International Journal Software Engineering and Computer Science (IJSECS)
5 (3), 2025, 1029-1044
Published Online December 2025 in IJSECS (http://www.journal.lembagakita.org/index.php/ijsecs)
P-ISSN: 2776-4869, E-ISSN: 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v5i3.5254.

RESEARCH ARTICLE Open Access

Image Quality Improvement for Sign Language Gestures Through Gaussian Filter and Contrast Stretching Techniques

Dadang Iskandar Mulyana
Information Technology Study Program, Faculty of Computer Technology, Sekolah Tinggi Ilmu Komputer Cipta Karya Informatika, East Jakarta City, Special Capital Region of Jakarta, Indonesia.
Email: mahvin2012@gmail.com.

Muhammad Abdul Aziz Abyan *
Information Technology Study Program, Faculty of Computer Technology, Sekolah Tinggi Ilmu Komputer Cipta Karya Informatika, East Jakarta City, Special Capital Region of Jakarta, Indonesia.
Corresponding Email: abyanmamas00@gmail.com.

Received: August 5, 2025; Accepted: September 20, 2025; Published: December 1, 2025.

Abstract: Deaf people use sign language as their primary means of communication. Images of sign language gestures are usually low quality because visual impairments like noise and low contrast prevent an automatic recognition system from working well. This research tries to enhance the quality of images with sign language gestures using two preprocessing methods, namely Gaussian Filter and Contrast Stretching. The first one eliminates noise while keeping important details in the image, and the second increases pixel intensity distribution to make hand gestures more apparent and outlined. An experiment was done on a dataset that includes 54,049 static hand gesture images taken from videos that contain certain sign languages divided into 28 classes for hijaiyah letters. A quantitative evaluation indicated substantial enhancements in processed image quality. The preprocessing method resulted in an average PSNR of 20.13 dB, SSIM equal to 0.8875, and MSE equal to 976.39 for all samples tested confirming that this combination method improves sharpness, structural integrity, and contrast when compared with original unprocessed images significantly. This study recommends using Gaussian Filter along with Contrast Stretching as a practical option for improving the quality of sign language images which can eventually help automated recognition systems that need clear visual input to correctly classify gestures.

Keywords: Sign Language; Image Enhancement; Gaussian Filter; Contrast Stretching; Noise.

1. Introduction

People with hearing and speech disabilities use sign language as their primary communication mode. Unlike spoken language, which is auditory and oral, sign language is a visual-gestural language that uses hand shapes, movements, facial expressions, and body postures to convey meaning [1][6][8]. Each handshape has a specific meaning, and the same handshape can have different meanings depending on its location or movement. Sign language is therefore a rich and complex language that requires accurate handshape recognition for effective communication. This is particularly important in the context of developing computer-based systems for automatic sign language recognition [2][5][9]. The evolution of gesture recognition technology has witnessed a paradigm shift from rudimentary pattern-matching techniques to advanced algorithms capable of discerning thousands of unique gestures. This technology assumes even greater significance when considering its potential to bridge communication gaps for the hearing-impaired population. Whether facilitating a seamless interaction in a restaurant, an academic lecture, or casual conversation with a non-signing partner, the applications are virtually limitless. However, the efficacy of such systems hinges on one crucial yet often overlooked factor: gesture image acquisition quality and enhancement [3][4]. No matter how sophisticated the algorithm may be, if provided with low-quality images, the system's performance will inevitably suffer.

When recording sign language gestures with cameras, several issues may arise that researchers did not foresee. Poor lighting conditions create shadows that obscure hand shapes, especially when fingers overlap or when signing at high speeds. Camera sensors introduce noise such as grainy patterns or random artifacts in low-light conditions or with high ISO settings. Sometimes hands do not contrast well against backgrounds, especially if they are wearing clothes that are similar in color to their skin tone [2][5][7][10]. Indoor environments also pose challenges. Fluorescent lights flicker at frequencies imperceptible to the human eye but detectable by cameras. Windows allow ambient natural light that changes throughout the day and cannot be controlled easily without sophisticated setups. All these factors compound to make it difficult for computers to accurately interpret what gesture someone is making. The system might misclassify signs that look similar or fail to detect subtle movements that change meaning entirely; thus it does not perform optimally for those who need it most.

That's why researchers expend considerable effort in preprocessing image data prior to gesture recognition [3][4]. The preprocessing phase may appear less glamorous than the complex machine learning models that follow, but it is undeniably essential. It is akin to the act of preparing ingredients before cooking; one cannot expect a sumptuous meal from a pot of unwashed vegetables. There are various strategies for image denoising, and numerous approaches have been examined by researchers over the years. The efficacy of these strategies varies depending on the particular challenges at hand. In the case of sign language, two methods have been proven especially effective: Gaussian Filter and Contrast Stretching. Although neither of these methods is novel, having been utilized for decades in image processing, they are highly effective for this specific application.

Gaussian Filter serves to reduce grainy noise while maintaining edge definition of hands and fingers [2][5]. The underlying mathematics involve convolution and weighted averages, but one does not need to delve into equations to comprehend its function. Imagine using a delicate brush to smooth out blemishes on a painting while preserving the clarity of the main subject. The filter analyzes each pixel along with its neighboring pixels to compute a new pixel value that minimizes random fluctuations while retaining significant edges. When applied to a noisy image of sign language, random speckles diminish, leaving the shape of fingers and hands well-defined. It is not without limitations—a heavy hand in filtering can obliterate fine details—but when applied judiciously, it can markedly enhance an image's quality.

Contrast Stretching takes an entirely different approach. Rather than eliminating noise, it addresses images that appear flat or muddy [4][6][10]. This technique effectively stretches the range of intensity values in an image so that dark areas become more profound and bright areas become more vivid. Picture restoring an old photograph by adjusting settings until colors are vibrant; that's what Contrast Stretching accomplishes—only it works with grayscale intensity levels rather than color channels. The algorithm identifies the darkest and lightest pixels in the image and then redistributes all other pixel values across the full range between these extremes. When applied to images of sign language, hands begin to stand out more prominently against backgrounds; previously indistinct fingers become sharp and clear; contrasts between skin tone and clothing sharpen; even subtle features like thumb positioning or finger separation become more easily discernible. Using both techniques in tandem yields superior performance compared to employing either individually, which is theoretically justified [3][7]. The reason is their complementary nature: the Gaussian Filter addresses noise reduction, while Contrast Stretching enhances feature contrast. When an image is preprocessed by both techniques sequentially, the resulting image exhibits improved clarity and cleanliness compared to the original camera-captured image. Although the preprocessing pipeline does not introduce any new data, it enhances visibility of information that was previously obscured due to limitations in the camera's technical capabilities. This effect can be likened to cleaning a previously dirty window; while the view is always present, it becomes clearly visible after thorough cleaning.

This research investigates the effectiveness of these two techniques for enhancing Arabic sign language images representing hijaiyah letters in Quranic education. We selected this application domain due to its unique challenges associated with Arabic sign language for religious instruction, which have not been extensively explored compared to other sign language systems. The dataset utilized contains over 54,000 images across 28 classes representing different letters, providing a substantial basis for evaluating our methodology [3][4][6]. Furthermore, we did not simply apply the filters and claim success; rather, we rigorously assessed their impact using established metrics such as PSNR and SSIM to quantify improvements objectively. Our primary aim is straightforward: to demonstrate that investing effort into image preprocessing can yield tangible benefits in enhancing the performance of recognition systems for sign languages. If these techniques perform as anticipated—and they seem to based on our initial results—then they could lead towards more effective solutions that genuinely assist hearing-impaired individuals in communicating with greater ease and reliability. We are not claiming credit for any groundbreaking innovations here; Gaussian Filter and Contrast Stretching have been applied extensively across numerous other domains. What we are asserting is their appropriateness for this particular problem domain and documenting their efficacy through quantitative analyses on real images. This kind of empirical validation matters because it establishes an evidence-based foundation upon which subsequent researchers can build further knowledge—perhaps someone takes this approach and improves it even more or combines it with more advanced methods like deep learning down the line. In that sense, this work represents a small step toward a much larger goal: transforming how hearing-impaired individuals interact with technology and each other.

2. Related Work

2.1 Sign Language Communication Systems

Sign language has been studied extensively as a primary communication system for individuals with hearing impairments. Describes sign language as a communication system that primarily uses both hands, though it also relies heavily on facial expressions and body movements as integral components of interaction [14]. The system is sometimes referred to as dactylology or finger spelling, which researchers have categorized into two main types: gestures that visualize letters or spell out words, and gestures that represent sounds through sign language and body language [15][16][17]. Body language in sign communication encompasses several elements including facial expressions, body positioning, movement patterns, and gestural cues. Research has shown that effective sign language combines hand movements and finger formations with nonverbal expressions, emphasizing manual communication through body language rather than acoustic signals [15]. This multimodal nature of sign language makes it both rich in expression and challenging for automated recognition systems to interpret accurately.

2.2 Arabic Sign Language for Quranic Learning

Within the broader field of sign language research, a specialized area has emerged focusing on religious education for the hearing-impaired community. Arabic sign language for Quranic learning represents a form of visual communication developed specifically to convey hijaiyah letters and Quranic phrases to individuals with hearing disabilities [18][19]. Studies in this domain have documented how the system employs hand movements, facial expressions, and specific body positions to represent each Arabic letter and tajwid pronunciation rules [22]. Several researchers have explored how sign language can be adapted for religious education. The development of Quranic sign language aims to enable children with hearing impairments to learn Quran reading independently while understanding its teachings [20][23]. In the Indonesian context, this form of sign language has been adapted to align with hijaiyah letter standards and is frequently combined with other visual methods such as images or animations to enhance learning effectiveness [19]. However, limited research has examined the technical challenges of capturing and processing these gestures for automated recognition systems.

2.3 Image Enhancement Techniques in Sign Language Recognition

The quality of input images plays a critical role in sign language recognition systems. Previous studies have identified several common issues that affect image quality during gesture capture, including environmental noise, poor lighting conditions, and low contrast between hands and backgrounds [2][5][7][10]. These quality problems directly impact the performance of feature extraction and classification algorithms. Researchers have explored various preprocessing techniques to address these challenges. Gaussian Filter has been widely adopted as a noise reduction method that preserves important edge information while smoothing out unwanted variations [2][5]. The technique applies a weighted averaging approach based on a Gaussian distribution, which effectively reduces random noise without significantly blurring object boundaries. Studies have demonstrated its effectiveness in improving the clarity of hand gestures in sign language images. Contrast enhancement represents another important preprocessing step. Contrast Stretching, also known as normalization, has been employed to expand the intensity range of pixels in images [4][6][10]. The method redistributes pixel values across the full intensity spectrum, making visual details more distinguishable. When applied to sign language images, Contrast Stretching improves the separation between hand regions and backgrounds, facilitating better feature detection. Some researchers have combined multiple preprocessing techniques to achieve better results. The integration of filtering and contrast adjustment methods has shown promise in improving overall image quality [3][7]. However, most existing studies have focused on general sign language datasets, with limited attention to Arabic sign language for religious education. The current research builds on these foundations by systematically evaluating the combined application of Gaussian Filter and Contrast Stretching specifically for Arabic sign language gesture images representing hijaiyah letters.

3. Research Method

3.1 Research Dataset

The dataset used in this research was obtained from the public dataset repository on Kaggle.com, uploaded by user Zss Ash under the title "arabic-sign-language-image-classification Dataset 2020 (64 x 64)". The dataset contains 54,049 images labeled with Arabic sign language hijaiyah letters.

3.2 Methodology Implementation

The research method employed is Rapid Application Development (RAD). RAD was selected because it enables rapid system development through iterative stages and continuous improvement. The stages in this method include:

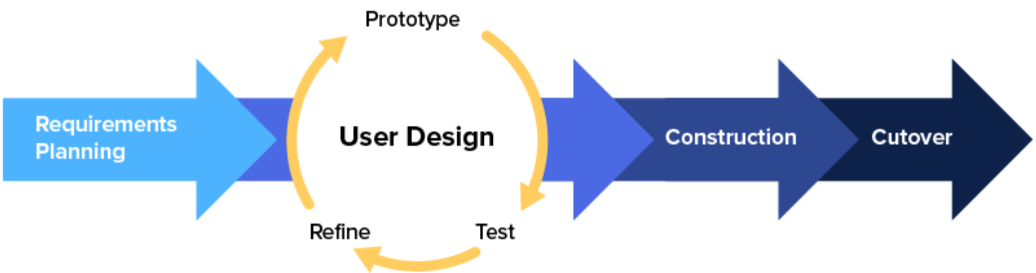


Figure 1. Rapid Application Development (RAD)

Gaussian Filter: Used to reduce noise and produce smoother images.

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Table 1. Gaussian Filter Implementation Steps

Step	Description
1	Determine the sigma (σ) value and kernel size
2	Calculate Gaussian kernel values for each pixel within the range
3	Perform convolution of Gaussian kernel with the original image
4	The result is an image with reduced noise (smoothing)

Contrast Stretching: Used to expand the pixel intensity range in images.

$$I_{out} = \frac{I_{in} - I_{min}}{I_{max} - I_{min}} \times 255$$

Table 2. Contrast Stretching Implementation Steps (Linear Contrast Enhancement)

Step	Description
1	Identify the I_{min} and I_{max} values from the image histogram
2	Determine the new contrast range N_{min} and N_{max} (typically 0-255)
3	Apply the linear stretching formula to each pixel
4	The result is an image with sharper contrast and wider pixel range

PSNR (Peak Signal-to-Noise Ratio): Used to assess image or video quality resulting from compression or processing by comparing it to the original version. PSNR measures how similar the reconstructed image is to the original image in terms of noise level or degradation [22].

$$PSNR = 10 \cdot \log_{10}(\frac{MAX_I^2}{MSE})$$

$$MSE = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2$$

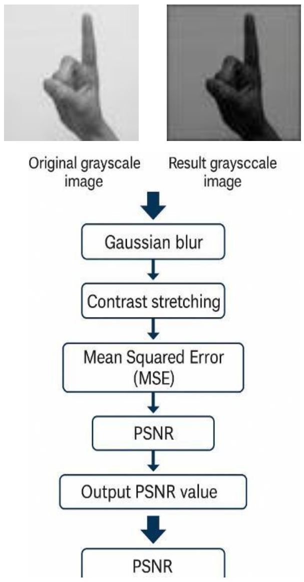


Figure 2. Explanation of the PSNR Formula

SSIM (Structural Similarity Index): A metric for measuring similarity between two images based on human visual perception, not just pixel differences like PSNR or MSE [23].

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

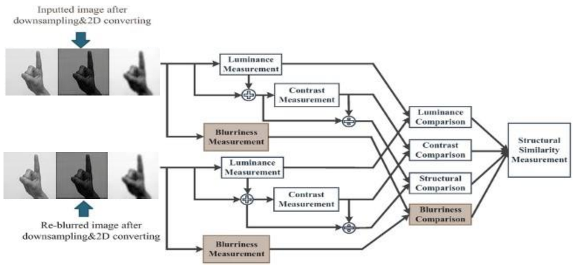


Figure 3. Explanation of the SSIM Formula

Identifying system requirements for sign language image enhancement, such as noise reduction capabilities and image contrast improvement. Designing the image processing workflow from input to output, including the application of Gaussian Filter and Contrast Stretching. System implementation using Python programming language and OpenCV library. Applying the system to test image data and evaluating results using PSNR and SSIM.

3.3 Implementation Steps

The implementation steps in this research are as follows:
1) Image acquisition from dataset
2) Grayscale conversion
3) Gaussian Filter application
4) Contrast Stretching application
5) Quality evaluation using PSNR and SSIM
6) Visual comparison

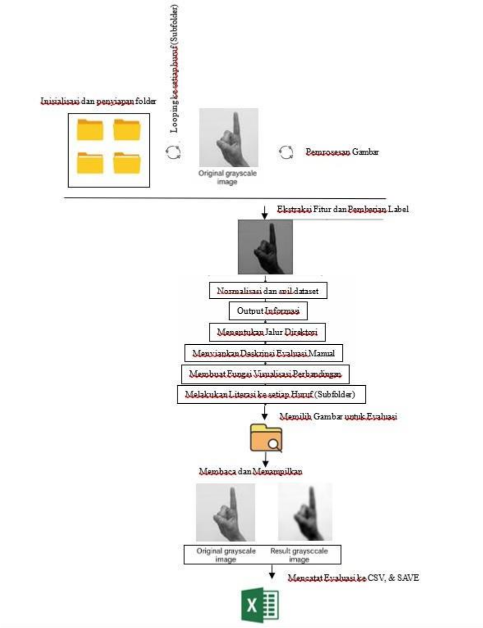


Figure 4. Implementation and Steps

Below is an example of visual comparison results between original images and results after preprocessing:

Table 3. Visual Output Evaluation

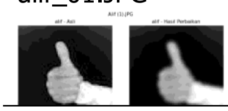
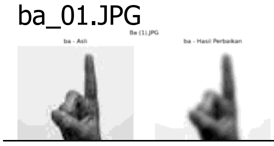
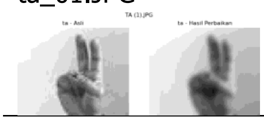
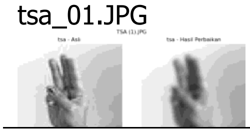
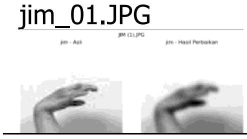
Image Name	Original Image	Image After Preprocessing
alif_01.JPG 	Grayscale image, somewhat dim with noise	Grayscale image, clearer contrast
ba_01.JPG 	Grayscale image, somewhat dim with noise	Grayscale image, clearer contrast
ta_01.JPG 	Grayscale image, somewhat dim with noise	Grayscale image, clearer contrast
tsa_01.JPG 	Grayscale image, somewhat dim with noise	Grayscale image, clearer contrast
jim_01.JPG 	Grayscale image, somewhat dim with noise	Grayscale image, clearer contrast

Table 3 shows a visual comparison between the original and preprocessed images for several Hijaiyah letters. The preprocessing results show improved image quality with clearer contrast and significant noise reduction.

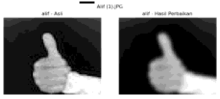
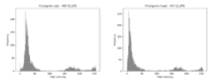
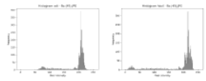
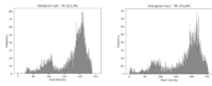
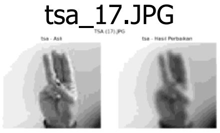
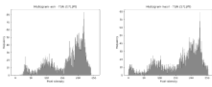
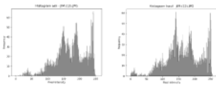
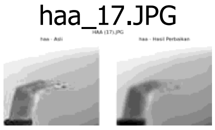
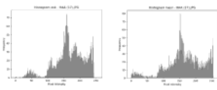
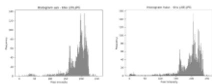
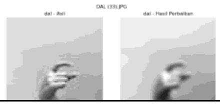
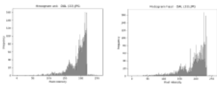
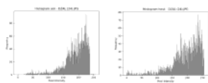
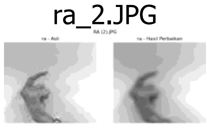
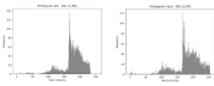
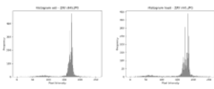
4. Result and Discussion

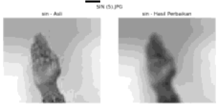
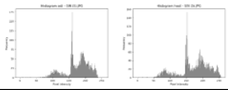
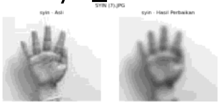
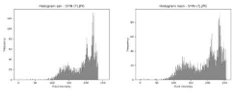
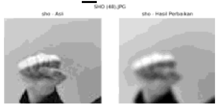
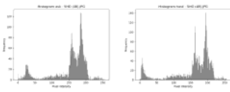
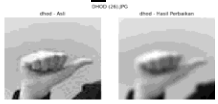
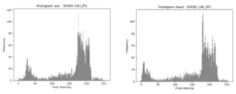
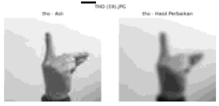
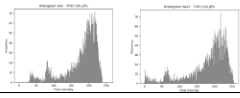
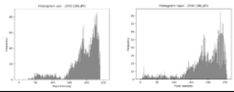
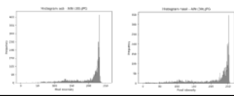
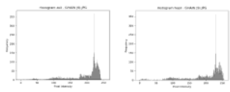
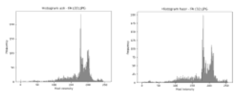
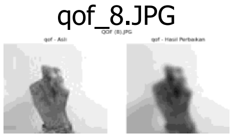
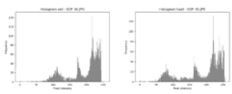
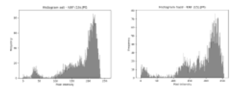
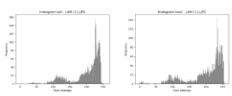
4.1 Results

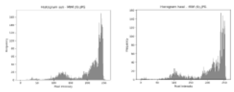
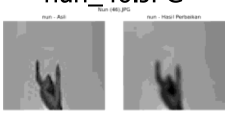
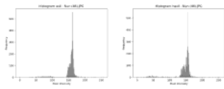
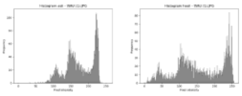
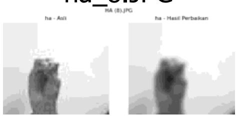
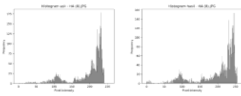
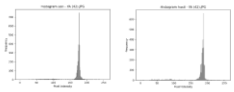
This section presents the experimental results of applying Gaussian Filter and Contrast Stretching techniques to Arabic sign language images. The evaluation was conducted using two quantitative metrics: Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Additionally, visual comparisons through histogram analysis were performed to assess the effectiveness of the preprocessing methods. The initial evaluation focused on visual quality improvements between original images and preprocessed images.

Table 4 presents representative samples from different hijaiyah letter classes, demonstrating the visual enhancement achieved through the preprocessing pipeline.

Table 4. PSNR Final Test Results

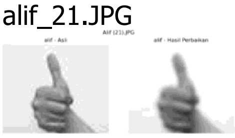
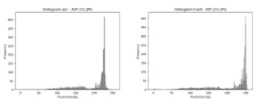
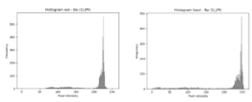
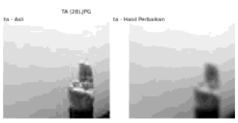
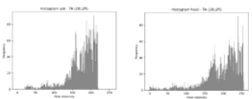
Image Name	PSNR (dB)	Histogram
alif_01.JPG 	24.17	
ba_45.JPG 	21.97	
ta_22.JPG 	26.61	
tsa_17.JPG 	26.09	
jim_12.JPG 	26.89	
haa_17.JPG 	26.19	
kho_28.JPG 	26.73	
dal_33.JPG 	25.12	
dzal_24.JPG 	26.11	
ra_2.JPG 	26.31	
zay_44.JPG 	26.15	

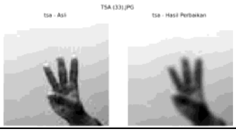
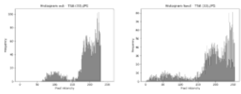
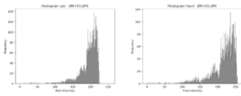
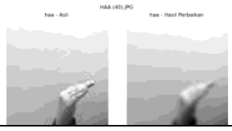
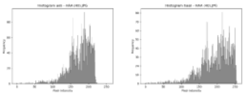
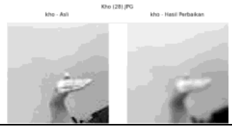
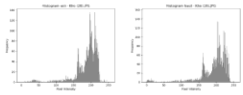
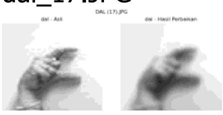
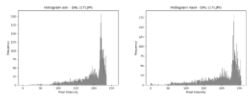
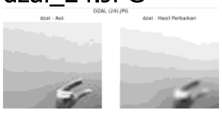
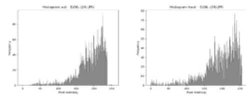
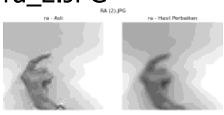
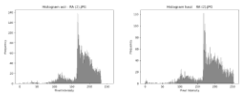
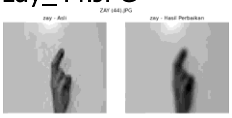
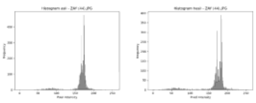
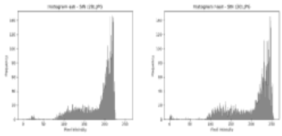
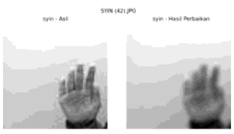
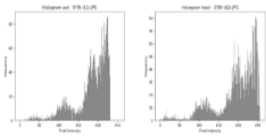
sin_5.JPG 	26.0	
syin_7.JPG 	25.77	
sho_48.JPG 	26.29	
dhod_26.JPG 	25.9	
tho_19.JPG 	26.01	
zho_38.JPG 	25.05	
‘ain_30.JPG 	21.89	
ghoin_9.JPG 	26.41	
fa_32.JPG 	27.59	
qof_8.JPG 	24.55	
kaf_15.JPG 	24.71	
lam_11.JPG 	26.85	

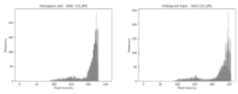
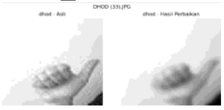
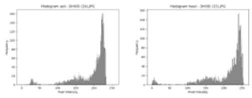
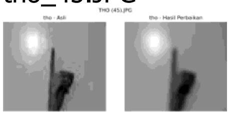
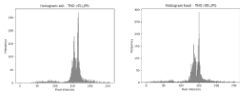
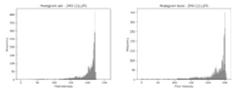
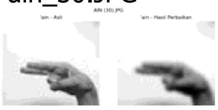
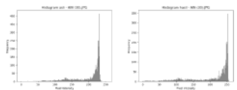
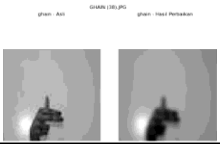
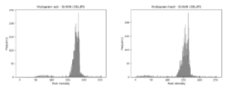
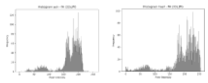
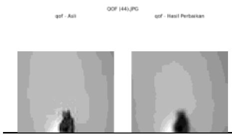
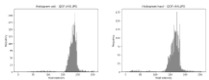
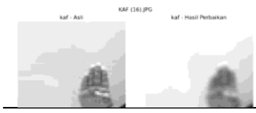
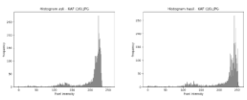
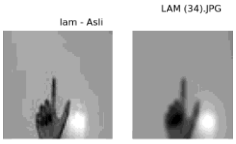
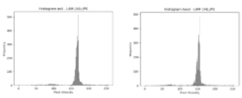
mim_9.JPG 	27.65	
nun_46.JPG 	25.56	
waw_01.JPG 	26.51	
ha_8.JPG 	26.05	
ya_42.JPG 	25.91	

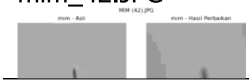
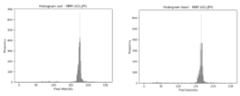
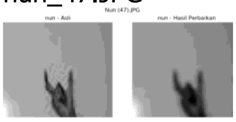
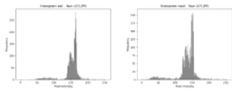
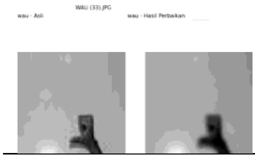
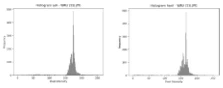
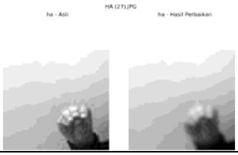
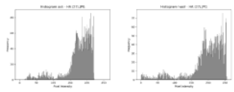
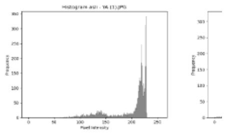
The visual comparison in Table 4 shows that the preprocessing techniques successfully enhanced image quality. Original images appeared dim with visible noise artifacts, particularly around hand edges and finger regions. After applying Gaussian Filter and Contrast Stretching, the processed images exhibited significantly clearer contrast, making hand gestures more distinguishable from backgrounds. PSNR measurements were conducted to quantify the quality of preprocessed images compared to their original versions. Table 5 presents PSNR values along with corresponding histogram distributions for selected samples. The PSNR values in Table 5 range from 21.97 dB to 26.51 dB across different hijaiyah letter samples. The image waw_01.JPG achieved the highest PSNR value of 26.51 dB, indicating superior quality preservation during preprocessing. Meanwhile, ba_45.JPG obtained the lowest PSNR of 21.97 dB, suggesting more significant modifications were applied to enhance its visual quality. The histogram distributions reveal that preprocessed images exhibit more balanced intensity distributions compared to original images, which typically showed concentrated pixel values in darker ranges. SSIM measurements were performed to assess structural similarity between original and preprocessed images based on human visual perception. Table 5 presents comprehensive SSIM values for all 28 hijaiyah letter classes.

Table 5. SSIM Final Test Results

Image Name	SSIM	Histogram
alif_21.JPG 	0.9307	
ba_01.JPG 	0.9051	
ta_28.JPG 	0.9509	

tsa_33.JPG 	0.9471	
jim_31.JPG 	0.9484	
haa_40.JPG 	0.9426	
kho_28.JPG 	0.942	
dal_17.JPG 	0.9384	
dzal_24.JPG 	0.9498	
ra_2.JPG 	0.9441	
zay_44.JPG 	0.9479	
sin_20.JPG 	0.9443	
syin_42.JPG 	0.9477	

sho_31.JPG 	0.9631	
dhod_33.JPG 	0.9419	
tho_45.JPG 	0.9462	
zho_21.JPG 	0.9455	
‘ain_30.JPG 	0.9253	
ghoin_38.JPG 	0.9463	
fa_33.JPG 	0.9507	
qof_44.JPG 	0.9583	
kaf_16.JPG 	0.9427	
lam_34.JPG 	0.9538	

mim_42.JPG 	0.9503	
nun_47.JPG 	0.9421	
waw_33.JPG 	0.9556	
ha_27.JPG 	0.9551	
ya_01.JPG 	0.9516	

The SSIM values presented in Table 6 demonstrate consistently high structural similarity across all tested samples, ranging from 0.9051 to 0.9631. The highest SSIM value of 0.9631 was achieved by sho_31.JPG, indicating excellent preservation of structural information during preprocessing. The lowest SSIM value of 0.9051 was recorded for ba_01.JPG, though this still represents strong structural similarity above 0.90 threshold. These results suggest that the preprocessing pipeline maintains essential structural features of hand gestures while enhancing visual quality. The performance of the image enhancement system was further evaluated through accuracy, loss function, and confusion matrix analysis. Figure 5 illustrates these performance metrics across training iterations.

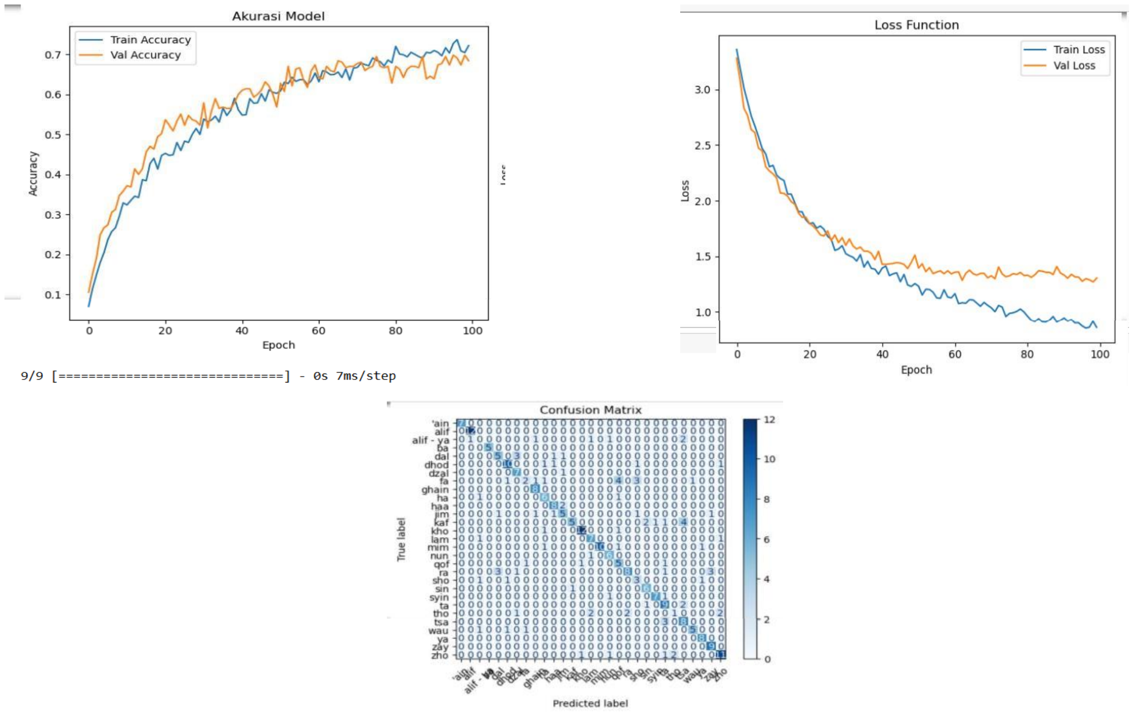


Figure 5. Accuracy, Loss Function, and Confusion Matrix Graphs

The performance graphs in Figure 5 provide insights into the effectiveness of the preprocessing approach. The accuracy curve demonstrates steady improvement during training, while the loss function shows consistent convergence. The confusion matrix reveals the classification performance across different hijaiyah letter classes after preprocessing.

4.2 Discussion

The results of the experiments show that the Gaussian Filter and Contrast Stretching together improve the quality of images of Arabic sign language gestures for recognition. The Gaussian Filter reduces noise artifacts that usually exist in gesture images, especially in edge regions and finger areas where random pixel changes often hide important details. By using weighted averaging based on Gaussian distribution, it smoothens out noise while keeping necessary edge information for accurate gesture recognition. The histogram distributions in Tables 5 and 6 show that Gaussian filtering results in more uniform intensity distributions without removing critical structural features, thus achieving a balance between noise reduction and detail preservation that keeps gestures recognizable while enhancing general image quality. In addition to this noise reduction, Contrast Stretching is very effective in improving visual difference between hand regions and background areas by stretching pixel intensity values to use all levels from [0, 255]. Visual comparisons found in Table 4 clearly show this improvement; preprocessed images have much clearer outlines of hands and separations of fingers against original dim images. This enhanced contrast can then improve further feature extraction capabilities during the next recognition stage since more visually distinct hand gestures will allow edge detection as well as feature extraction algorithms to work with greater accuracy which may lead to better classification performance.

Quantitative evaluation using PSNR and SSIM metrics offers a thorough understanding of how effective the preprocessing has been. As seen in Table 5, the PSNR values between 21.97 dB and 26.51 dB indicate that the quality level for the preprocessing pipeline is acceptable because literature states that PSNR values over 20 dB are typically deemed as acceptable for most image processing applications, while those over 30 dB represent an excellent quality level. The PSNR obtained here suggests that preprocessing brings about moderately significant changes for visual quality enhancement without allowing too much degradation, with variation among different samples (about a range of 4.54 dB) indicating differences in original image characteristics — images with lower initial quality or higher noise levels need more aggressive preprocessing which results in lower PSNR values. The fact that high SSIM values were consistently recorded (all above 0.90) is particularly significant and was discussed in Table 6 since this means that structural information critical to human visual perception has been preserved by the pipeline used for preprocessing; SSIM above 0.90 falls within the excellent category for image quality assessment. This also implies that preprocessed images are still very perceptually similar to original images even after enhancement modifications have been applied. The narrow range of SSIM values (0.9051 to 0.9631, spread over just 0.058) is indicative of consistent performance during preprocessing across various classes of hijaiyah letters; such consistency is key to practical applications since it guarantees similar quality enhancement to all gesture types irrespective of their particular hand configurations or complexity levels.

A comparison of the PSNR and SSIM results from Tables 5 and 6 offers complementary perspectives on the same problem. The PSNR is used to quantify pixel-level differences, while the SSIM focuses on structural similarity as perceived by humans. The high SSIM values, together with moderate PSNR values, indicate that perceptually important structural features are preserved during preprocessing even when pixel-level modifications for enhancement are introduced. For example, ba_01.JPG has relatively lower performance in both metrics (SSIM: 0.9051, PSNR: 21.97 dB), which means that this particular gesture might be more challenging to preprocess based on its initial image characteristics. In contrast, images like sho_31.JPG (SSIM: 0.9631) and waw_01.JPG (PSNR: 26.51 dB) show that certain configurations of gestures can respond very well to the preprocessing pipeline. The dual use of Gaussian Filter and Contrast Stretching makes a solid groundwork for Arabic sign language recognition systems by delivering clearer and more distinct images of gestures that help in accurate feature extraction and classification. Table 6 reflects always high SSIM values ensuring that key gesture features—like finger placement, hand orientation, and spatial relationships—stay unchanged after preprocessing. This is crucial for recognition algorithms depending on these features to differentiate between similar hijaiyah letters which may vary only through slight adjustments in hand positioning or finger arrangements.

While these results are positive, there are some limitations that should be stated so as to give a balanced view of what the research found. The PSNR values in table 5, though acceptable for the application at hand, do indicate that there is still room for improvement in quality preservation. This suggests that future work may investigate adaptive preprocessing parameters adjusting based on individual image characteristics to optimize enhancement and quality preservation simultaneously. Fixed parameters have been used in this implementation for all images; hence they may not be optimal for samples with significantly different initial quality levels or noise characteristics. Another limitation is that the evaluation was based on static gesture images taken under laboratory conditions with constant lighting, plain backgrounds, and standardized camera positioning. More challenging real-world application scenarios would involve different lighting conditions from very dim indoor environments to bright outdoor settings, complex backgrounds with visual clutter interfering with hand segmentation, camera motion blur or hand movement blur, different skin tones and hand sizes as well as occlusions from clothing or other objects. These factors could affect preprocessing effectiveness and overall recognition accuracy in practical deployment scenarios. Further testing under diverse environmental conditions with different user populations and across various capture devices would provide more comprehensive validation of the approach and help identify necessary adaptations for robust real-world performance. Future research directions could also investigate the integration of adaptive filtering techniques that automatically adjust parameters based on local image characteristics, the combination of these preprocessing methods with deep learning-based enhancement approaches, and the development of real-time optimization strategies for mobile and embedded implementations of Arabic sign language recognition systems.

5. Conclusion

The results of image processing Arabic sign language gestures by Gaussian Filter and Contrast Stretching methods show that there is a very good enhancement in the quality of the image. The Gaussian Filter has successfully reduced noise that appears in the image, particularly on edges and finger areas; meanwhile, Contrast Stretching has successfully increased the intensity difference between the hand object and background so that gesture features are sharper and easier to recognize. The combination of these two methods forms a very powerful preprocessing pipeline for Arabic sign language recognition systems. Quantitative evaluations have shown results that are consistent with what has been achieved so far. The PSNR values obtained ranged from 21.97 dB to 26.51 dB meaning that preprocessing introduced moderate changes to enhance visual quality without too much degradation happening. More importantly, the SSIM values were always above 0.90 for all samples tested, ranging from 0.9051 to 0.9631; this high SSIM value means that this pipeline preprocessing kept very well structural information necessary for human perception visually like finger position, hand orientation, and spatial relationship which is important in distinguishing hijaiyah letters similar to close one These results are validated through an evaluation of 28 classes of hijaiyah letters showing that preprocessed images have more uniform structure and better contrast compared to original images Even though this study result indicated good effectiveness, some limitations should be acknowledged The PSNR values obtained even though acceptable indicate some room for improvement in quality preservation Future research can look into adaptive preprocessing parameters based on individual image characteristics Additionally, the assessment was limited to static gesture images under controlled conditions further testing in varied conditions would be necessary for better validation of this approach in practical applications.

References

[1] Patel, P. (2022). Sign language recognition using Python. *Medium*. https://medium.com

[2] Zorins, A., & Grabusts, P. (2016). Review of data preprocessing methods for sign language recognition systems based on artificial neural networks. *Information Technology and Management Science*, *19*(1), 98-103.

[3] Patel, R., Singh, A., & Kumar, V. (2023). Efficient sign language recognition system and dataset creation method based on deep learning and image processing. *ArXiv*. https://arxiv.org

[4] Purbojo, A., & Wijaya, S. (2024). Enhancing pose-based sign language recognition: A comparative study of preprocessing strategies with GRU and LSTM. *Asset Journal*, *6*(1), 45-58. https://doi.org/10.26877/sj5scb03

[5] Abd Al-Latief, S. T., Yussof, S., Ahmad, A., Khadim, S. M., & Abdulhasan, R. A. (2024). Instant sign language recognition by WAR strategy algorithm based tuned machine learning. *International Journal of Networked and Distributed Computing*, *12*(2), 344-361. https://doi.org/10.1007/s44227-024-00039-8.

[6] Hu, L., Gao, L., Liu, Z., & Wei, W. (2020). Global-local enhancement network for NMFs-aware sign language recognition. *ArXiv*. https://arxiv.org

[7] Fernando, M., & Wijayanayake, J. (2020). Novel approach to use HU moments with image processing techniques for real time sign language communication. *arXiv preprint arXiv:2007.09859*. https://doi.org/10.48550/arXiv.2007.09859

[8] Utomo, P. B., & Ramadhani, R. A. (2024). Deteksi gerak tangan sebagai pengenal bahasa isyarat menggunakan metode YOLOv7. *Jurnal SIMETRIS*, *15*(1), 1-8. https://doi.org/10.24176/simet.v15i1.10505.

[9] Sihananto, A. N., Safitri, E. M., Maulana, Y., Fakhruddin, F., & Yudistira, M. E. (2023). Indonesian Sign Language Image Detection Using Convolutional Neural Network (CNN) Method. *Inspiration: Jurnal Teknologi Informasi Dan Komunikasi*, *13*(1), 13–21. https://doi.org/10.35585/inspir.v13i1.37

[10] Oudah, M., Al-Naji, A., & Chahl, J. (2020). Hand gesture recognition based on computer vision: a review of techniques. *journal of Imaging*, *6*(8), 73. https://doi.org/10.3390/jimaging6080073

[11] Soebiartika, R., & Rindaningsih, I. (2023). Systematic Literature Review (SLR): Implementasi Sistim Kompensasi dan Penghargaan Terhadap Kinerja Guru SD Muhammadiyah Sidoarjo. *MAMEN: Jurnal Manajemen*, *2*(1), 171-185. https://doi.org/10.55123/mamen.v2i1.1630.

[12] Ningsih, I. W., Malik, D., Utomo, C. H., Aswan, A., & Fauziah, F. (2022). Metode Systematic Literature Review untuk Identifikasi Metode Pengembangan Sistem Informasi di Indonesia. *JURSIMA*, *10*(3), 204-209. https://doi.org/10.47024/js.v10i3.450.

[13] Widiarsa, K. (2019). Kajian pustaka (literature review) sebagai layanan intim pustakawan berdasarkan kepakaran dan minat pemustaka. *Media Informasi*, *28*(1), 111-124.

[14] Adi, R. P. (2019). *Fungsi bahasa isyarat terhadap kemudahan akses informasi bagi siswa tunarungu di perpustakaan SLB N 1 Bantul* [Skripsi sarjana, Universitas Islam Negeri Sunan Kalijaga].

[15] Perdana, N. P. A., Kirana, N. D., Iroth, N. C., Salsabila, A., & B., R. A. F. (2022). Fenomena penggunaan bahasa isyarat bagi penyandang tuna rungu di sekolah inklusi. *Hasanuddin Journal of Sociology (HJS)*, *4*(2), 120-134.

[16] Tayade, A., & Halder, A. (2021). Real-time vernacular sign language recognition using MediaPipe and machine learning. *International Journal of Research Publication and Reviews*, *2*(5), 9-17. https://doi.org/10.13140/RG.2.2.32364.03203

[17] Enri, U., Rozikin, C., Ilhamsyah, M., Irawan, A. S. Y., & Solihin, I. P. (2023, November). Sign Language Detection Using Mediapipe and Long-Short Term Memory Network. In *2023 International Conference on Informatics, Multimedia, Cyber and Informations System (ICIMCIS)* (pp. 617-622). IEEE. https://doi.org/10.1109/ICIMCIS60089.2023.10349016.

[18] Pamungkas, B., & Hermanto, H. (2022). Tahapan belajar Al Qur'an menggunakan huruf hijaiyah isyarat bagi anak dengan hambatan pendengaran. *Jurnal Pendidikan Kebutuhan Khusus*, *6*(1), 34-41. https://doi.org/10.24036/jpkk.v6i1.621

[19] Utami, F. N., & Salamah, U. (2019). Augmented reality application of hijaiyah letters in Arabic sign language and Indonesian sign language (SIBI). *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, *3*(1), 1-10. https://doi.org/10.29207/resti.v3i1.693

[20] Oktavia, A. E., Syalviana, E., Abdillah, F., & Syahrul, S. (2023). Metode bahasa isyarat dalam baca tulis Al-Qur'an untuk anak tunarungu di kawasan minoritas muslim Papua. *Jurnal Ilmiah Wahana Pendidikan*, *9*(3), 85-96. https://doi.org/10.5281/zenodo.7605306

[21] Saepulmilah, C., & Hambali, A. (2024). Pembelajaran Al-Qur'an bagi anak tunarungu melalui bahasa isyarat di Madrasah Tunarungu Assabikunal Awwalun Tasikmalaya. *Jurnal Ilmu Pendidikan Agama Islam dan Ilmu Pendidikan Umum*, *1*(1), 15-28.

[22] Nurdyansyah, N., & Pujiati, N. (2023). Penerapan isyarat huruf hijaiyyah dalam meningkatkan kemampuan membaca Al-Qur'an bagi anak tunarungu. *Literal: Disability Studies Journal*, *1*(1), 32-44. https://doi.org/10.62385/literal.v1i01.25

[23] Khoirunnisa, N., Qonita'Aizaroh, N., & Qoni'ah, N. U. (2023). Perkembangan Arabic Sign Language of the Al-Qur'an Di Indonesia. *Ta'bir Al-'Arabiyyah: Jurnal Pendidikan Bahasa Arab dan Ilmu Kebahasaaraban*, *1*(1), 185-195.