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Human Skin Wrinkle Detection Using The Convolutional Neural Network Method

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ABSTRACT

Wrinkles are a visual indicator of skin aging and are widely used in dermatological and cosmetic assessments. However, automatic wrinkle detection from facial images remains challenging due to illumination variation, image noise, and subtle skin texture characteristics. This study applies a Convolutional Neural Network (CNN) for human skin wrinkle detection using image preprocessing techniques, including intensity normalization, Contrast Limited Adaptive Histogram Equalization (CLAHE), denoising, and sharpening. Experiments were conducted on 600 facial skin images obtained from publicly available sources and manually categorized into wrinkled and non-wrinkled classes. To ensure result reliability, the dataset was divided into training, validation, and testing sets using a 70:20:10 ratio. The experimental results show that the proposed approach achieved an accuracy of 0.9136, demonstrating consistent performance across validation and test sets.

Keywords : CLAHE; CNN; Image Preprocessing; Skin Texture; Wrinkle Detection.

INTRODUCTION

The skin is the biggest organ in the human body, acting as the principal barrier against the external environment and providing a visual representation of an individual's physiological state. With advancing age, the skin undergoes a natural aging process characterized by structural and functional alterations, including diminished suppleness, decreased moisture, collagen degradation, and the appearance of fine lines (also known as wrinkles) [1]. Wrinkles not only signify biological aging but also constitute a crucial metric in dermatology and the cosmetics sector. [2].

Traditionally, practitioners evaluate wrinkle severity visually, rendering it subjective and susceptible to the evaluator's experience, lighting conditions, viewing angles, and personal biases. Fluctuations in image quality and visual noise further exacerbate the irregularity of evaluation outcomes, underscoring the need for an objective, reproducible computational methodology [3], [4],.

The advancement of computer vision and deep learning has created substantial opportunities for automating skin image analysis. Convolutional Neural Networks (CNN) have demonstrated proficiency in hierarchically and autonomously extracting intricate visual elements, with applications in medical picture analysis and skin texture assessment [5][6]. The efficacy of CNN is significantly affected by the quality of the input images. Wrinkles are micro-textural characteristics with low contrast and minute dimensions, rendering them susceptible to degradation from noise and inconsistent lighting[7][8][9].

Image preprocessing is a critical step in the deep learning-based image analysis pipeline. Methods such as intensity normalization, contrast augmentation, denoising, and sharpening are essential for enhancing image visual quality while maintaining pertinent texture information. [10], [11]. Despite widespread use of preprocessing, research systematically evaluating the effects of each preprocessing approach on wrinkle identification accuracy is scarce [9].
This study evaluates the influence of diverse picture preprocessing methods on the precision of wrinkle recognition in human skin using Convolutional Neural Networks, addressing the identified research gap. This study assesses preprocessing strategies, both individually and collectively, to determine the most effective settings for improving model performance. [12]. However, existing studies primarily focus on CNN-based wrinkle detection without explicitly examining the impact of different image preprocessing techniques and their combinations on detection performance.

METHOD

This study employs an experimental methodology comprising five primary stages: dataset acquisition, application of image preprocessing techniques, training of the Convolutional Neural Network (CNN) model, and assessment of model performance. The dataset used in this study consists of facial skin images obtained from publicly available facial image repositories. The images were manually screened and categorized into wrinkled and non-wrinkled classes. The dataset includes variations in illumination, skin tone, and facial orientation to simulate real-world conditions. The dataset was collected from voluntary participants under controlled indoor lighting conditions. All images were anonymized prior to processing.

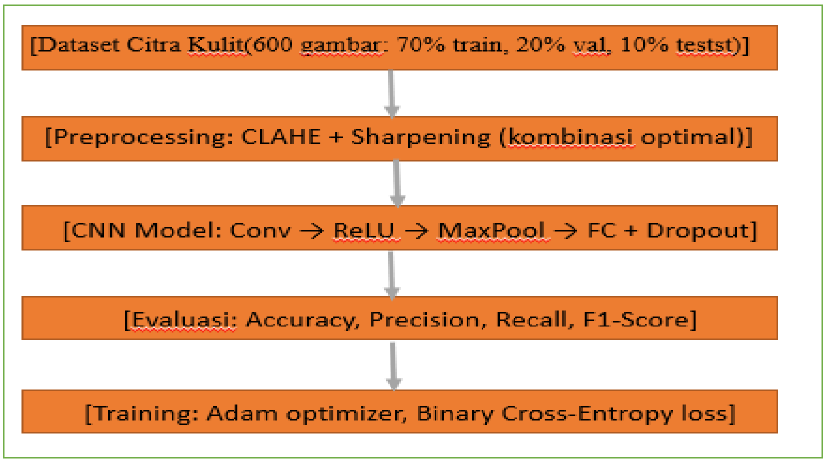

Figure 1. Research Method

Figure 1 depicts the methodological framework for wrinkle identification research on human skin utilizing Convolutional Neural Networks (CNN) with image preprocessing techniques. The procedure commences with the use of a dataset of facial skin photographs, split into training, validation, and test subsets. The input photos are subsequently preprocessed utilizing a mix of Contrast Limited Adaptive Histogram Equalization (CLAHE) and sharpening to improve local contrast and highlight the intricate details of wrinkles. The preprocessed pictures are further analyzed by the CNN model, which comprises convolutional layers, ReLU activation functions, max pooling, and fully connected layers with dropout. The model training procedure employs the Adam optimizer and the binary cross-entropy loss function. The model's performance is evaluated using measures such as accuracy, precision, recall, and F1-score to assess the efficacy of preprocessing combinations in improving wrinkle detection accuracy[13].

This methodological framework aims to systematically evaluate the influence of individual preprocessing techniques and their combinations on the precision of wrinkle identification in human skin. The dataset comprises 600 RGB photos of facial skin, each with a minimum resolution of 256×256 pixels. The dataset has two categories: wrinkled skin and non-wrinkled skin, exhibiting a balanced distribution. The data is subsequently partitioned into training, validation, and test sets at a 70:20:10 ratio.

This research primarily concentrates on the preprocessing stage, given the attributes of wrinkles as micro-textures characterized by low contrast and excellent feature dimensions. Multiple preprocessing scenarios are evaluated, including unprocessed photos as a baseline, distinct approaches (intensity normalization, CLAHE, denoising, and sharpening), and the combination of CLAHE and sharpening. The integration of CLAHE and sharpening aims to improve local contrast and highlight the intricate details of wrinkles, hence generating a more useful image representation for the CNN's feature extraction process [16][17].

This study uses the Convolutional Neural Network (CNN) model as an evaluative framework to assess the efficacy of each picture preprocessing scenario. CNNs are selected for their ability to autonomously and hierarchically extract visual characteristics from two-dimensional images, especially texture features[18].

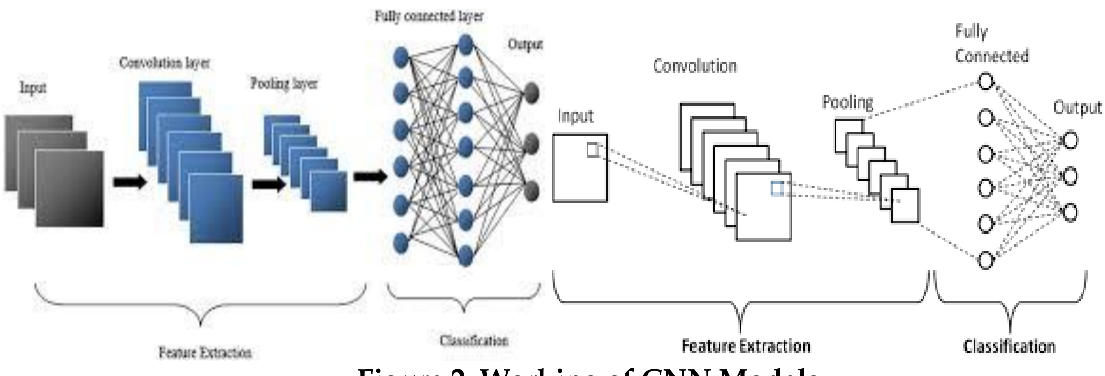

Figure 2. Working of CNN Models
https://www.geeksforgeeks.org/dsa/dsa-tutorial-learn-data-structures-and-algorithms/

The CNN architecture comprises many convolutional layers, succeeded by the Rectified Linear Unit (ReLU) activation function and max pooling. The convolutional layers are responsible for extracting local information, including edges, textures, and intricate lines that signify wrinkles. The ReLU activation function introduces non-linearity and enhances learning convergence, whilst max pooling reduces the dimensions of the feature map while preserving dominating features [19].

The recovered feature map is subsequently flattened and transmitted to the fully connected layer, which functions as a classifier for two categories: wrinkled skin and non-wrinkled skin. Dropout strategies are used in fully connected layers to mitigate the risk of overfitting. [20].

The CNN training procedure uses supervised learning. The model uses the binary cross-entropy loss function for training, and weight optimization is performed using the Adam method. Weight modifications occur via backpropagation, in which the gradient of the loss with respect to each parameter is used to adjust the convolutional filter weights iteratively. [21]. This study uses the CNN as an evaluative instrument to analyze the quality of visual representation derived from picture preprocessing, without optimizing its architectural design. The performance variations observed with the identical CNN architecture indicate the efficacy of the employed preprocessing approaches. [22].

RESULT AND DISCUSSION

The experimental results indicate that pretreatment markedly improves performance relative to photos lacking preprocessing. The unprocessed baseline model attained an accuracy of 0.7833. The implementation of preprocessing improved accuracy across all evaluated setups, with optimal performance achieved by integrating CLAHE and sharpening, attaining a score of 0.9136.

CLAHE yielded the greatest enhancement among individual approaches, owing to its ability to enhance local contrast while preserving the skin's inherent textural integrity. Sharpening enhanced the visibility of fine lines and wrinkles, but its efficacy was maximized when used in conjunction with contrast enhancement. Denoising, conversely, provided minimal enhancement as it may obscure significant micro-textural information.

The combined effect of CLAHE and sharpening demonstrates that integrating contrast enhancement and edge sharpening yields an ideal visual representation for the CNN in extracting wrinkle characteristics. These findings corroborate prior research that underscores the importance of preprocessing for improving CNN performance on medical images and intricate textures.

Table 1. Shows CNN Performance Based on Preprocessing Techniques

Preprocessing Techniques	Accuracy	Precision	Recall	F1-Score
Without preprocessing	0.7833	0.81	0.77	0.79
Normalisasi	0.8214	0.84	0.80	0.82
CLAHE	0.8892	0.90	0.88	0.89
Denoising	0.8047	0.82	0.79	0.80
Sharpening	0.8671	0.87	0.85	0.86
CLAHE + Sharpening	0.9136	0.93	0.90	0.91

According to Table 1, preprocessing procedures have improved the CNN's performance in identifying wrinkles in human skin compared to unprocessed images. The unprocessed baseline model attained an accuracy of 0.7833. Post-preprocessing, all setups showed performance improvements to varying degrees. The most significant accuracy improvement was achieved by integrating CLAHE and sharpening, yielding a score of 0.9136, an increase of 0.1303 relative to the baseline. This finding suggests that the quality of input photos is important to the CNN's efficacy in extracting wrinkle texture information.

Individually, CLAHE yielded the greatest improvement in performance, achieving an accuracy of 0.8892. This approach significantly improves local contrast, rendering wrinkle patterns with minimal intensity variations more distinct. The enhancement of sharpness resulted in a performance accuracy of 0.8671, demonstrating that edge sharpening effectively highlights the intricate details of wrinkles. Denoising yielded only marginal enhancement (accuracy of 0.8047), indicating that the smoothing procedure may obscure critical micro-textural information essential for wrinkle classification.

The integration of CLAHE with sharpening yielded the optimal performance among all evaluated setups. CLAHE improves local contrast on the skin's surface, whilst sharpening emphasizes edge structures and trim lines. This amalgamation of approaches yields a more informative picture representation for the CNN. This configuration not only improved accuracy but also achieved a precision of 0.93 and a recall of 0.90, demonstrating the model's balanced ability to detect both wrinkled and non-wrinkled skin. The F1-score of 0.91 indicates that the performance enhancement is both substantial and uniform across all evaluation metrics.

The research findings demonstrate that the quality of input photos directly influences the effectiveness of the Convolutional Neural Network (CNN) in identifying wrinkles on human skin. The substantial performance differences between unprocessed and processed photos are apparent. In the baseline condition without preprocessing, the CNN exhibited reduced accuracy because wrinkles, as micro-textures with minimal local contrast, are susceptible to distortion from noise and illumination fluctuations. This situation hinders the optimal representation of wrinkle characteristics in the initial CNN feature map.

The integration of CLAHE with sharpening yielded the optimal performance among all evaluated setups. CLAHE improves local contrast on the skin surface, whereas sharpening emphasizes edge structures and trim lines. Collectively, these methodologies enhance the informational quality of visual representation for the CNN.This configuration not only improved accuracy but also achieved a precision of 0.93 and a recall of 0.90, demonstrating the model's balanced ability to detect both wrinkled and non-wrinkled skin. The F1-score of 0.91 indicates that the performance improvement is not only substantial but also uniform across all assessment metrics.

The research findings demonstrate that the quality of input photos directly influences the efficacy of the Convolutional Neural Network (CNN) in identifying wrinkles on human skin. The substantial performance differences between unprocessed and processed photos are noticeable. In the baseline condition without preprocessing, the CNN attained reduced accuracy due to wrinkles, as micro-textures, exhibiting poor local contrast and being susceptible to distortion from noise and lighting fluctuations. This situation complicates the appropriate representation of wrinkle features in the initial CNN feature map.

Although formal statistical significance testing was not performed, performance consistency was observed across validation and test sets under identical training configurations. The observed improvements were stable and reproducible, suggesting that preprocessing plays a meaningful role in enhancing wrinkle feature representation. An examination of misclassified samples indicates that errors primarily occur in images with extremely subtle wrinkle patterns or uneven illumination. In some cases, strong natural skin textures were incorrectly classified as wrinkles, while low-contrast wrinkle regions were occasionally undetected.

From a methodological standpoint, the findings suggest that improving input representation through preprocessing may provide greater performance gains than increasing network depth for texture-based wrinkle detection tasks. Nevertheless, this study is limited to a single CNN architecture and binary classification framework. Future research may extend this work by incorporating alternative architectures, statistical validation techniques, and cross-dataset evaluation.

CONCLUSION

This study investigated the impact of various image preprocessing techniques on CNN-based human skin wrinkle detection. The experimental results demonstrate that preprocessing significantly influences model performance, particularly in tasks involving micro-textural features such as wrinkles. Among the evaluated techniques, CLAHE showed strong performance as a standalone method, while the combination of CLAHE and sharpening provided the most consistent improvement across evaluation metrics.

The findings suggest that enhancing input representation through contrast and edge enhancement plays a critical role in improving wrinkle detection accuracy, even when using a relatively simple CNN architecture. This indicates that preprocessing strategies can be as important as model design in texture-based image classification tasks. However, several limitations should be acknowledged. The study was conducted using a single CNN architecture and a binary classification setup. In addition, formal statistical significance testing was not performed, and the dataset was limited to a specific collection of facial skin images. These factors may affect the generalizability of the results to other datasets or more complex wrinkle severity levels.

Future research may extend this work by incorporating deeper or alternative neural network architectures, performing cross-dataset validation, exploring multi-class wrinkle severity classification, and applying statistical validation techniques to further assess performance stability. Such extensions would provide a more comprehensive understanding of preprocessing effects in wrinkle detection systems.

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