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# *PATTERN CLASSIFICATION SIGN LANGUAGE USING FEATURES DESCRIPTORS AND MACHINE LEARNING*

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***Abstract***

*Sign language is way of communication for the deaf and speech impaired. In Indonesia, the utilization of a standardized language involves the incorporation of American Sign Language (ASL). ASL is employed for various communication needs, ranging from basic alphanumeric fingerspelling (A-Z and numbers) to the more complex SIBI form (comprising gesture vocabulary) in everyday interactions as well as formal contexts. This surge in the digitization of sign language underscores the ongoing advancements in research and development. The challenge in this research lies in the ability to recognize American Sign Language (ASL) with diverse intensities and invariant backgrounds. Therefore, the study emphasis is on proposing a suitable segmentation method comparison for multi-intensity ASL cases. Subsequently, global feature descriptor methods, including Color Histogram, Hu Moments, and Haralick Texture techniques, are applied for feature extraction. The result of the Logistic Regression method versus the supervised Random Forest checks accuracy and suitability in identifying ASL fingerspelling. The findings of this research is predictive value of logistic regression is 48%, with class Y having the highest precision (0.86), class V having the lowest accuracy (0.16), and class L having the highest recall (0.73). The maximum precision in classes B, F, H, I, K, Y, and Z is 1.00, and the lowest in class U is 0.58, while the highest recall is in class G, which is 1.00. The lowest is in class V, while the predictive value from the random forest is 86 percent. Class H has the greatest f1 score (0.99), while class U has the lowest f1 score (0.64). The Random Forest method outperforms the two methods suggested in the paper, according to the comparison.*

**Keywords**: *Color histogram, Fingerspelling, Haralick texture, Hu Moment, Logistic regression segmentation.*

## 1. INTRODUCTION

Digital image recognition and identification systems often experience data acquisition interference (noise), which in this case study includes brightness, background complexity, and blur. Brightness is a condition that indicates whether a space is bright or dark. This study separated light noise into two categories: too dark and too bright.

The detection of the foreground is hampered by background complexity due to variations in background colors and patterns. In addition, blur occurs when the object is disrupted during the acquisition by movement or attention. Therefore, it becomes difficult to overcome this problem by distinguishing the difference between the foreground and background so that objects may be identified [1]. There are numerous methods for solving the aforementioned issues. One of them is then classified as the feature recognition technique. Next, the feature recognition technique is used with the feature descriptor stage and then extracted to be used as input for performing classification techniques. Finally, classification techniques are used to determine objects labeled according to predefined features to recognize them according to criteria.

Likewise, with classification techniques, the most frequently researched and favored classification technique is Artificial Intelligence (AI). AI is the simulation of human intelligence in machines programmed to think like humans and imitate their actions. AI Machine Learning (ML) is one of the most frequently used forms of technology because it is lighter and more straightforward than deep learning (DL). Besides that, ML usually only manages soft data and not big data, so for this study, ML was chosen to be used as an introduction [2]. However, DL is commonly used in handling feature-packed and heterogeneous data cases. In research [3], the classification technique consists of several stages: pre-processing, feature description and extraction, training and testing, and results. The types of classification often used in several studies are supervised, unsupervised, and hard classification. Research conducted by [4] found that the hybrid method or supervised method concerning feature extraction techniques produces an accuracy level that is close to or follows expectations.

One of the feature extractions used in several studies is global features [5]. In feature extraction, there are also problems with dependence on the object's moment to be extracted, in other words. This study has limited research in classification due to the moment of the item depending on the data point and shape reconstruction [6]. Based on several previous studies, the authors propose a method to overcome this problem, namely the Hu Moments method, which is supported by Haralick's color histogram and color texture [8]. In addition to feature extraction, the contribution is objecting recognition or identification to take features that have been extracted supervised or unsupervised. By conducting a literature review, the researcher chose a one-layer neural network approach, namely Logistic Regression, compared to the supervised Random Forest (RF) approach. Based on these various reviews, this work proposes to improve the pattern classification in American Sign Language (ASL) using Global Descriptor Feature.

The structure of this work's content is as follows. The relevant research was given and addressed in section 2. Next, section 3 briefly discusses the experiment setup and dataset. Continue section 4 discussed more details regarding the experiment results. Conclusions and prospective research are presented in Section 5.

## 2. DIGITAL IMAGE PROCESSING

Image can be defined as a function of two variables, such as (x, y), where itself is the amplitude (e.g., brightness) of the image at the coordinates (x, y). In a digital image [m, n] is an image in 2D discrete space derived from an analog image (x, y) in a 2D continuous space through a sampling process, which is what we can call digitization. Images also often experience a decrease in good quality due to light, noise, too much contrast, lack of sharpness (blur), and so on, which causes the loss of information to be conveyed. To obtain existing information, the image received needs to be improved. The field of study concerning this matter is image processing. Image processing is image processing, especially using computers to better quality [9].

Image processing was developed with the objectives of enhancing image display, compressing image files while preserving image quality, restoring images to their original states, and accentuating specific features to facilitate comprehensive analysis. The definition of image processing is a branch of informatics to improve image quality so that the quality is better or easier to interpret by humans and computers. The input of an image processing program is an image, and the output is also an image.

### 2.1. Color Image

Color image, often referred to as RGB image, is a color model consisting of red, green, and blue combined to form a wide array of colors. Each base color, such as red, can be assigned a range of values. For computer monitors, the content should be at least = 0 and maximum = 255. This 256-scale option is based on expressing the eight-digit binary number used by computer machines. In this way, a mixture of 256 x 256 x 256 = 1677726 colors will be obtained [14]. If all three color channels have zero values, no light is emitted, and the resulting color is black (on a monitor, for example, it cannot be blacker than the surface of a monitor that produces 0 light). When all three color channels are set to their maximum values (255 at a color byte depth), the resulting color is white. This type of color mixing is also called "additive color mixing": Shape the color representation of a digital image can be seen in Figure 1 and 2.

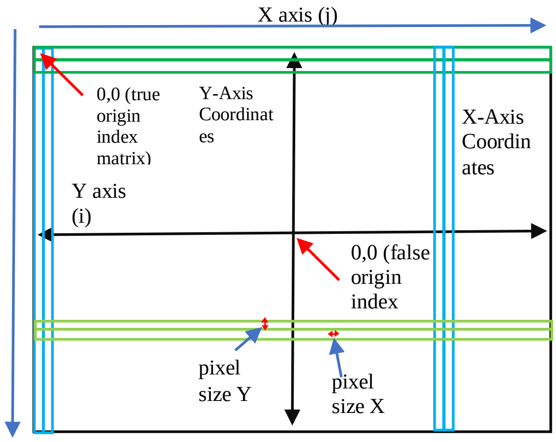



Figure 1. Digital image coordinate system

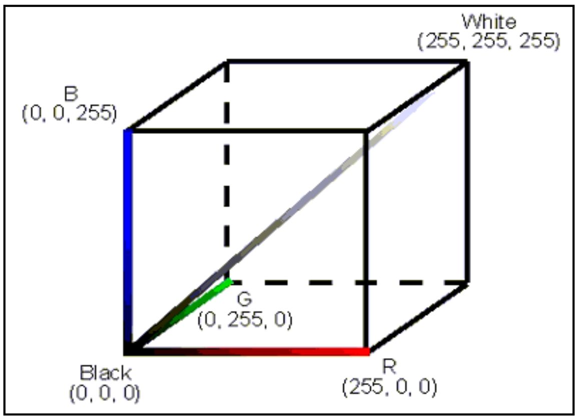



Figure 2. RGB color representation in digital images

### 2.2. Feature extraction

Feature extraction will produce characteristics that will be used in the image to identify and classify objects. This feature extraction process will use these characteristics in pattern recognition to determine the final grade. Each image will have different features so that one embodiment can be distinguished from another; features can further clarify the difference pattern, which will significantly facilitate the separation between classes in the grouping process.

### 2.2.1. Color Histogram

In image processing and photography, a color histogram represents the distribution of colors in an image. For digital photos, a color histogram represents the number of pixels with a color in each list of fixed color ranges, spanning the image color space, the set of all possible colors in Figure 3 [10]. Figure 4 A color histogram can be constructed for any color space, although this term is more often used for three-dimensional spaces such as RGB or HSV. For monochromatic images, the term intensity histogram can be used instead. For multi-spectral photos, where each pixel is represented by an arbitrary number of measurements (for example, outside of three measures in RGB), the color histogram is N-dimensional, with N being the number of steps taken. Each action has its range of wavelengths of the light spectrum, some of which may be outside the visible spectrum [11]. A color histogram can also be represented and displayed as a subtle function defined in a color space close to the pixel number.

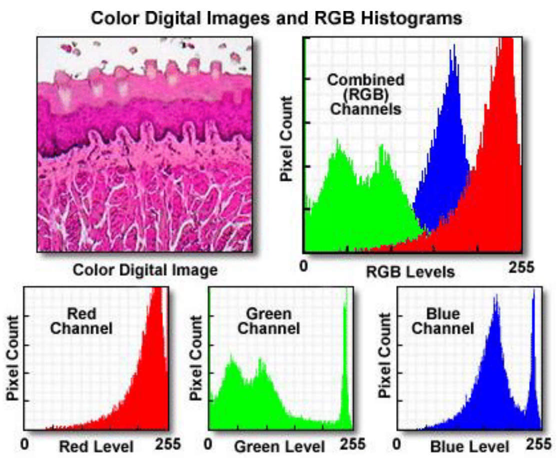



Figure 3. Examples of RGB Color Histogram Settings in Image A.

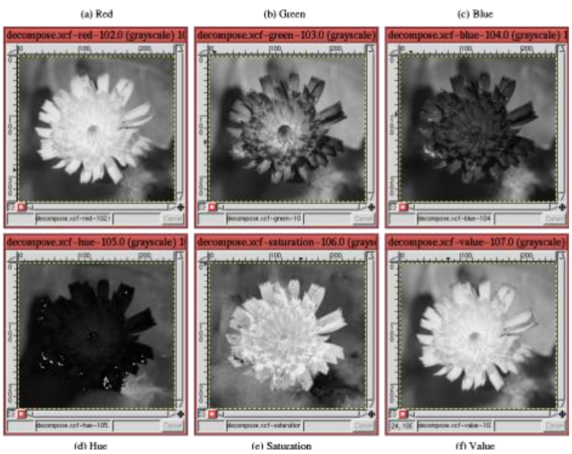



Figure 4. Sample Image on RGB Channel and HSV Channel

### 2.2.2. Hu Moments

In image processing, computer vision, and related fields, the image moment is a certain weighted average (moment) of the intensity of the image pixels, or a function of the moment, usually chosen to have an interesting property or interpretation. Picture moments are useful for depicting objects after segmentation. Simple properties of images found through image moments include the area (total intensity), its centroid, and information about its orientation [12]. The non-orthogonal centered moment is an invariant translation and can be normalized as a fingerspelling ASLn with scale change. However, allowing the invariants to rotate requires reformulation. Hu describes two different methods for producing the invariant rotational moment. The first uses a principal axis method but note that this method can be broken when the image does not have a unique central axis.

### 2.2.3. Haralick Textures

Image texture is a quantification of the spatial variation of the grayscale value. Haralick et al. (1973) suggested using a gray level co-incidence rate matrix (GLCM). This method is based on the ASLn fingerspelling probability distribution of pixel pairs. GLCM shows how often each gray level occurs in pixels located in fixed geometric positions relative to each other pixels as a function of the gray level. An important component is the definition of the eight cells of nearest neighbor resolution in Figure 5, which defines different matrices for different angles (0 °, 45 °, 90 °, 135 °) and the distance between horizontal neighboring pixels. 3x3 window definition and spatial ASLn fingerspelling for calculating Haralick texture sizes. Pixels 1 and 5 are 0 ° (horizontal) closest neighbors to the center pixel *; pixels 2 and 6 are the 135 ° most immediate neighbors; pixels 3 and 7 are 90 ° most immediate neighbors, and pixels 4 and 8 are 45 ° closest neighbors to the center pixel.

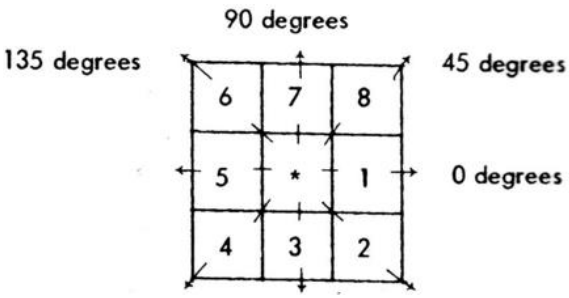



Figure 5. The windowing principle of Haralick Texture

$$\mathbf{G} = \begin{bmatrix} p(1,1) & p(1,2) & \cdots & p(1,N_g) \\ p(2,1) & p(2,2) & \cdots & p(2,N_g) \\ \vdots & \vdots & \ddots & \vdots \\ p(N_g,1) & p(N_g,2) & \cdots & p(N_g,N_g) \end{bmatrix} \quad (1)$$

Through Equation 2, it is stated that this matrix is a square with dimensions Ng, where Ng is the number of gray levels in the image. The elements [i, j] of the matrix are generated by counting the number of times a pixel with a value of i is adjacent to a pixel with a value of j and dividing the entire matrix by the total number of comparisons made. Therefore each entry is considered the probability that a pixel of weight I will find adjacent to a pixel of value j.

### 2.3. Light Intensity

Light intensity is a fundamental physical quantity to measure the power emitted by a light source in a certain direction per unit angle. The SI unit of light intensity is Candela (Cd). In the fields of optics and photometry (photography), the ability of the human eye is only sensitive and can see the light with a certain wavelength (visible light spectrum), which is measured in this fundamental quantity.

$$I_v = 683 \int_0^{\infty} I(\lambda)\bar{y}(\lambda)d\lambda \qquad (2)$$

Where,
$I_v$ : Light intensity in Candela units
$I$ : Radian intensity in W/sr units
$\bar{y}(\lambda)$ : Standard intensity function

## 3. METHOD

This section discusses the proposed methods, such as feature extraction methods and language pattern classification. The more detailed process includes image pre-processing, image feature extraction, image training process, and finally, image matching or testing process along with displaying the results.

### 3.1. Research Frameworks

The research flow serves as a guideline for conducting focused research, outlining overarching steps to be followed. This study uses image processing by pre-processing, namely the size and gray scaling (except for Color Histogram), carried out with three invariant moments: Hu Moments, Haralick Texture, and Color. The design framework is the system's design to be designed and related to the created network. The chart that describes the system design can be seen in Figure 4. The system's design is important in the development of the ASL fingerspelling recognition system. This process structure consists of setting the dataset, pre-processing, feature descriptors, feature extraction, modeling machine learning to training and testing. For a more precise flow of the software development process, Figure 6 shows the proposed process flow.

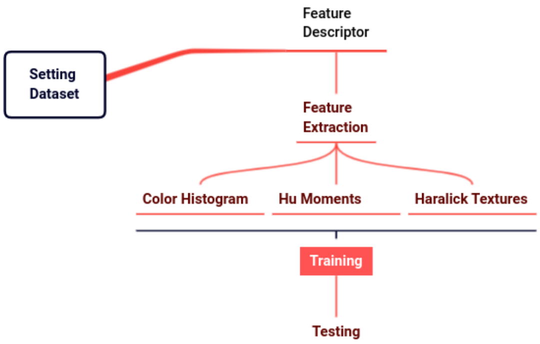
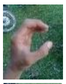
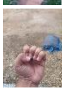
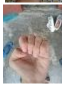



Figure 6. Frameworks of the ASL fingerspelling identification system

### 3.2. Dataset

The dataset utilized in this study is a primary dataset obtained from Universitas Dinamika Bangsa. This dataset is highly challenging, exhibiting a wide range of diversity in patterns and colors. For this research, Table 1 represents the dataset comprising 17 types of ASL Fingerspelling, with each class containing 80 images, resulting in a total of 1360 images available for training and testing the proposed model.

Table 1. Dataset

| **Name of Fingerspelling ASL** | **Example of Image** | | | |
|---|---|---|---|---|
| | **1** | **2** | **3** | **4** |
| *A* |  |  |  |  |
| *B* |  |  |  |  |
| *C* |  |  |  |  |
| *D* |  |  |  |  |
| *E* |  |  |  |  |
| ... | … | … | … | … |
| Z |  |  |  |  |

### 3.3. Feature extraction

This study used 3 (three) feature extraction: Haralick Texture, Hu Moments, and Color Histogram. In this subsection discuss how to feature extraction works. The feature extraction process's flow is shown in the figure 7.

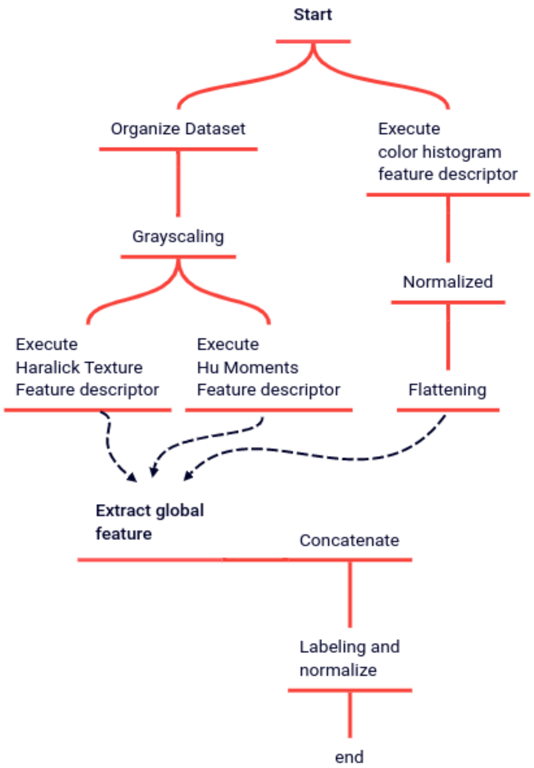



Figure 7. Flowchart of Feature Descriptor and Extraction

### 3.3.1. Color Histogram

The color histogram is a way to describe the content or color content by counting each color that appears in an image in order of color formed more quickly. Then a process is needed for color quantization because the counting process number of RGB color variations tends to take a long time. Color quantization is the division of color components in a certain distance range. Quantization is used because several colors look very or almost similar, so the human eye is difficult to distinguish even considering the same color. Histograms can consist of up to 48 bins, the color that each bin describes a range of pixel values. This range represents each component RGB which has a high-intensity level difference. Each bin's value was normalized by dividing the bin's value by the total number of pixels in the image. The histograms in this study consisted of 8 color bins with a range of 0-31, 32-63 etc. This aim of reducing the color bin which will be used as an image feature.

### 3.3.2. Hu Moments

Hu Moments have been extensively used in image analysis, pattern and object identification, image classification, and template matching as fundamental feature descriptors. Hu moments have two benefits: (2) Hu moments are invariant with regard to translation, scaling, and rotation. (1) The first absolute orthogonal invariant of Hu moments can assess the degree to which the energy is focused on the center of energy gravity for two-dimensional data. It is logical to deduce that Hu moments may be useful for describing the relationship between neighboring Mel filter coefficients inside a frame and the relationship between neighboring frames.

### 3.3.3. Haralick Texture

Haralick Texture uses the concept of the Gray Level Co-occurrence Matrix (GLCM) calculation, where the method calculates the occurrence of adjacent gray-level images. GLCM is a technique for obtaining a 2nd order statistical value by calculating the probability of fingerspelling ASLn proximity between two pixels at a certain distance (***d***) and certain angle ($\boldsymbol{\theta}$). The widely used θ values are 0 °, 45 °, 90 °, and 135 °. The GLCM $P_d[i,j]$ is defined by first specifying the displacement vector $d = (dx, dy)$ and counting all the pixel pairs separated by $d$ those having the gray level $i$ and $j$. GLCM is defined as: $P_d[i,j]$ where $n_{ij}$ , the number of appearances of the pixel value $(i,j)$ located at a distance in the image.

### 3.4. Detection using Machine Learning

Machine learning leverages provided data to extract insights and understand the underlying information. Once the training phase of a machine learning algorithm is completed, the subsequent crucial step involves evaluating the algorithm's performance. In the context of this journal, we propose the utilization of the Logistic Regression and Random Forest methods.

### 3.4.1. Logistic Regression

Linear Regression provides a continuous output, but Logistic Regression provides constant work. Examples of sustainable creation are house prices and share prices. Models of discrete outputs predict whether the patient has cancer or not, indicating whether the customer will be loyal. Linear Regression is estimated using the Ordinary Least Squares (OLS) approach, while Logistic Regression is calculated using the Maximum Likelihood Estimation (MLE) method [13]. MLE is a "likelihood" maximization method, whereas OLS is a distance-minimizing approach. Maximizing the likelihood function determines the parameters most likely to produce the observed data. From a statistical point of view, MLE assigns mean and variance parameters to determine specific parametric values for a particular model. This parameter can predict the data required in a normal distribution [14].

### 3.4.2. Random Forest

Random Forest is an alternative classification algorithm that achieves good accuracy without many searches on training parameters. It is also the reason for the re-popularity of the Random Forest in the classification problem. Random Forest is a set of decision trees whose prediction results are taken from the most votes from the prediction of a group of decision trees in it. In addition to classification problems such as predictions, Random Forest is also widely researched and developed for Computer Vision problems [15], [16]. The random forest is a classification method consisting of a structured set of decision trees where independent random vectors are identically distributed. Each decision tree assigns a unit vote to the most popular class on the input x.

## 4. RESULTS AND DISCUSSION

Image testing used primary datasets totaling 2080 images with 26 types of classes with various backgrounds and different intensities. This stage is carried out to test the proposed method to perform feature extraction on various types of background and light intensity and test which classification method is better, whether by Logistic Regression or Random Forest.

### 4.1. Result of Experiments

Table 2. Results of Extraction

| Name of Fingerspelling ASL | Grayscaling | | | |
|---|---|---|---|---|
| | 1 | 2 | 3 | 4 |
| *A* | | | | |
| *B* | | | | |
| *C* | | | | |
| *D* | | | | |
| *E* | | | | |
| … | | | | |
| Z | | | | |

The experiment of this work is Improve Pattern Classification on American Sign Language (ASL) using comparison global descriptor feature of the Color Histogram, Hu moment and Haralick Texture to classify the American Sign Language (ASL) Pattern. The first step is pre-processing of the dataset. Table 2 is the result of pre-processing in grayscale image that initial stage of feature extraction using Hu moment and Haralick texture. For more details, the value of the pre-processing results for each Hu moment is shown in Table 3 and the Haralick moment in Table 4. The main stage is the identification/recognition of objects being experimented with in the system. The number of output nodes is determined based on the area of the item (geometry) that must be recognized. Meanwhile, the number of nodes in the hidden layer is determined based on experimental results, where the number of nodes that are too small will cause the training process not to produce a stable weight. Nevertheless, too many nodes will cause the training process to be slower.

Table 3. Results of Hu Moments Feature Extraction

| | | | | | | |
|---|---|---|---|---|---|---|
| 1.2479567 5e-03 | 8.9194166 9e-08 | 7.6675969 4e-12 | 2.9850086 3e-12 | -2.255 4770 1e-24 | -4.284 5489 6e-16 | -1.410 1412 5e-23 |

Table 4. Haralick Feature Extraction Results

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6.70487757e-04 | 3.02937912e+01 | 9.91397249e-01 | 1.76077147e+03 | 3.28158146e-01 | 2.53990700e+02 | 7.01279207e+03 | 8.20385581e+00 | 1.12033144e+01 | 5.26891662e-04 | 3.36942000e+00 | -4.47075596e-01 | 9.99127397e-01 |

### 4.2. Discussion

Figure 8 results from predictive Logistic Regression reaching 48%, with the highest precision in class Y, which is 0.86. The lowest in class V is 0.16, while the highest recall is in class L, which is 0.73, and the lowest is in class V, namely 0.17, then the highest f1-score was in class Z 0.965, and the lowest was in class V, namely 0.17.

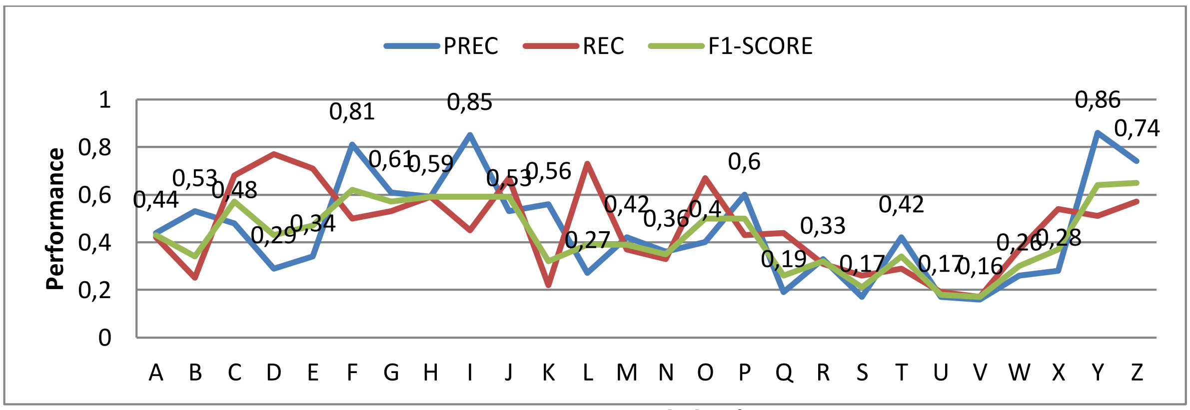


Figure 8. Logistic Regression Method Performance

Figure 9 is a result of predictive from Random Forest is 86%, with the highest precision in classes B, F, H, I, K, Y, and Z, namely 1.00.T, the lowest in class U, namely 0.58, while the highest recall is in class G which is 1.00. Then the highest f1-score in class H, namely 0.99, and the lowest in class U, namely 0.64. Thus the Random Forest method is the best method of the two methods proposed in the study. Random Forest succeeded in increasing the accuracy value of Fingerspelling ASL pattern recognition.

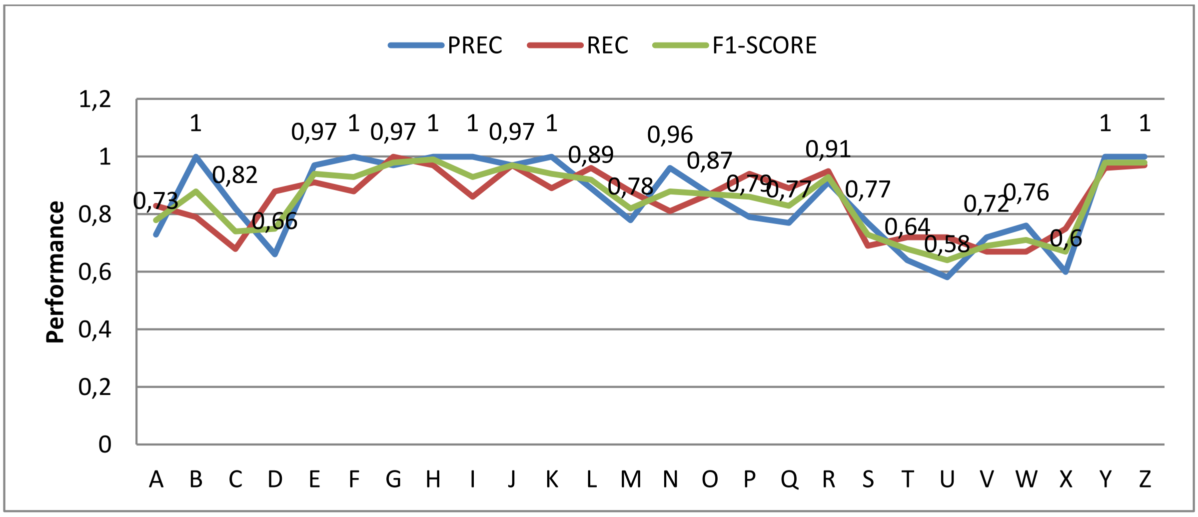



Figure 9. Random Forest Method Performance

Figure 10 shows the classes that have the best performance in this experiment. In Logistic Regression, classes L, V, and Y have the best precision, recall, and f-1 scores, among other courses. Meanwhile, in Random Forest, classes B, F, H, I, K, Y, and Z have the best precision, recall, and f-1 scores. From the results, concluded that overall, class Y is the class with the best results for the two proposed methods.


Figure 10. Classes with stable and highest prediction results in Logistic Regression and Random Forest

## 5. CONCLUSION

This research has successfully measured the level of light intensity from the diversity of backgrounds for ASL fingerspelling patterns by applying Random Forest through several global feature extraction processes. The feature, namely Hu Moments, Haralick Texture, and Color Histogram, where position, texture, and color features are classified using Logistic Regression and Random Forest. The data can read the image moments that have been rotated, translation, and scaled by looking at the price, rec, and f-1 scores that do not experience a value of 0 in both methods. The Random Forest method's performance measures the measurement of light intensity from the diversity of the background for the ASL fingerspelling pattern with the highest accuracy value in the class Y image. The experiment's results were successfully improved by cluster segmentation or using the number of decision trees in the Random Forest classification training process.

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## REFERENCES

[1] A. Khan, I. Alam, M. F. Khan, I. Ahmed, Z. U. Islam, and M. Azam, "A comprehensive analysis of adaptive image restoration techniques in the presence of different noise models," *Found. Univ. J. Eng. Appl. Sci. (HEC Recognized Y Categ. ISSN 2706-7351)*, vol. 1, no. 2, pp. 6–13, 2020.

[2] H. W. A. Internet, "a S Urvey of I Ntegrating," *Communications*, vol. 6, no. 3, pp. 14–30, 2007.

[3] H. ZainEldin *et al.*, "Brain Tumor Detection and Classification Using Deep Learning and Sine-Cosine Fitness Grey Wolf

Optimization," *Bioengineering*, vol. 10, no. 1, pp. 1–19, 2023, doi: 10.3390/bioengineering10010018.

[4] M. Sheykhmousa, M. Mahdianpari, H. Ghanbari, F. Mohammadimanesh, P. Ghamisi, and S. Homayouni, "Support Vector Machine Versus Random Forest for Remote Sensing Image Classification: A Meta-Analysis and Systematic Review," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 13, pp. 6308–6325, 2020, doi: 10.1109/JSTARS.2020.3026724.

[5] A. Latif *et al.*, "Content-based image retrieval and feature extraction: A comprehensive review," *Math. Probl. Eng.*, vol. 2019, 2019, doi: 10.1155/2019/9658350.

[6] M. Keivani, J. Mazloum, E. Sedaghatfar, and M. B. Tavakoli, "Automated analysis of leaf shape, texture, and color features for plant classification," *Trait. du Signal*, vol. 37, no. 1, pp. 17–28, 2020, doi: 10.18280/ts.370103.

[7] A. Indian and K. Bhatia, "Offline Handwritten Hindi Numerals Recongnition using Zernika Moments," *Int. J. Tomogr. Simul.*, vol. 32, no. 2, 2019.

[8] G. Ramesh, J. Logeshwaran, J. Gowri, and A. Mathew, "The management and reduction of digital noise in video image processing by using transmission based noise elimination scheme" *ICTACT J. IMAGE VIDEO Process.*, vol. 9102, no. November, pp. 2797–2801, 2022, doi: 10.21917/ijivp.2022.0398.

[9] P. H. Gonçalves Dias Diniz, "Chemometrics-assisted color histogram-based analytical systems," *J. Chemom.*, vol. 34, no. 12, pp. 1–27, 2020, doi: 10.1002/cem.3242.

[10] Z. AlQadi, "A Highly Secure and Accurate Method for RGB Image Encryption," *Int. J. Comput. Sci. Mob. Comput.*, vol. 9, no. 1, pp. 12–21, 2020

[11] P. K. Athira, C. J. Sruthi, and A. Lijiya, "A Signer Independent Sign Language Recognition with Co-articulation Elimination from Live Videos: An Indian Scenario," *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 3, pp. 771–781, 2022, doi: 10.1016/j.jksuci.2019.05.002.

[12] A. Tyagi and S. Bansal, "Feature Extraction Technique for Vision-Based Indian Sign Language Recognition System: A Review," in *Computational Methods and Data Engineering*, 2021, pp. 39–53.

[13] W. Liu, S. Zeng, G. Wu, H. Li, and F. Chen, "Rice seed purity identification technology using hyperspectral image with lasso logistic regression model," *Sensors*, vol. 21, no. 13, 2021, doi: 10.3390/s21134384.

[14] M. M. Chen and M. C. Chen, "Modeling road accident severity with comparisons of logistic regression, decision tree and random forest," *Inf.*, vol. 11, no. 5, 2020, doi: 10.3390/INFO11050270.

[15] T. Lan, H. Hu, C. Jiang, G. Yang, and Z. Zhao, "A comparative study of decision tree, random forest, and convolutional neural network for spread-F identification," *Adv. Sp. Res.*, vol. 65, no. 8, pp. 2052–2061, 2020, doi: 10.1016/j.asr.2020.01.036.

[16] M. Subramanian, V. Lingamuthu, C. Venkatesan, and S. Perumal, "Content-Based Image Retrieval Using Colour, Gray, Advanced Texture, Shape Features, and Random Forest Classifier with Optimized Particle Swarm Optimization," *Int. J. Biomed. Imaging*, vol. 2022, 2022, doi: 10.1155/2022/3211793.