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A Sign Language Recognition using Improved Grey Wolf Optimization based neural networks

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ABSTRACT

Sign language was developed to enable the deaf and hard of hearing community to communicate with society and convey information. It is the primary means by which they can interact with each other, as well as with the general population. The automatic gesture recognition system described in this paper uses Gray Wolf Optimization (GWO) to identify the most relevant features from a set of gesture images, with the aim of improving model performance. The main steps of the system are explained, including image preprocessing, feature extraction, GWO-based feature selection, classifier training, and evaluation. The proposed model achieved an accuracy of 99.9%.

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1. Introduction

People with hearing and speech impairment face challenges communicating with others. They rely on sign language, a visual form of communication using hand gestures. Since most hearing people are not fluent in sign language, it is necessary to use computers to bridge the gap by associating sign language gestures with their corresponding meanings.[1]. Based on the kind of movement, there are two types of gestures: dynamic and static. Gestures that are generated in a motionless manner while accounting for time variations are known as static gestures. Dynamic gestures, on the other hand, focus entirely on movement. Static modes are used by the majority of recognition systems in use today to effectively address static signal recognition issues [2]. Similarity is a major issue in fixed signal recognition; two signs may appear identical when executed because of similarities in the way the fingers bend and the orientation of the wrists relate to one another. This uncertainty could result in erroneous categorization and lower accuracy.[3]. Although sign language is used globally, it is not a universal language. Different sign languages have developed at the regional level, such as International Sign Language (ISL) in India, American Sign Language (ASL) in the USA, Arabic Sign Language (ArSL) in Arabic-speaking regions, and others. These regional sign languages have their own distinct vocabulary and grammatical structures.[4] Therefore, we propose a system that focuses on using machine learning techniques to recognize the sign language gestures of individuals and thus convert them into text so that others can understand and communicate with them to overcome this problem. Our proposed system is to obtain the image and

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perform image processing techniques on it, such as pre-processing and feature extraction using the histogram of oriented gradients (HOG) technique, then select the features using the developed gray wolf algorithm, and finally classify them using ANN.

2. Related Works

A brief overview of previous research on sign language recognition is provided in this section. In 2018, Rahul D. Raj and Ashish V. Jaasuja used (ANN) as a classifier and (HOG) method to extract features from hands. Their system achieved hand gesture recognition accuracy of up to 99.01%.[5].

In 2018, Arya Thongtawi proposed a simple and effective features extraction method to identify American Sign Language letters. The proposed method uses the fingertip, the amount of (NwE), and three other techniques. The final frame (Delang) contains (Fcen), the (AngF), and the difference in angles between the first finger and the first finger. (ANN) is then used to classify the extracted features. These experiments achieved recognition accuracy of up to 95%.[6].

In 2020, M.M. Qamar Al-Zaman A vision-based method using CNN to recognize handwritten Arabic letters and translate them into Arabic audio is proposed in this work. This technology provides up to 90% accuracy. [7].

In a 2021 study, researchers (including Gangpile Shen) used Mediapipe Hands to track hand joints from webcam footage (RGB images). They extracted two types of features: distances between key hand points and angles between 3D hand vectors and reference axes. To classify hand signals into letters, they used classifiers such as (SVM) and (GBM). The system achieved high accuracy on three datasets: Finger Spelling A (87.60%), ASL Alphabet (99.39%), and Massey dataset (98.45%).[8].

In 2022, Sandhya Rani Bansal et al. They proposed a feature selection technique called hybrid mRMR-PSO. Features are extracted through (HOG) from input gestures. PSO selects a subset of features. It has been comprehensively tested on three different sign languages (ISL, ASL.ArSL) with accuracy (99%, 91%, 93%).[4].

And in 2023, George Ragan et al. They proposed a method for automatic detection of sign language alphabets. Here, KNN classification is implemented using a combination of features acquired using manual methods and deep learning models. The newly proposed IBROA is used for feature selection. The results indicate that combining features and feature selection using IBROA is beneficial. The proposed approach achieved an accuracy of 88.27 in the ASL alphabet and 80.08 in the ASL MNIST alphabet. [9].

Maheen Moghbeli Damaneh et al. in 2023 they present a novel deep-learning neural network architectureThey used three methods CNN, Gabor , ORB feature descriptor filter. These features are then combined and form the final feature vector. The proposed system is applied to the three different databases of Massey, ASL Alphabet, and ASL. The average accuracy of the proposed structure is 99.92%. ,99.8% and 99.80% respectively[10].

In 2023, Khan Pathan and others proposed an effective technique for detecting American Sign Language (ASL) on the 'finger spelling' group, where they processed images using two layers in which the first fully processed the images and in the second extracted hand features through (CNN) model. They achieved 98.981% accuracy. [11].

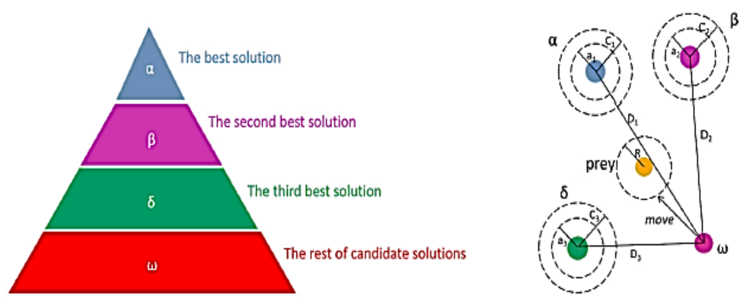
Table 1 - methodology and accuracy for the mentioned literature.

No.	Author and year	Data – set	Methods	Accuracy	
1	Ashish Jasuja and Rahul D. Raj	BSL	(ANN) as a classifier, and a (HOG) for . feature extraction	99.01 %	No major limitations mentioned
2	Arya Thongtawi	ASL	ANN	%95	No details about the computational complexity of the proposed method are mentioned, making it difficult to evaluate its computational efficiency.
3	M. M. Kamruzzaman	ArASL2018	CNN	90 %	It focuses on the Arabic language only, which limits the generalization of the results to other languages
4	Gangpile Shen	Finger Spelling , ASL Alphabet and Massey dataset	Mediapipe, SVM, GBM	(87.60%), (99.39%), (98.45%).	did not explore more advanced feature extraction techniques.
5	, Sandhya Rani Bansal	(ISL, ASL.ArSL)	mRMR-PSO	(99%, 91%, 93%).	Not enough detail has been provided on the parameters of the PSO algorithm and how to adjust them, making it difficult to evaluate their impact on selection results.
6	George Ragan	ASL MNIST alphabet	KNN, IBROA	88.27 , 80.08	Using only two datasets may limit the generalizability of results to larger, more diverse datasets.
7	Maheen Moghbeli Damaneh	Massey, ASL Alphabet, and ASL	CNN, Gabor , ORB	. 99.92%. ,99.8% and 99.80%	Not enough details are provided about the neural network architecture used, making it difficult to evaluate generalizability.
8	, Khan Pathan	ASL	(CNN)	98.981%	focused only on the “finger spelling” group in American Sign Language, which limits the generalizability of the results to the entirety of sign language, which includes body movements and facial expressions in addition to hand movements.

3. Grey wolf optimization algorithm

In 2014, the original gray wolf improvement (GWO) was introduced by Mirjalili et al. Which was inspired by the social intelligence of gray wolf packs in the social hierarchy[12].There are four wolves defined in GWO algorithm.

1. Alpha wolf: the leader of the group.
2. Beta: the lower-ranking member of the wolves.
3. Delta wolves: Who are ruled by the alpha and beta wolves.
4. Omega wolves: the least important members of the pack. as illustrated in Figure 1(a).



(a) The leadership hierarchy of wolves (b) The hunting behavior of wolves

Fig. 1 - Grey wolf social rank and hunting behaviour.

The hunting procedure is simulated mathematically as follows:

a.Finding the prey:

$$\vec{C}=|\vec{C}.\vec{X}_P(t)-\vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1)=\vec{X}_P(t)-\vec{A}.\vec{D} \quad (2)$$

$$\vec{A}=2\vec{a}.\vec{r}_1-\vec{a} \quad (3)$$

$$\vec{c}=2.\vec{r}_2 \quad (4)$$

Where Xa, Xb, Xc, and Xd represent the roles of the search space the of alpha, beta, delta, omega, and wolf as, respectively.

b. Update the status of the potential location of the prey:

$$\vec{D}_\alpha=|\vec{C}_1.\vec{X}_\alpha-\vec{X}| \quad (5)$$

$$\vec{D}_\beta=|\vec{C}_2.\vec{B}_\beta-\vec{X}| \quad (6)$$

$$\vec{D}_\delta=|\vec{C}_3.\vec{X}_\delta-\vec{X}| \quad (7)$$

Where D_alpha is the distance between the current wolf and the alpha wolf, C1 = 2 * r2 is a coefficient that decreases linearly from 2 to 0 over the course of iterations, X_alpha is the position of the alpha wolf, X is the position of the current wolf.

$$\vec{X}_1=\vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha) \quad (8)$$

$$\vec{X}_2=\vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta) \quad (9)$$

$$\vec{X}_3=\vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \quad (10)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \quad (11)$$

Where: $\vec{X}$(t+1) represent New Wolf position in the next iteration . $\vec{X}_1$, $\vec{X}_2$, $\vec{X}_3$: represent Alpha, Beta, and Delta wolf positions respectively in the current iteration .

c. Attacking the prey:

The gray wolf achieves the hunt by attacking prey and quantitatively modeling devaluation

$$\vec{A}=2\vec{a}\vec{r}_1 - \vec{a} \quad (12)$$

a is random value in the interval [−2a, 2a], which a is decreased from 2 to 0 over the course of iterations [13]. as shown in Figure 1(b)

4. Methodology

In this research, a sign language recognition system is developed using neural network technology enhanced with the improved gray wolf optimization (IGWO) algorithm. The main stages of the proposed system and the tools and resources that were used in this work are explained in this section in addition to... As shown in Figure 2, we describe the proposed method in detail.

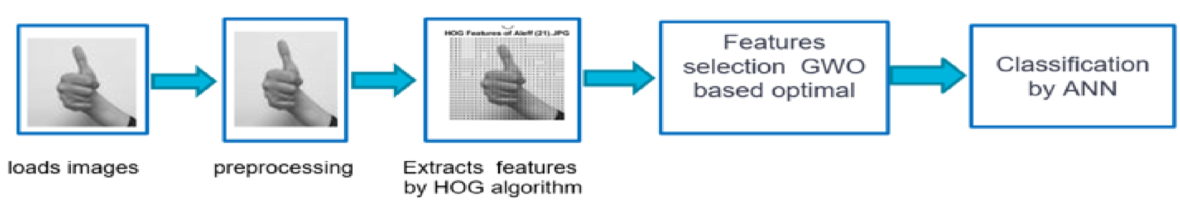


Fig. 2 - Overview of the proposed model.

5. Problem Statement

Two limitations of a system that could potentially use computer vision to interpret sign language or other body movements are Limited Light Conditions: The system may not work well in low light or bright light as it relies on the ability to see the hand clearly. And differences in Sign Language: Sign languages can vary depending on the region or individual. The system may not be able to recognize all differences

6.Model Architecture

There are two main challenges in using computer vision to interpret sign language:

1. Limited Ambient Lighting: Computer vision and vision-based devices will not perform well under inappropriate lighting conditions, affecting their ability to see the hand and product realistically.

2. The diversity of sign languages across regions and individuals represents a major task for mastery-based models, as they may not be able to understand all of those differences.

a. Preprocessing

At this stage, we resize the image to the desired output size (128 x 128) and normalize the pixel values of the resized image to the range [0, 1] by dividing by 255. Then Convert the image to a grayscale. This is a common pre-processing step before images are fed into a machine-learning model.

b. Feature extraction

At this stage, we extracted features using the Histogram of Oriented Gradients (HOG) technique on the previously processed images by setting the cell size for HOG feature extraction to 8x8 pixels. And create a shape and draw the grayscale image with the HOG visualization overlay feature. This can be useful for further analysis or as a pre-processing step for machine learning tasks.

-Histogram of Oriented Gradients (HOG)

HOG is a universal feature descriptor for object detection. HOG uses the orientation and gradient information corresponding to the first-order derivative of the image to calculate features. The edge direction $\theta(x, y)$ and gradient magnitude $\nabla G(x, y)$ are calculated using these equations:

$$\theta(x.y)=\arctan G_y/G_x \quad (13)$$

$$|\nabla G(x.y)|=\sqrt{G_y^2+G_y^2} \quad (14)$$

Here, Gx and Gy are the gradients of the image in the X-direction and Y-direction, respectively.[4]

c. Feature selection

An important process in image processing is the feature selection (FS) step because the image contains different details, some of which are ineffective. If the specific information about the image is strong, the classification step will be more efficient. So the goal of this step is how to get this effective result with the least amount of data per image[14].In this context, we use the Improved Gray Wolf algorithm(IGOW) to identify a subset of the most relevant features from the input data. This step is part of updating wolf positions in the IGWO algorithm. The purpose of this step is to incorporate information from all three wolf species into the new placement of the current wolf. The reason behind this is as follows:

Alpha and Beta wolf sites are the two best solutions. By taking the average of these two locations, the algorithm essentially combines the knowledge and experience of the two wolves. This helps guide the current wolf towards a promising area of search space.

$$\text{combined}=(X1+X2)/2 \quad (15)$$

Where x1 represents the alpha wolf and x2 represents the beta wolf After combining the alpha and beta positions, the algorithm merges the wolf-delta position (the third best solution) by averaging the combined alpha-beta and delta positions. This helps improve the current wolf situation, considering information from all three wolf species.

$$X(t+1)=(\text{combined}+X3)/2 \quad (16)$$

Where x3 represents the wolf delta.

d. Classification by Artificial Neural Network (ANN)

Artificial neural networks (ANNs) are a mathematical learning technique used in cognitive psychology and artificial intelligence. Artificial neural networks are computational models designed to mimic the neural structure and function of the human brain. Figure 3 shows the architecture of the artificial neural network [15]

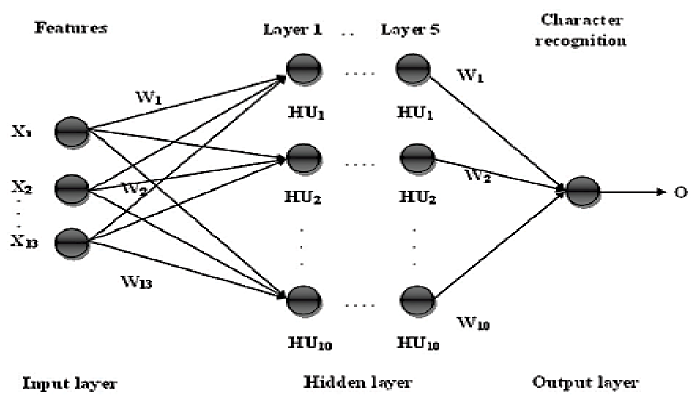


Fig. 3 - ANN architecture[16].

ANN was used for the following reasons:

1. ANN has been proven to be an effective classifier for sign language recognition tasks. Since many previous studies used ANN as a classifier and achieved high discrimination accuracy,
2. ANN is well suited to handle the complexity and diversity of sign language gestures.
3. ANN can learn basic patterns and features in sign language gesture data through the training process, without having to manually extract and select features.
4. The document notes that sign language recognition faces challenges such as similarity between different sign gestures, which may lead to classification errors. The ability of ANNs to learn discriminative features from data can help address these challenges and improve the overall accuracy of a sign language recognition system

7.Data Set

A.ArASL The Arabic Sign Language alphabet dataset presented by Latif et al. It consisted of 54,049 images. 40 volunteers collected more than 32 standard Arabic signs and alphabets. They created a comma-separated values (CSV) file containing the label of each image [17]. It is available online at https://data.mendeley.com/datasets/y7pckrw6z2/1.

Fig. 4 - Arabic sign language alphabets of dataset [17]

B. American Sign Language (ASL Alphabet)

The American Sign Language alphabet dataset consists of 87,000 color images with dimensions of 200 × 200 pixels. It contains 29 classes, ranked from zero to twenty-eight, and has a one-to-one relationship with each symbol of the American alphabet, from A to Z. A sample ASL alphabet database of images is shown in Figure{Formatting Citation}. It is available online at https://www.kaggle.com/datasets/grassknoted/asl-alphabet.

Fig. 5 - A sample of the ASL alphabet database. [18]

C. Indian sign language

The dataset considered for implementation is taken from Kaggle, the Indian Sign Language dataset [20], which contains 35 clues for the alphabets from 1 to 9 and from a to z. Figure 1 shows the data available for each number and alphabet in the Kaggle dataset for Indian Sign Language. The difference between ASL and ISL dataset is that in ISL both hands are used for the gesture and hence it is complex when compared to ASL[19]. https://www.kaggle.com/datasets/prathumarikeri/indian-sign-language-isl

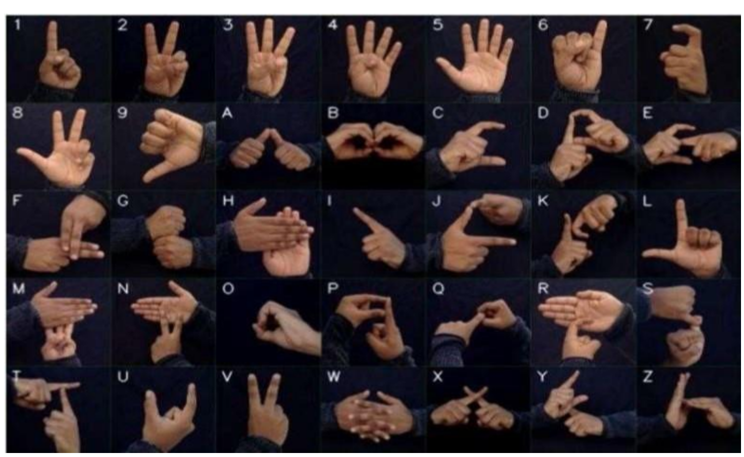


Fig. 6 - Indian sign language for numbers and alphabets [20]

8. Evaluation Measures

In this work, we use Accuracy metric to assess the proposed system to measure the resulting performance. The metric calculates the number of correct predictions divided by the number of predictions, computed as:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (17)$$

where TP is the number of the true positive samples, TN is the number of the true Negative samples, FP is the number of False positive samples, and FN is the number of the false negative samples

9. Results and Discussion

This work was carried out on a Lenovo Core i5 11th generation computer with 16 RAM . A MATLAB is used in this work to create a sign language recognition system. The study takes 2000 images from the data collection, The model achieves an accuracy of up to 99.9.

The error graph displays the image classification performance, dividing the errors into training and validation bins. Blue bars represent the distribution of training errors, while orange bars represent the distribution of validation errors. The nomogram helps evaluate model fit and generalization capabilities

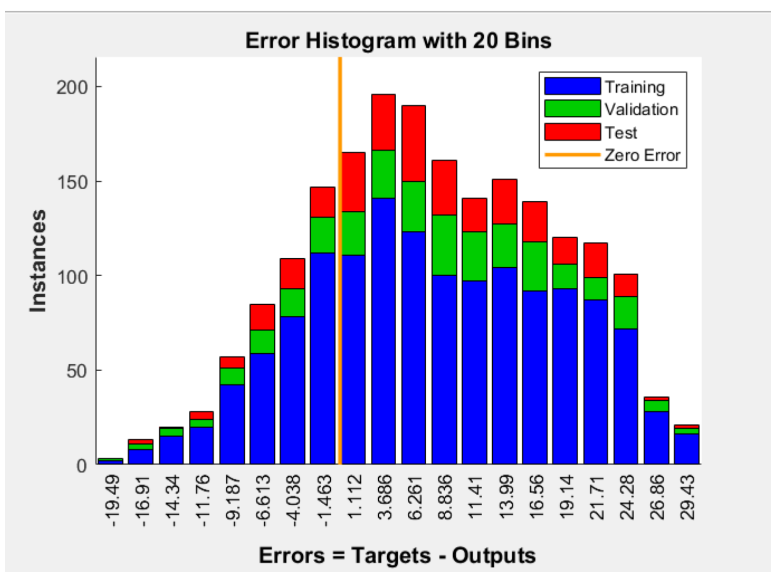


Fig. 7 - Error histogram

Figure (7) is a 20-bin error histogram of the neural network training process, showing the distribution of errors on the training, validation, and testing datasets. The x-axis represents the error values, calculated as the difference between the target and the neural network outputs, while the y-axis indicates the number of instances (iterations) of each error value. The graph is divided into three color-coded sections: blue for training errors, green for validation errors, and red for testing errors. The orange line at zero error represents the ideal point where target equals output. The graph reveals how neural network predictions deviate from actual targets across different subsets of the data. Most errors are centered on zero, indicating that the model predictions are generally close to targets. However, there are noticeable errors on either side of zero, with some boxes showing higher cases, especially in the negative range. This indicates that the model tends to underestimate targets more frequently than overestimate them. The distribution of errors across the training, validation, and test datasets is relatively consistent, with training errors being the most common, followed by validation and test errors. This consistency is crucial because it indicates that the model generalizes well to unseen data, not just the data it was trained on.B. Second, we compare the proposed system with four recent models. In Table 2, we show the evaluation metrics on a (ArASL ,ASL ,ISL) dataset with the four models tested and the proposed model. The accuracy of our model was superior to the four models

Table 2 - comparison among methods used.

Data set	Method	Accuracy
mRMR-PSO	ArSL +ASL +ISL	93% + 91% +99%
IBROA+KNN	ASL Alphabet + MNIST	88.27% + 80.08 %
SVM +GBM	Massy + ASL Alphabet + Finger Spelling	99% + 87% + 98
ANN	ArASL	90%
Our model	ArSL +ASL +ISL	99.8 + 98.7 +99.9

- The ArASL dataset appears to be the most challenging, with most methods achieving lower results on it. The use of a variety of methods (feature extraction techniques, classification algorithms) indicates that there is no single method that is ideal for all problems. In general, methods using a combination of several techniques (such as SVM+GBM and our method) achieved better performance.

9. Conclusion

In this research, we designed a sign language recognition system using three datasets (ArASL), (ASL), and (ISL). The proposed system focused on static gesture recognition by pre-processing input images, extracting features using histogram of oriented gradients (HOG) technique, and then selecting the most relevant features using IGWO algorithm. The selected features were then classified using an artificial neural network.The results showed that the proposed system achieved an accuracy of 99.9% in the sign language gesture recognition task. This highlights the effectiveness of the GWO-based feature selection approach in identifying the most discriminating features for accurate classification. The system provides a promising solution to bridge the communication gap between the deaf and hard of hearing community and the general population by automating the process of translating sign language gestures into text.Future work could explore extending the system to handle dynamic gestures as well, further improving the model's robustness and generalization capabilities. In addition, system integration with real-time video processing can enable seamless sign language interpretation in interactive communication scenarios.

References

[1] A. Sreenivas, "Indian Sign Language Communicator Using Convolutional Neural Network," *Int. J. Adv. Sci. Technol.*, vol. 29, no. 3, pp. 11015–11031, 2020, [Online]. Available: https://www.researchgate.net/publication/343263135_Indian_Sign_Language_Communicator_Using_Convolutional_Neural_Network

[2] M. Xing, J. Hu, Z. Feng, Y. Su, W. Peng, and J. Zheng, "Dynamic hand gesture recognition using motion pattern and shape descriptors," *Multimed. Tools Appl.*, vol. 78, no. 8, pp. 10649–10672, Apr. 2019, doi: 10.1007/s11042-018-6553-9.

[3] A. H. Alrubayi *et al.*, "A pattern recognition model for static gestures in malaysian sign language based on machine learning techniques," *Comput. Electr. Eng.*, vol. 95, Oct. 2021, doi: 10.1016/j.compeleceng.2021.107383.

[4] S. R. Bansal, S. Wadhawan, and R. Goel, "mRMR-PSO: A Hybrid Feature Selection Technique with a Multiobjective Approach for Sign Language Recognition," *Arab. J. Sci. Eng.*, vol. 47, no. 8, pp. 10365–10380, Aug. 2022, doi: 10.1007/s13369-021-06456-z.

[5] J. Singhai, S. Gupta, Maulana Azad National Institute of Technology, IEEE Asia-Pacific Region. MP Subsection, IEEE Asia-Pacific Region. Bombay Section, and Institute of Electrical and Electronics Engineers, *2018 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS) : February 24-25, 2018, Maulana Azad National Institute of Technology, Bhopal*.

[6] A. Thongtawee, O. Pinsanoh, and Y. Kitjaidure, "A Novel Feature Extraction for American Sign Language Recognition Using Webcam," *BMEiCON 2018 - 11th Biomed. Eng. Int. Conf.*, pp. 1–5, 2019, doi: 10.1109/BMEiCON.2018.8609933.

[7] M. M. Kamruzzaman, "Arabic Sign Language Recognition and Generating Arabic Speech Using Convolutional Neural Network," *Wirel. Commun. Mob. Comput.*, vol. 2020, 2020, doi: 10.1155/2020/3685614.

[8] J. Shin, A. Matsuoka, M. A. M. Hasan, and A. Y. Srizon, "American sign language alphabet recognition by extracting feature from hand pose estimation," *Sensors*, vol. 21, no. 17, Sep. 2021, doi: 10.3390/s21175856.

[9] R. G. Rajan, P. S. Rajendran, J. Mulerikkal, and R. Surendiran, "Automatic Detection of Sign Language Fingerspelling on Combined Features and Feature Selection using Improvised Battle Royale Optimisation Algorithm," *SSRG Int. J. Electr. Electron. Eng.*, vol. 10, no. 5, pp. 69–78, 2023, doi: 10.14445/23488379/IJEEE-V10I5P107.

[10] M. M. Damaneh, F. Mohanna, and P. Jafari, "Static hand gesture recognition in sign language based on convolutional neural network with feature extraction method using ORB descriptor and Gabor filter," *Expert Syst. Appl.*, vol. 211, Jan. 2023, doi: 10.1016/j.eswa.2022.118559.

[11] R. K. Pathan, M. Biswas, S. Yasmin, M. U. Khandaker, M. Salman, and A. A. F. Youssef, "Sign language recognition using the fusion of image and hand landmarks through multi-headed convolutional neural network," *Sci. Rep.*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-43852-x.

[12] J. Wang, D. Lin, Y. Zhang, and S. Huang, "An adaptively balanced grey wolf optimization algorithm for feature selection on high-dimensional classification," *Eng. Appl. Artif. Intell.*, vol. 114, Sep. 2022, doi: 10.1016/j.engappai.2022.105088.

[13] N. Paharia, R. S. Jadon, and S. K. Gupta, "Optimization of convolutional neural network hyperparameters using improved competitive gray wolf optimizer for recognition of static signs of Indian Sign Language," *J. Electron. Imaging*, vol. 32, no. 02, Apr. 2023, doi: 10.1117/1.jei.32.2.023042.

[14] R. M. Abdulhamied, M. M. Nasr, and S. N. Abdulkader, "Real-time recognition of American sign language using long-short term memory neural network and hand detection," *Indones. J. Electr. Eng. Comput. Sci.*, vol. 30, no. 1, pp. 545–556, 2023, doi: 10.11591/ijeecs.v30.i1.pp545-556.

[15] A. N. Kumar and G. Geetha, "Recognizing Ancient South Indian Language Using Opposition Based Grey Wolf Optimization," *Intell. Autom. Soft Comput.*, vol. 35, no. 3, pp. 2619–2637, 2023, doi: 10.32604/iasc.2023.028349.

[16] J. Zupan, "Introduction to Artificial Neural Network (ANN) Methods : What They Are and How to Use Them *.," no. September, pp. 327–352, 1994.

[17] E. Aldhahri *et al.*, "Arabic Sign Language Recognition Using Convolutional Neural Network and MobileNet," *Arab. J. Sci. Eng.*, vol. 48, no. 2, pp. 2147–2154, Feb. 2023, doi: 10.1007/s13369-022-07144-2.

[18] J. Fregoso, C. I. Gonzalez, and G. E. Martinez, "Optimization of convolutional neural networks architectures using pso for sign language recognition," *Axioms*, vol. 10, no. 3, 2021, doi: 10.3390/axioms10030139.

[19] T. Kujani and V. Dhilipkumar, "Multiple Deep CNN models for Indian Sign Language translation for Person with Verbal Impairment," *Int. J. Intell. Syst. Appl. Eng.*, vol. 10, no. 3, pp. 382–389, 2022.

[20] B. M. Gunji, N. M. Bhargav, A. Dey, I. K. Zeeshan Mohammed, and S. Sathyajith, "Recognition of Sign Language Based on Hand Gestures," *J. Adv. Appl. Comput. Math.*, vol. 8, pp. 21–32, 2022, doi: 10.15377/2409-5761.2021.08.3