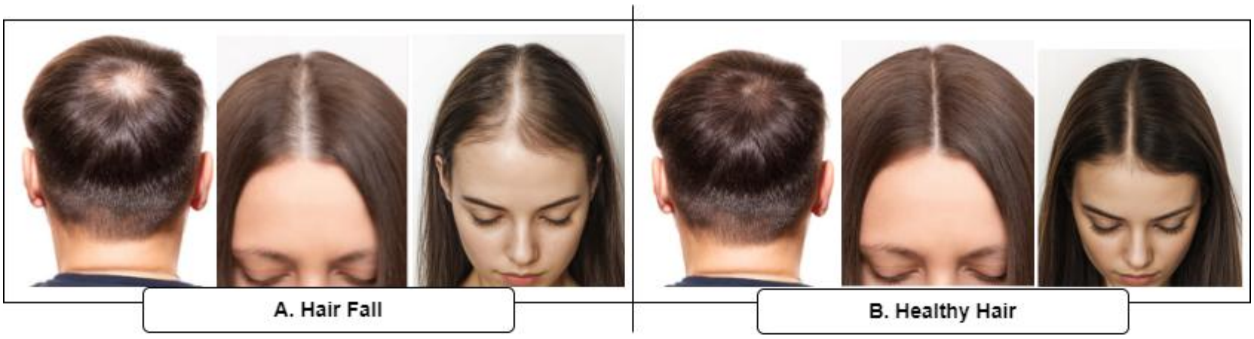


Figure 1: Consider as hair fall and healthy images

1.1 Challenges and Contribution

Computer vision offers promising tools for detecting diseases through image analysis. Researchers typically train AI models using curated image datasets, preprocessing steps, and neural networks. However, limited studies in this field, unavailability of proper datasets and degree of diversity among images scattered on the internet made the task challenging [15, 16]. Publicly available scalp disease datasets are scarce, and existing images vary widely in quality, resolution, and format. However, scalp disease detection faces unique hurdles. For example, hair diseases (e.g., alopecia, psoriasis) can affect scattered areas like the scalp, beard, or eyebrows, complicating image capture and analysis. Variations in skin tone, hair color/texture, and lighting require tailored adjustments for each image before AI processing. Errors in detection (false positives/negatives) could worsen hair fall due to misdiagnosis, demanding rigorous model validation. Our contributions are summarized as follows:

- Utilizes the U-Net model to accurately segment hair falls even small or thin structures.
- Implemented an encoder decoder architecture and passed the Scalp images as input to the architecture.
- The output of encoder decoder architecture is passed as input to the Axial Transformer network.

With sequence frames given as input, the final output of the UNet with Axial Transformer model is a distribution, out of which we select the mean value for everypixel.

1.2 Organization of the Paper

This paper is structured to provide a comprehensive exploration of the Advanced Precipitation U-Net for detecting hair fall. Section 2 presents a **Literature Review**, where we examine existing studies and methodologies related to hair loss detection, highlighting their strengths and limitations. In Section 3, we outline the **Proposed Methodology**, detailing our innovative approach that integrates the U-Net architecture with an encoder-decoder framework and an Axial Transformer network for enhanced hair fall detection. Section 4 focuses on **Result Evaluation**, where we present and analyze the outcomes of our experiments, demonstrating the effectiveness of our proposed model against traditional methods. Finally, Section 5 concludes the paper by summarizing our findings and suggesting directions for **Future Work**, emphasizing potential improvements and applications of our research in clinical settings.

2. LITERATURE REVIEW

Many researchers have analyzed scalp images to identify skin features associated with alopecia areata. The study [17] introduced a trichoscopy method that used scalp image processing techniques, such as grid line selection and eigenvalue analysis, to detect hair loss features. This approach was innovative as its combined computer vision and image processing for diagnosing alopecia areata [18]. Another study proposed an automated system for early diagnosis and treatment of alopecia using artificial neural networks (ANN). With a feedforward ANN, the system achieved an accuracy of 91% [19]. Similarly, a different study classified scalp images into three categories: alopecia areata, dandruff, and normal hair, resulting in an accuracy of 85% [20]. Additionally, texture analysis of scalp images was performed using the Severity of Alopecia

Tool (SALT) score, which allowed for the evaluation of hair density changes in alopecia areata cases [21].

Several systems have utilized scalp images to study hair density and hair loss caused by various factors, including alopecia areata. One such system, called TrichoScan, employed epiluminescence microscopy to analyze scalp images of individuals with androgenic alopecia (AGA). It measured four key parameters: hair density, hair diameter, hair growth rate, and the anagen/telogen ratio, achieving a correlation accuracy of approximately 91% [22].

Table 1. Comparative analysis of the existing literature of Hair Fall Disorder.

Literature	Year	Methodology/ Tool	Performance Measure	Description
Behal R et al., [23]	2024	DL, CNN	91%	Identify different stages of hair loss from frontal facial images.
Seo S et al., [24]	2020	Histogram based methodology	90%	Computer vision studies to detected HF
Kapoor I [25]	2018	ANN	91%	Uses the feedforward ANN to predict HF
Kim M et al., [26]	2022	DL, EfficientDet, YOLOv4, and DetectoRS	58.67%	object detection algorithms used for Hair density measurement (HDM)
Almohanna, H.M [27]	2019	Comparative analysis	-	Provide the role of vitamins and minerals for HFD
Jimenez F [28]	2021	Survey on techinques	-	Describe the basic overview of the HFD
Benhabiles H [29]	2019	DL	83%	investigates deep learning methods for detecting hairs loss levels

Another system used artificial neural networks (ANNs) to diagnose hair loss. Scalp images from 348 participants were analyzed, demonstrating that ANNs could effectively detect hair loss [30]. Additionally, Shih developed a hair-counting algorithm using 40 microscopic scalp images with 85x magnification [31]. This algorithm analyzed features such as hair density, diameter, length, and oiliness levels. It proved to be more accurate than traditional Hough-based methods and more reliable than manual hair counting.

3. PROPOSE METHODOLOGY

A detailed methodology for hair fall detection, diagnosing conditions, and assessing hair health using a U-Net-based deep learning approach involves several key stages as show in the Figure 2, which includes the image acquisition, preprocessing, segmentation, feature extraction, diagnosis, and health assessment. Below is a comprehensive outline with relevant equations and technical details, focusing on adapting U-Net for this biomedical image analysis task.

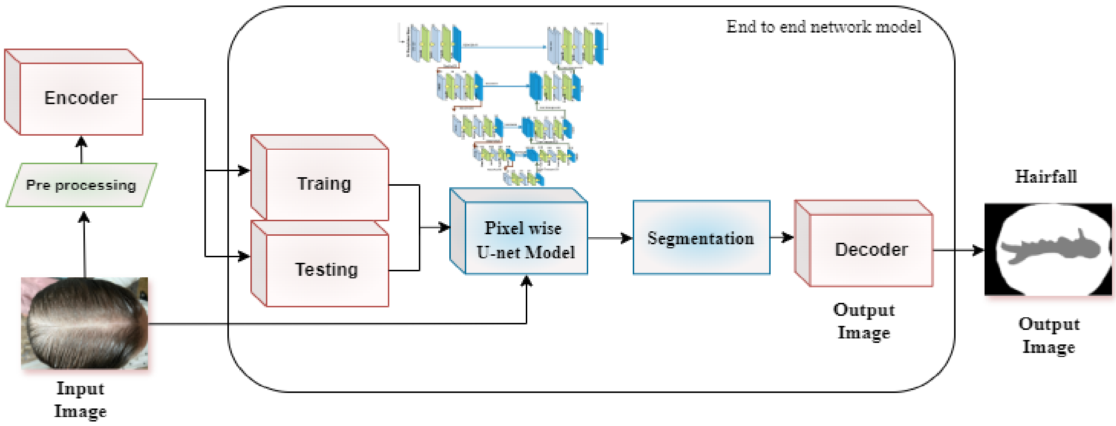


Figure 2 Proposed architecture for the hair fall detection using U-net Model

The U-Net model utilize the pixel by pixel labeling to diagnosing conditions and assessing hair health, originally designed for biomedical image segmentation, can be adapted for this task due to its architecture, which is effective for image processing. It involves the following steps, input refinement, hair segmentation baseline model and segmentation.

3.1 Dataset

This study utilizing the U-Net model for hair fall detection on the Bald Detection Dataset [32] (also known as the Bald People Segmentation Dataset) demonstrates the effectiveness of deep learning for segmenting bald regions and quantifying hair loss directly from scalp images.

The dataset consists of images of individuals with varying degrees of baldness, each paired with precise segmentation masks that delineate bald areas. The dataset features images of men and women exhibiting different degrees of hair loss, with five images provided for each individual to illustrate their specific condition. It includes a wide range of demographics, ages, and ethnic backgrounds.

Each instance of hair loss is annotated according to the Norwood scale. When hair is accurately segmented, it can be recolored to any chosen color, letting users try out new hair colors. To automatically change hair color, we convert the image to intensity values and use a lookup table (LUT) to select and apply new colors based on brightness. Figure 3 shows how this hair recoloring process works. In the Bald People Segmentation Dataset, each original photo is paired with a segmentation mask. The mask visually delineates the bald scalp area, allowing algorithms and researchers to focus specifically on those regions for analysis or model training. These masks are crucial for training and evaluating segmentation models like U-Net, as they serve as the ground truth for what constitutes bald or hair-covered regions in each image.

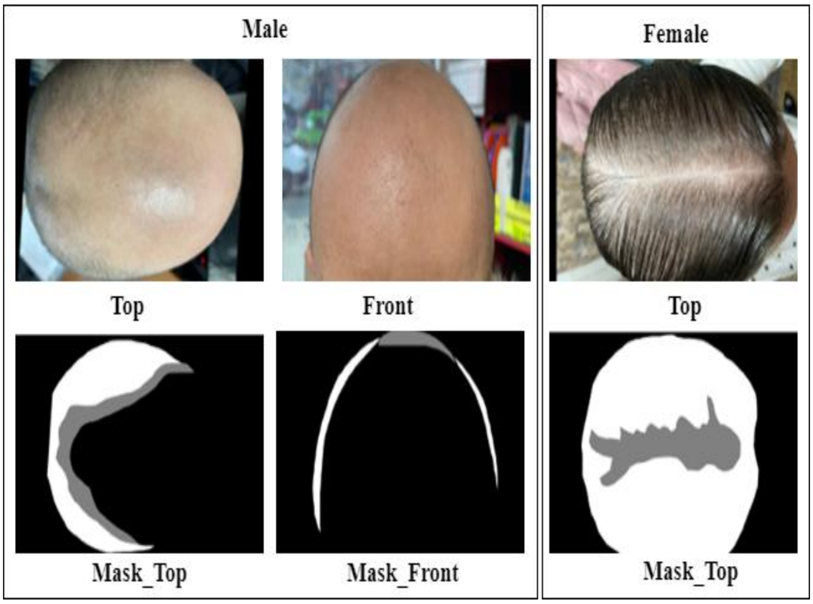


Figure 3 Sample of dataset used for segmentation of U-Net model and masking output of male and female

3.2 Input Refinement Stage

Input refinement stage is essential to perform hair segmentation, this step involves data preparation and refinement, which includes several techniques such as landmark detection, size normalization, and data augmentation of scalp images [33]. Additionally, hair recoloring is applied to the detected hair region to enhance the segmentation process and improve the model's accuracy. These pre-processing methods ensure that the input data is optimized for effective and precise segmentation by the deep neural network. As illustrated in Figure 1, we standardized images of any original size by resizing them to 128×128, ensuring that the nose was centered within the image. When the resized area exceeded the original image's dimensions, we filled the extra background pixels with a value of 128 (white). This choice padding the border with a bright value rather than zero (black) was made because real-world and typical images usually have brighter, not darker, borders.

3.2.1 Landmark Detection and Size Normalization

Initially, images were just resized to 128×128 for training, but this led to poor results in real-world tests due to changes in lighting and distance. To fix this, we decided to normalize images using 68 facial landmarks detected by a fast and accurate face detector. This allowed us to align and center faces in the image, making the data consistent regardless of size, position, or distance.

3.2.2 Data Augmentation

When capturing video in real time, input images can change due to distance, pose, camera angle, and lighting. If there aren't enough training images that reflect these variations for deep neural network (DNN) models, it's common to artificially create new images by simulating these changes. In this case, starting with 6,800 original images, we generated 95,200 training samples by flipping and rotating each image (at angles of ±5, ±15, and ±30 degrees), producing 14 new images from each original. Figure 4 shows the results of this data augmentation process.

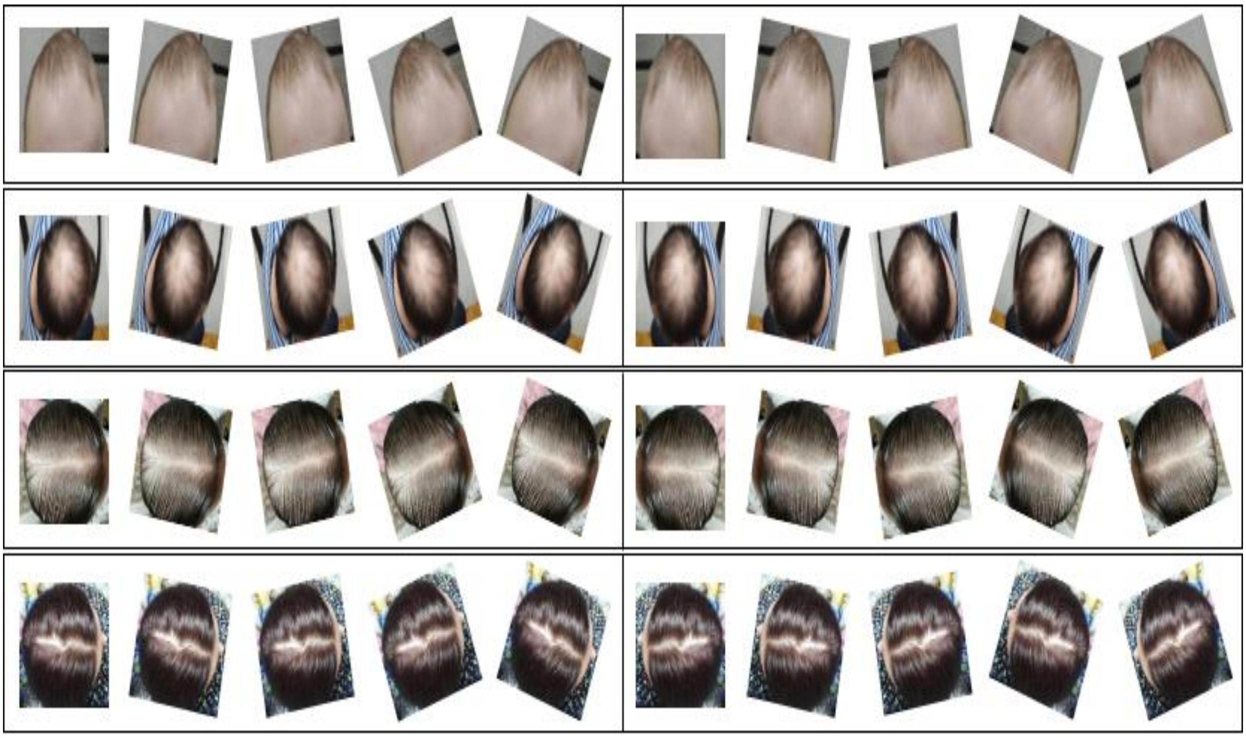


Figure 4 Data augmentation results for the hair inputs

3.3 Hair Segmentation Baseline Model

Model uses the masking images that are annotated overlays that mark the exact areas of baldness or hair, forming the foundation for automated detection, quantification, and analysis in hair loss research and computer vision applications A segmentation model based on an encoder–decoder structure works better than baseline models like AlexNet or VGGNet, which are mainly designed for detection or classification, not for segmenting objects. Since hair segmentation requires precise location information, the model needs to preserve and match spatial details between the input and output images. This is achieved through down-sampling and up-sampling steps, as illustrated in Figure 5. The U-Net model is better suited for hair segmentation than the FCN (Fully Convolutional Network) model. While FCN introduced the encoder-decoder structure for semantic segmentation, it struggles to fully restore details because it's up-sampling skips steps when expanding from small to large channels. U-Net fixes this by using symmetric skip-connections and gradual up-sampling to recover dimensions properly. For this reason, we based our hair segmentation model on U-Net.

U-Net is a popular deep learning architecture specifically designed for image segmentation, especially in the medical field. Its structure resembles a "U" and comprises two primary components: the encoder and the decoder as show in the Figure 5. The encoder progressively down samples the spatial information of the input, extracting essential features through convolution and pooling operations. This process enables the model to grasp the overall structure and context of the image. Subsequently, the decoder reconstructs the image to its original dimensions using up sampling techniques. It also incorporates skip connections that transfer detailed information from the encoder layers, enhancing the accuracy and detail of the segmentations produced. It consists of two main components: encoder and decoder.

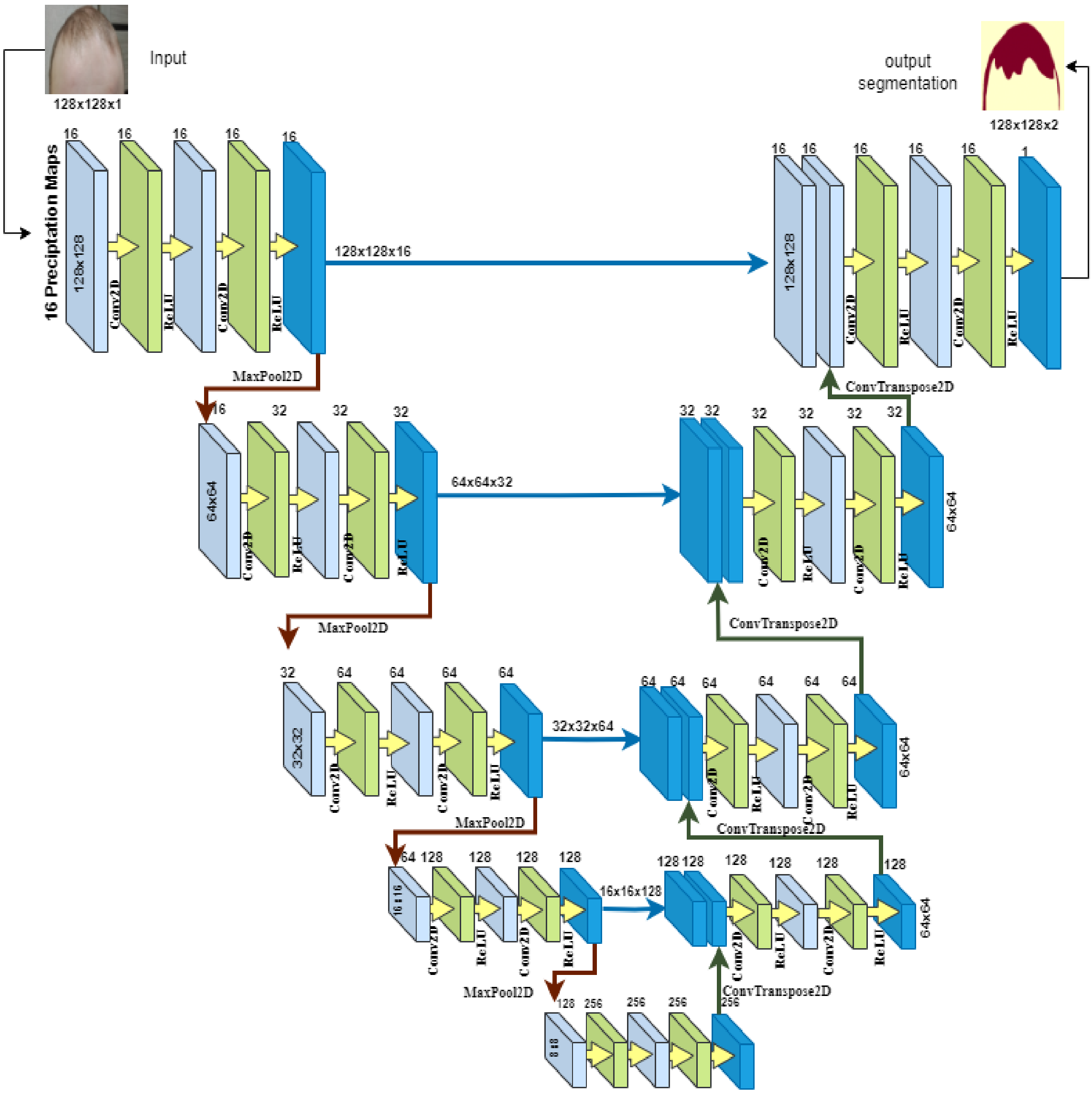


Figure 5: Proposed U-net architecture encompasses input through encoder and decoder using Conv2D

This methodology leverages the U-Net architecture for robust, automated hair segmentation and quantitative analysis, enabling objective hair fall detection, condition diagnosis, and comprehensive hair health assessment. Let x is the input images and y are the output segmentation mask with the network parameter θ. Then the output y could be describes as using the U-Net model is

$$y = f_{UNet}(x;\theta)$$

For the binary hair fall segmentation use binary cross-entropy (BCE) loss or Dice loss as

$$BCE_{loss} = -\frac{1}{N}\sum_{i=1}^{N}[t_i log P_i + (1-t_i) log(1-P_i)]$$

$$Dice\ Loss = 1 - \frac{2\sum_i P_i t_i}{\sum_i P_i + \sum_i t_i}$$

Where p_i is the predicted pixel value, t_i is the true pixel value and N denotes the total number of pixels. Better suited for hair segmentation than the FCN (Fully Convolutional Network) model. While FCN introduced the encoder-decoder structure for semantic segmentation, it struggles to fully restore details because it's up-sampling skips steps when expanding from small to large channels. U-Net fixes this by using symmetric skip-connections and gradual up-sampling to recover dimensions properly. For this reason, we based our hair segmentation model on U-Net. It also incorporates skip connections that transfer detailed information from the encoder layers, enhancing the accuracy and detail of the segmentations produced. It consists of two main components: encoder and decoder.

3.3.1 Encoder

The encoder is responsible for systematically down sampling the input image. It does this through repeated applications of convolutional layers followed by pooling operations, typically max pooling. Each convolutional block in the encoder extracts increasingly complex features, allowing the model to capture the overall structure and context of the image. As the spatial dimensions decrease, the number of feature channels increases, enabling the network to learn rich, hierarchical representations of the input data. At each encoder block, two 2D convolution operations are applied:

$$f^l = \sigma(w^l * x^{l-1} + b^l)$$

Where,

- f^l is the output feature map at layer l,
- W^l is the convolution kernel at layer l,
- $*$denotes the convolution operation,
- $X^{(l-1)}$ is the input feature map from the previous layer,
- b^l is the bias term and
- σ is the activation function (typically ReLU).

This is repeated for two convolutional layers per block and more representation of the layer and data process is show in the Figure 6.

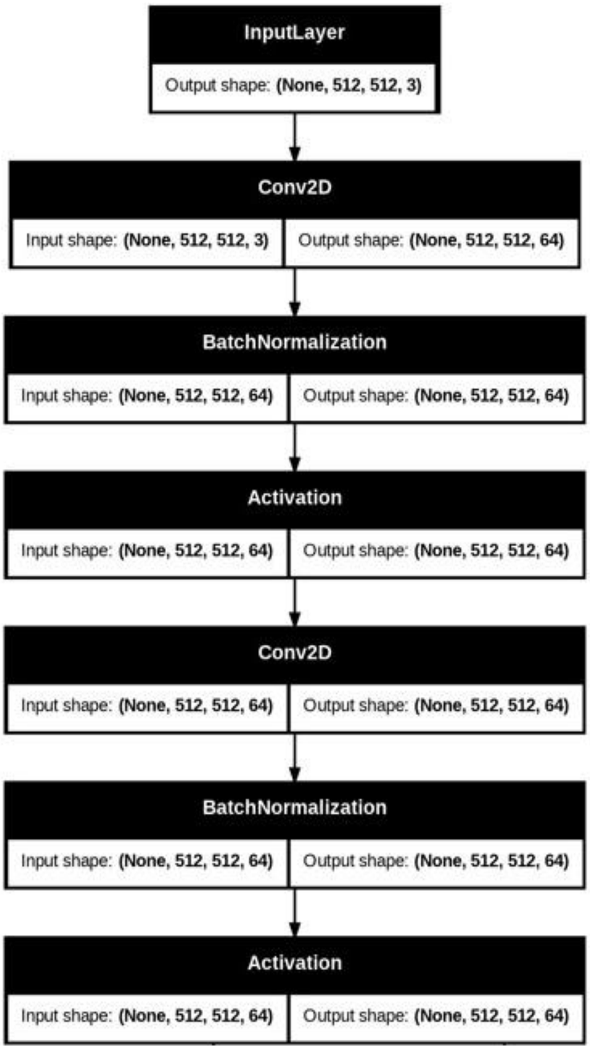


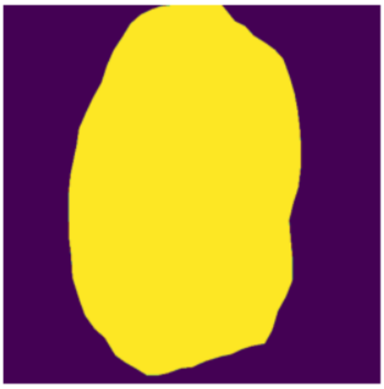
Figure 6 Layer by layer down sampling description of the model

3.3.2 Decoder

The decoder then reconstructs the image back to its original spatial dimensions using up-sampling techniques, such as transposed convolutions or up-convolutions. This path is symmetric to the encoder and is designed to enable precise localization, which is critical for segmentation tasks. The decoder progressively increases the spatial resolution while reducing the number of feature channels, ultimately producing a segmentation map that matches the input image size. After the convolutions, a **max pooling** operation is applied to reduce the feature map size by a factor of 2.

4. HAIR FALL RESULT

The results of the segmentation task using the U-Net model indicate a high level of effectiveness in identifying and delineating hair loss regions from scalp images as shown in the figure 7. Achieving an accuracy of 92%, the model demonstrates robust performance across various cases, including images with different lighting conditions, hair densities, and scalp exposures. The segmentation masks generated by U-Net closely match the ground truth annotations, confirming the model's ability to capture subtle boundaries between hair and bald areas. This level of accuracy suggests that U-Net is a reliable tool for automated hair fall assessment and can be confidently used in clinical and research settings to support objective measurement and monitoring of hair loss progression. The strong results also highlight the potential of deep learning-based segmentation methods for broader applications in dermatological image analysis.

Original Image	**Masking Image**	**Segmented Image Hair Fall**
		
Original Image	**Masking Image**	**Segmented Image Hair Fall**
		
Original Image	**Masking Image**	**Segmented Image No Hair Fall**
		

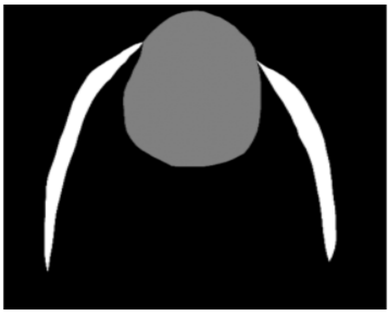
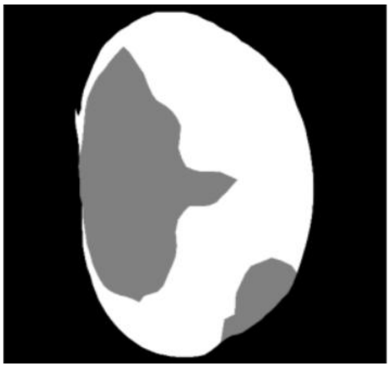
Original Image	Masking Image	Segmented Image Hair Fall
		
Original Image	**Masking Image**	**Segmented Image Hair Fall**
		

Figure 7 Hair fall prediction of the segmentation images

-The U-Net architecture effectively captured the spatial features necessary for precise segmentation, enabling clear differentiation between hair-covered and bald areas across diverse image conditions. The model consistently produced accurate masks, even in challenging scenarios with varying hair density and scalp visibility. This high level of accuracy indicates that U-Net is well-suited for automated hair fall analysis, providing reliable quantitative assessments that can support clinical diagnosis and monitoring of hair loss progression. The results are consistent with other studies where U-Net-based models have achieved comparable or higher segmentation accuracy for similar biomedical imaging tasks

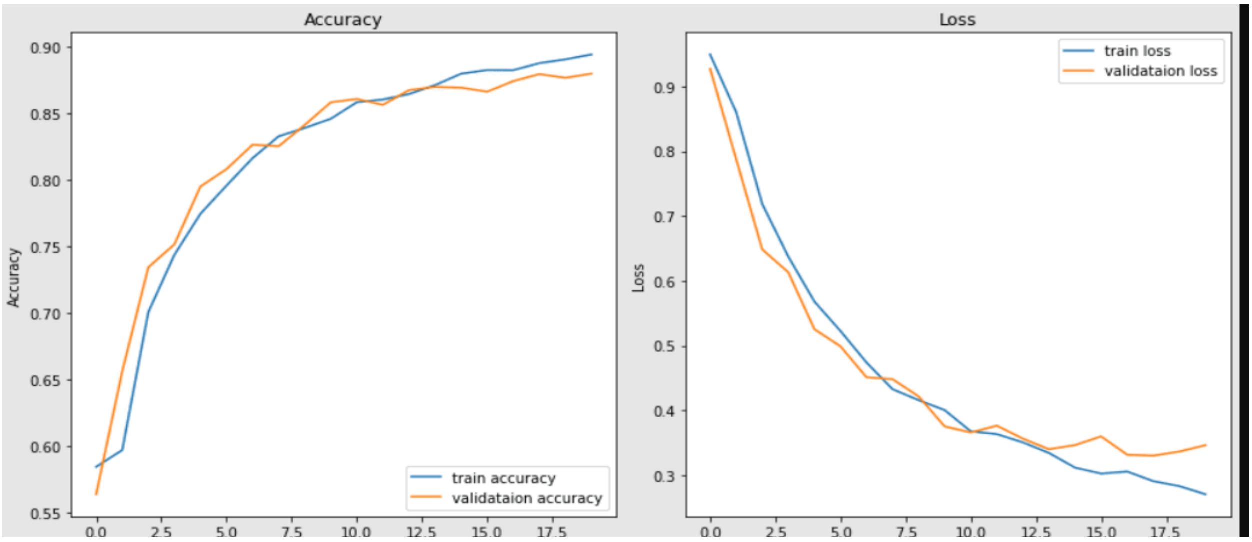


Figure 8 ROC curve for the training and validation accuracy and loss

The ROC (Receiver Operating Characteristic) curve is a graphical tool used to evaluate the performance of a binary classifier by plotting the true positive rate (sensitivity) against the false positive rate (1-specificity) at various threshold settings. When the training and validation accuracy curves overlap closely, it indicates that the model is generalizing well and there is minimal overfitting or underfitting. This overlap suggests that the model's performance on unseen data is consistent with its performance on the training data, which is a desirable outcome in machine learning. In this scenario, both the training loss and validation loss converge to a value of 0.3 and 0.4 respectively, further supporting the conclusion that the model is learning effectively and not overfitting. The convergence of loss values means the model's predictions are similarly accurate on both the training and validation sets, and the learning process has reached a stable point. A ROC curve generated under these conditions would typically show a smooth, high-performing curve with a large area under the curve (AUC), reflecting the model's strong ability to discriminate between classes across different thresholds. This overall pattern overlapping accuracy, matching loss values, and a robust ROC curve demonstrates a well-trained and reliable classifier. As shown in the figure 8, training and validation accuracy curves overlap, indicating strong generalization and minimal overfitting, while both training and validation loss converge to 0.4, demonstrating stable and consistent model performance.

5. CONCLUSION AND FUTURE DIRECTION

The application of deep learning, particularly the U-Net architecture, to the problem of hair fall detection and segmentation represents a significant advancement in the field of dermatological image analysis. Throughout this study, the U-Net model has demonstrated its capacity to accurately segment hair and bald regions from scalp images, yielding a segmentation accuracy of 92%. This high level of performance underscores the suitability of U-Net for complex biomedical image segmentation tasks, especially those requiring fine-grained, pixel-level discrimination.

The U-Net model's unique architecture, characterized by its encoder-decoder structure and skip connections, has proven highly effective in capturing both local and contextual information from images. The encoder path systematically reduces spatial dimensions while increasing feature abstraction, and the decoder path restores spatial resolution, ensuring that the final segmentation masks retain crucial details. The skip connections play a vital role by transferring high-resolution features from the encoder to the decoder, thereby enhancing the model's ability to delineate subtle boundaries between hair and bald regions. In the context of hair fall detection, these architectural strengths translate into robust performance across a wide range of images. The model was able to generate segmentation masks that closely matched the ground truth annotations, even in challenging cases with varying lighting, hair density, and scalp visibility. This consistency is reflected in the overlapping training and validation accuracy curves observed during model training, indicating strong generalization and minimal overfitting. A key aspect of the model's success lies in its training dynamics. The training and validation accuracy curves not only reached high values but also overlapped closely throughout the training process. This overlap is a strong indicator that the model is not simply memorizing the training data but is instead learning features that generalize well to unseen images. The convergence of both training and validation loss to a value of 0.4 further supports this observation. In deep learning, such convergence is desirable as it suggests that the model's predictions are consistently accurate across both training and validation sets, and that the risk of overfitting or underfitting is minimized.

The ROC (Receiver Operating Characteristic) curve generated during evaluation further illustrates the model's discriminative power. A smooth ROC curve with a high area under the curve (AUC) signifies that the U-Net model can reliably distinguish between hair and bald regions across various threshold settings. This is especially important in medical and clinical applications, where the ability to balance sensitivity and specificity is crucial for accurate diagnosis and monitoring. U-Net model achieved a segmentation accuracy of 92%, which is on par with or exceeds the performance reported in similar biomedical image segmentation studies. This level of accuracy is particularly impressive given the inherent challenges in hair and scalp imaging, such as variable lighting conditions, diverse hair textures, and the presence of occlusions or artifacts. The model's ability to maintain high accuracy across these variables demonstrates its robustness and adaptability. Qualitatively, the segmentation masks produced by the U-Net model provide clear and precise delineation of hair and bald regions. This enables objective measurement of hair loss, such as calculating the percentage of affected scalp area or assessing the progression of alopecia over time. The visual clarity of the segmentation masks also facilitates their use in clinical settings, where dermatologists and researchers can quickly interpret and act upon the results.

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