BIG DATA MINING AND ANALYTICS
ISSN 2096-0654 06/10 pp321–335
Volume 6, Number 3, September 2023
DOI: 10.26599/BDMA.2022.9020036

# An Intelligent Heuristic Manta-Ray Foraging Optimization and Adaptive Extreme Learning Machine for Hand Gesture Image Recognition

Seetharam Khetavath, Navalpur Chinnappan Sendhilkumar, Pandurangan Mukunthan, Selvaganesan Jana, Lakshmanan Malliga, Subburayalu Gopalakrishnan, Sankuru Ravi Chand, and Yousef Farhaoui*

**Abstract:** The development of hand gesture recognition systems has gained more attention in recent days, due to its support of modern human-computer interfaces. Moreover, sign language recognition is mainly developed for enabling communication between deaf and dumb people. In conventional works, various image processing techniques like segmentation, optimization, and classification are deployed for hand gesture recognition. Still, it limits the major problems of inefficient handling of large dimensional datasets and requires more time consumption, increased false positives, error rate, and misclassification outputs. Hence, this research work intends to develop an efficient hand gesture image recognition system by using advanced image processing techniques. During image segmentation, skin color detection and morphological operations are performed for accurately segmenting the hand gesture portion. Then, the Heuristic Manta-ray Foraging Optimization (HMFO) technique is employed for optimally selecting the features by computing the best fitness value. Moreover, the reduced dimensionality of features helps to increase the accuracy of classification with a reduced error rate. Finally, an Adaptive Extreme Learning Machine (AELM) based classification technique is employed for predicting the recognition output. During results validation, various evaluation measures have been used to compare the proposed model's performance with other classification approaches.

**Key words:** hand gesture recognition; skin color detection; morphological operations; Multifaceted Feature Extraction (MFE) model; Heuristic Manta-ray Foraging Optimization (HMFO); Adaptive Extreme Learning Machine (AELM)

---

• Seetharam Khetavath is with the Department of Electronics and Communication Engineering, Chaitanya (Deemed to be University), Warangal 506001, India. E-mail: seetharamkhetavath@gmail.com.
• Navalpur Chinnappan Sendhilkumar and Pandurangan Mukunthan are with the Department of Electronics and Communication Engineering, Sri Indu College of Engineering & Technology, Sheriguda, Hyderabad 501510, India. E-mail: sendhilkumarnc@gmail.com; mukunthanece@gmail.com.
• Selvaganesan Jana and Subburayalu Gopalakrishnan are with the Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai 600062, India. E-mail: seljana.1995@gmail.com; drsgk85@gmail.com.
• Lakshmanan Malliga is with the Department of Electronics and Communication Engineering, Malla Reddy Engineering College for Women (Autonomous), Telangana 500100, India. E-mail: dr.malligalakshmanan18@gmail.com.
• Sankuru Ravi Chand is with the Department of Electronics and Communication Engineering, Nalla Narasimha Reddy Education Society's Group of Institutions-Integrated Campus, Hyderabad 500088, India. E-mail: ravichandsankuru1@gmail.com.
• Yousef Farhaoui is with STI Laboratory, the IDMS Team, Faculty of Sciences and Techniques, Moulay Ismail University of Meknès, Errachidia 52000, Morocco. E-mail: y.farhaoui@fste.umi.ac.ma.
* To whom correspondence should be addressed.
Manuscript received: 2022-09-17; accepted: 2022-09-29

## 1 Introduction

In recent time, the gesture recognition[1, 2] of sign languages has increasingly developed due to the rapid development of computer technology and interface. Sign language recognition[3, 4] is mainly developed for deaf and dump people for communication. The Sign Language Recognition (SLR) is considered as the supporting language used by the deaf and dumb people. With the help of sign language, they can communicate with the outer world. Generally, there are different types of sign languages used over the world, which includes American Sign Language (ASL), Spanish sign language, Indian Sign Language (ISL), British Sign Language (BSL), etc. The Indian people could use the ISL language, but the grammar is same as all sign languages throughout the world[5]. Here, the hand gestures are represented as the alphabets of sign languages, which can be used for establishing the proper inter-communication between the deaf and dump people. The sample sign language hand gestures are shown in Fig. 1.

Moreover, the hand gesture image recognition system[6, 7] can be extensively used in many application systems such as medical, gaming controls, home appliances, car driving, sign language representation, communication systems, and interaction with computers. In gaming control system, the 3D modeling based augmented reality system could be used for controlling the hand gestures, which provides the user friendly interface for controlling the virtual movements. In the medical application system, the wearable recognition devices could be used for enabling remote monitoring and controlling operations. Moreover, it is also used in the home appliances such as smart TV, computer, music player, etc., where the automatic controlling of devices has been actuated by using the hand gesture recognition system. It is also used for controlling the robotics by providing proper instructions to actuate them. Then, it could be used for tracking and locating the operations in the graphic editor controlling system. In the conventional works[8], there are different types of image processing techniques[9–11] such as segmentation, feature extraction, optimization, and classification used for hand gesture image recognition and classification. Normally, the segmentation techniques[12, 13] are mainly used for segmenting the gesture region from the given inputs for recognition, which includes RGB conversion, binary operations, morphological operations, canny edge detection, and gray scale conversion.

**Fig. 1 Sample hand gestures.**

Similar to that, the feature extraction and selection methodologies[14–16] are used for extracting the most suitable features from the segmented image for training the models. Finally, classification techniques[17] are used for accurately predicting the gesture based on the optimal set of features. However, the existing works[18–20] are facing the difficulties of high complexity in operations, inaccurate or over segmentation affecting the performance of classifier, and more time consumption. Hence, the proposed work object is to develop an efficient hand gesture image recognition system by an intelligent image processing methodologies. The main contributions of this work are as follows:

- To accurately segment the gesture region from the given inputs, the skin color detection and morphological operations are performed.
- To extract a multiple number of features from the segmented image for improving the accuracy of recognition, the Multifaceted Feature Extraction (MFE) model is employed.
- To select the best suited features based on the global optimal solution, the Heuristics Manta-ray Foraging Optimization (HMFO) technique is utilized.
- To exactly predict the recognized label with high accuracy and reduced false positives, an Adaptive Extreme Learning Machine (AELM) algorithm is deployed.

The remaining portions of this paper are structuralized into the followings. Section 2 reviews the conventional image processing techniques such as feature extraction, segmentation, optimization, and classification for hand gesture image recognition with its advantages and disadvantages. Section 3 presents the working methodology of the proposed hand gesture recognition system with its overall flow and algorithmic illustrations. Section 4 evaluates the results of both conventional and proposed techniques by using various performance metrics. Finally, Section 5 concludes the paper with its future work.

## 2 Related Work

This section reviews some of the conventional works related to hand gesture image recognition and classification. Also, it discusses about the advantages and disadvantages of various image processing techniques based on its key features and working principles.

Cheok et al.[21] conducted a comprehensive review on various image processing techniques used for hand gesture image recognition and classification. Here, the vision based gesture image recognition system was examined with its stages of preprocessing, segmentation, feature extraction, and classification. Typically, the preprocessing was mainly used for noise elimination and image quality enhancement, because the performance of recognition highly depended on the quality of inputs. Here, the different types of preprocessing models such as median filtering, Gaussian filtering, mean filtering, and histogram equalization models were discussed. Also, the region-based and context-based segmentation models were investigated for detecting the region by suppressing the backgrounds. Moreover, the Shift Invariant Feature Transform (SIFT) and Speeded Up Robust Feature (SURF) based extraction models were suggested for obtaining the relevant set of features used for classification. Finally, some of the unsupervised machine learning techniques were examined for recognizing the hand gestures from the given images according to the set of features. Li et al.[9] employed a Convolutional Neural Network (CNN) model for developing the hand gesture recognition system. The main intention of this work was to accurately recognize the gestures by using the error propagation algorithm. Here, the network stability test was conducted for analyzing the stability and convergence speed of optimization. The major benefits of this work were increased accuracy, reduced time consumption, and optimal performance. However, it faced the difficulties of increased complexity in algorithm design and high error rate.

Devineau et al.[3] introduced a 3D hand gesture image recognition framework using the CNN technique. The main intention of this paper was to utilize the full hand skeleton for analyzing the dynamic hand gesture images. Moreover, the effectiveness of this model was tested according to the coverage of hand shape. The key benefit of this work was that it does not require the recurrent cells for recognition, which helps to reduce the complexity of operations. Yet, it limits with the problems of increased misclassification outcomes and high false positives. Chen et al.[22] deployed the Gaussian Mixture Model (GMM) for improving the region accuracy and boundary accuracy of hand gesture image recognition system. The main contribution of this work was to optimize the segmentation process for improving the overall performance recognition and classification.

In addition to that, the Expected Maximization (EM) technique was used to predict the sign of segmented image based on the maximum likelihood estimation. The advantages of this work were accurate segmentation and improved recognition rate. Bhuvaneshwari and Manjunathan[23] deployed a long term recurrent convolution network for improving the efficiency of gesture recognition system. In this model, the visual feature extraction and sequence learning processes were performed for increasing the accuracy of recognition and classification. However, this technique requires more time for training and testing the models, which degrades the performance of entire recognition system. Pinto et al.[24] implemented the CNN based deep learning model for hand gesture recognition and classification. This framework includes the stages of color segmentation, morphological operations, hand contour estimation, CNN classification, and recognition. Here, the training loss and accuracy have been estimated for validating the recognition performance of the gesture recognition system.

Mujahid et al.[25] implemented a lightweight hand gesture recognition model for real time applications with the use of deep learning mechanism. Here, You Only Look Once (YOLO) based CNN technique was implemented for improving the process of recognition, which includes the operations of filtering, quality enhancement, segmentation, and classification. The major advantage of this work was that it has an increased ability to handle the large dimensional datasets with reduced complexity of operations. Mohammed et al.[26] presented a detailed survey for analyzing the different types of machine learning techniques used for hand gesture image recognition system, which includes supervised learning, unsupervised learning, and semi-supervised learning. Moreover, this work examined the efficiency and performance of each machine learning model according to its stages of operations like preprocessing, feature extraction, and classification. Rzecki[27] implemented an advanced time series based classification approach for the hand gesture image recognition system. Here, the $k$-means data clustering was utilized to predict the results based on the distance values. Moreover, the parameter optimization was performed to increase the training accuracy of classification. However, this work had the major limitations of increased misclassification results, error values, and reduced accuracy.

Sagayam and Hemanth[28] employed an Artificial Bee Colony (ABC) optimization based 1-D HMM for developing the hand gesture image recognition and classification system. Here, the ABC optimization technique was mainly used to compute the optimal fitness value for selecting the features. Chung et al.[29] employed a deep CNN technique for developing an enhanced hand gesture recognition system, which includes the major processes of hand detection, tracking, and recognition. Here, the Kernelized Correlation Filtering (KCF) technique was utilized to preprocess the given hand image for noise removal, and it helps to improve the accuracy of recognition. During classification, the parameters such as learning rate, dropout, and batch size were estimated for improving the recognition rate. Ozcan and Basturk[30] utilized a heuristic optimization based CNN technique for hand gesture recognition system. The main purpose of this work was to tune the hyper-parameters of CNN based on the best optimal solution provided by the ABC technique. In this model, the convolution and pooling layers were used for feature learning, then flatten, fully connected, and softmax layers were used for classification. This kind of optimization based classification technique could efficiently improve the performance of hand gesture recognition and classification.

According to this review, it is analyzed that conventional works are highly focusing on developing the optimization based classification frameworks for hand gesture image recognition. Also, the existing works utilized different types of segmentation and feature extraction methodologies for improving the accuracy of recognition. However, it faced the difficulties related to the factors of high complexity in computational operations, increased training and testing time, high error values, and inability to handle large dimensional datasets. Hence, the proposed work intends to utilize an advanced image processing methodologies for developing an efficient hand gesture image recognition and classification system.

## 3 Proposed Methodology

This section presents the clear description about the research methodology used for hand gesture recognition and classification. The main contribution of this work is to accurately predict the hand gesture by using an advanced methodologies with reduced computational complexity and error rate. The overall flow of the proposed hand gesture image recognition system is shown in Fig. 2, which includes the following stages of operations:

- Hand gesture image segmentation;
- Multifaceted Feature Extraction Model (MFE);

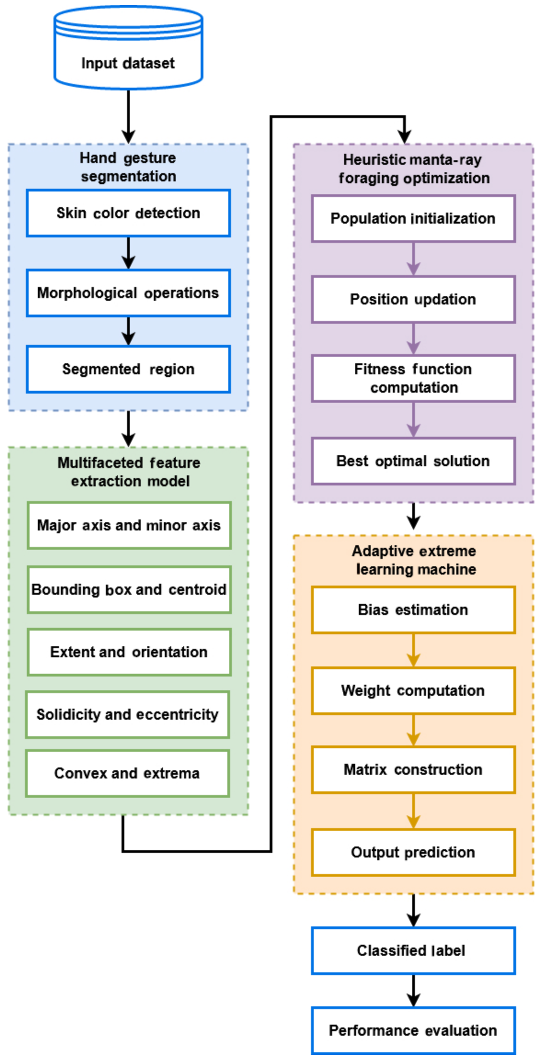



**Fig. 2 Flow of the proposed system.**

- Heuristic Manta-ray Foraging Optimization;
- Adaptive Extreme Learning Machine (AELM).

Initially, the input hand image is obtained from the datasets for processing, and it is segmented for extracting hand gesture region. During this process, the skin color detection and morphological operations have been performed for segmenting the accurate region of hand gesture. After that, the segmented portion of image can be used for feature extraction, where a multiple number of features are extracted for improving the process of recognition. Consequently, the HMFO technique is employed for optimally selecting the best number of features to train the classifier for increasing the accuracy of prediction. It also helps to reduce the required amount of time for training and testing the data and minimize the complexity of operations. Finally, an AELM technique is utilized for recognizing the hand gesture based on the optimal number of features. The major benefits of this work were increased recognition rate, accuracy, and optimal performance outcome.

### 3.1 Hand image segmentation

Segmentation is considered as one of the essential steps of hand gesture recognition system that helps to obtain an improved classification rate. In this model, the gesture is accurately extracted from the background for an effective processing. In the conventional works, region of interest extraction is considered as the major problem that affects the overall accuracy of recognition system. Hence, this work intends to accurately segment the hand gesture region from the given input by suppressing the background portion based on the skin color detection and morphological operations. Typically, the morphological operations involve the processes of basic operations (i.e., erosion and dilation) and derivative estimation (i.e., open and close skeleton). In addition to that, the edge detection is performed to identify the boundary region from the neighboring portions for differentiating it with each other based on the grey level. During this process, the Hue Saturation Value (HSV) color space model is utilized for skin color detection, where the illumination invariance is obtained by eliminating the value of $V$ and using the values of $H$ and $S$. Then, the histogram model is utilized for computing the threshold value in order to differentiate both the skin color and non-skin color portions. Here, the main reasons of using the HSV color model are high robustness against the variations of scaling, lighting, and rotation. Normally, the input images obtained from the dataset are in the form of RGB, and converted into the HSV model for further processing, which is accomplished by using the following equations:

$$H = \begin{cases} \theta, & \text{Green} \geqslant \text{Blue}; \\ 2\pi - \theta, & \text{Green} < \text{Blue} \end{cases} \tag{1}$$

$$S = \frac{\max(\text{Red}, \text{Green}, \text{Blue}) - \min(\text{Red}, \text{Green}, \text{Blue})}{\max(\text{Red}, \text{Green}, \text{Blue})} \tag{2}$$

Moreover, the values of hue and saturation lie within the threshold of $0° < \text{hue} < 25°$ and $0° < \text{saturation} < 180°$. Consequently, the morphological operations are applied to accurately identify the gestures according to the connection property of detected skin portions. During this process, the erosion and dilation processes have been performed on the binary image, where the value of 1 indicates the skin color, and 0 indicates the non-skin portions. Then, the erosion is performed to structure the elements, and the dilation is applied to develop the regions that are lost due to erosion. Here, the morphological filtering is mainly utilized for labeling the binary image into the group of pixels for identification. This segmented region can be further used for feature extraction process.

### 3.2 Multifaceted Feature Extraction (MFE) model

In this phase, the multiple number of features is extracted from the segmented image by using the Multifaceted Feature Extraction (MFE) model, which helps to increase the accuracy of recognition. It includes the features of major-minor axis, centroid, extent, orientation, solidicity, eccentricity, convex, and extreme, which are calculated as follows:

$$M_A = \sum L(a,b) \tag{3}$$

$$M_B = \sum S(a,b) \tag{4}$$

where $M_A$ and $M_B$ indicate the lengths of major and minor axis correspondingly, and $L(a,b)$ and $S(a,b)$ are the major and minor axis values, respectively.

$$\mathrm{Cen}_S = \left(\frac{a_1+a_2}{2}, \frac{b_1+b_2}{2}\right) \tag{5}$$

$$\mathrm{Ex}_S = \frac{T_P}{\mathrm{BT}_P} \tag{6}$$

where $\mathrm{Cen}_S$ indicates the centroid, $\mathrm{Ex}_S$ denotes the extent, $T_P$ defines the total number of pixels in the segmented image, and $\mathrm{BT}_P$ indicates the total number of pixels in the bounded region.

$$\mathrm{Con}_S = \sum \mathrm{Co}_I(a,b) \tag{7}$$

$$\mathrm{So}_S = \frac{T_P}{H_A} \tag{8}$$

$$\mathrm{Eccen}_S = \frac{\mathrm{Fo}_D}{\mathrm{se}_m} \tag{9}$$

where $\mathrm{Con}_S$ denotes the convex area, $\mathrm{Co}_I$ is the convex image, $\mathrm{So}_S$ defines the solidicity, $H_A$ is the hull area of shape, $\mathrm{Eccen}_S$ is the eccentricity, $\mathrm{Fo}_D$ is the foci distance, and $\mathrm{se}_m$ is the semi major axis.

### 3.3 Heuristic Manta-ray Foraging Optimization

After extracting the features, the most optimal number of features is selected based on the best fitness value by using the HMFO technique. It is one of the meta-heuristic optimization techniques and extensively used for solving the multi-objective problems. Here, the major reasons of using this technique are that it efficiently identifies the global optimum solution with reduced number of iterations and increased convergence speed of processing, and improves the performance of recognition. In this work, the HMFO mechanism is used for selecting the optimal features to training the model of classifier, because the performance of hand gesture recognition classifier highly depends on the number of suitable features for training the models. During this process, the behavior and positions of manta-ray can be changed based on its food source, as illustrated below:

$$\mathrm{Po}_{i,j}(K+1) = \begin{cases} \mathrm{Po}_{i,j}(K) + x(:)(B_{L,j}(K) - \mathrm{Po}_{i,j}(K)) + \\ \varphi(B_{L,j}(K) - \mathrm{Po}_{i,j}(t)),\ \forall i = 1, j \in \mathrm{Nu}_v; \\ \mathrm{Po}_{i,j}(K) + x(:)(\mathrm{Po}_{i-1,j}(K) - \mathrm{Po}_{i,j}(K)) + \\ \varphi(B_{L,j}(K) - \mathrm{Po}_{i,j}(K)), \forall i=1, j \in \mathrm{Nu}_v, \forall i>1\text{: } \mathrm{Nu}_p \end{cases} \tag{10}$$

where $\mathrm{Po}_{i,j}$ is the position of manta-ray, $\varphi$ is the random position, $B_L$ denotes the best location of $j$, $K$ is the number of iteration, $\mathrm{Nu}_v$ defines the number of variables, and $\mathrm{Nu}_p$ indicates the number of populations. After finding the food source, the new positions of manta-ray are updated and adjusted with the best position, as shown below:

$$\mathrm{Po}_{i,j}(K+1) = \mathrm{Po}_{i,j}(K) + \mathrm{CP}\cdot (x_2 B_{L,j} - x_3 \mathrm{Po}_{i,j}(K)), \forall i \in \mathrm{Nu}_p \tag{11}$$

$$\varphi = 2 \cdot x(:) \cdot \sqrt{|\log(x(:))|} \tag{12}$$

$$\mathrm{Po}_{i,j}(K+1) = \begin{cases} \mathrm{Po}_{i,j}(K) + x(:)(B_{L,j}(K) - \mathrm{Po}_{i,j}(K)) + \\ \varphi(B_{L,j}(K) - \mathrm{Po}_{i,j}(K)), \forall i = 1, j \in \mathrm{Nu}_v; \\ \mathrm{Po}_{i,j}(K) + x(:)(\mathrm{Po}_{i-1,j}(K) - \mathrm{Po}_{i,j}(K)) + \\ \varphi(R_{H,j}(K) - \mathrm{Po}_{i,j}(K)), \forall i=1, j \in \mathrm{Nu}_v, \forall i>1: \mathrm{Nu}_p \end{cases} \tag{13}$$

where CP represents the control system of MRSO and $R_H$ represents the random value. Based on this, the best optimal solution is estimated for increasing the overall accuracy of classification, and the fitness of the $i$-th solution is computed as follows:

$$\mathrm{Fit}_i = \pi_1(1 - \mathrm{Acc}_i) + \pi_2 \times \frac{\mathrm{OS}_i}{S_F} \tag{14}$$

where $\mathrm{Fit}_i$ indicates the $i$-th solution, $\pi_1$ and $\pi_2$ are the balancing parameters, $\mathrm{Acc}_i$ defines the accuracy of the $i$-th solution, $\mathrm{OS}_i$ represents the size of optimal features, and $S_F$ is the set of features. The algorithmic steps involved in this technique are given in Algorithm 1.

### 3.4 Adaptive Extreme Learning Machine (AELM)

Classification is the final stage of hand gesture image recognition system, and its accuracy remains to be a major consideration in any recognition system, because the reduced classification accuracy leads to

**Algorithm 1 Manta-Ray Search Optimization (MRSO)**

**Input:** Set of extracted features;
**Output:** Best selection of parameters $\text{Optimal}_F$;
1: Initialize the input parameters with the set of IP $= [\text{IP}_1, \text{IP}_2, \ldots, \text{IP}_{S_F}]$ with the random positions;
2: Initialize the iteration value as $K = 1$;
3: While $I \leqslant I_{\max}$
4: The objective function obj $(\text{IP}_i)$ is estimated for all manta-rays with respect to the initial position;
5: The current best position is deliberated as the global best solution $B_L$;
6: Estimate the fitness value by using Eq. (14);
7: For $i = 1$ to $S_F$
IF rand() $< 0.5$
Update the position of manta-ray using Eq. (10);
Else
If $\frac{I}{K_{\max}} <$ rand()
The position of manta-ray $\text{IP}_i$ is updated by using Eq. (13);
Else
The position of manta-ray $\text{IP}_i$ is updated;
End if
The position has been updated by using Eq. (11);
End for;
Estimate the fitness value of the manta-rays;
$K = K + 1$
End while;
8: Return the optimal set of parameters $\text{Optimal}_F = B_L$;

misclassification of gestures which in turn deflects in proper communication of messages. Hence, an efficient and intelligent machine learning classification technique is employed in this work named as AELM, which accurately predicts the classified label. Here, the major benefits of using this technique are as follows: more efficient in high dimensional spaces, reduced time consumption for both training and testing, high recognition accuracy, and minimized computational complexity. This technique comprises the layers of input, hidden, and output, in which the input weights are randomly defined and obtained by the input layer.

Then, the hidden layer processes the information with the bias according to the input weights, and output layer produces the finalized result of classification. Here, the following operations are done:

- The biases and input weights are randomly selected.
- Then, the output matrix of the hidden layer is constructed.
- The moore-penrose generalization model is utilized to estimate the weight value of the output layer.

In this model, the output function of hidden layer is formed by using the following model:

$$H_d(a) = R(x_d, y_d, a) \tag{15}$$

where $H_d$ indicates the $d$-th hidden node, and $x_d$ and $y_d$ are the hidden node parameters. Then, the output function is determined as follows:

$$\text{OF}_M(a) = \sum_{n=1}^{M} \omega_{d_2} h_d(a) \tag{16}$$

$$H(a) = [R(H_{d_1}(a), H_{d_2}(a), \ldots, H_M(a))] \tag{17}$$

Consequently, the output matrix $E$ of hidden layer is constructed for the obtained training samples $T_s$, as shown below:

$$E = \begin{bmatrix} H(a_1) \\ H(a_2) \\ \vdots \\ H(aT_s) \end{bmatrix} = \begin{bmatrix} R(x_1, y_1, a_1) & R(x_2, y_2, a_2) & \cdots & R(x_M, y_M, a_M) \\ R(x_1, y_1, a_2) & R(x_2, y_2, a_3) & \cdots & R(x_M, y_M, a_{M+1}) \\ \vdots & \vdots & \vdots & \vdots \\ R(x_1, y_1, a_N) & R(x_2, y_2, a_{N+1}) & \cdots & R(x_M, y_M, a_{T_s}) \end{bmatrix} \tag{18}$$

$$\text{Tar}_M = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_{T_s} \end{bmatrix} \tag{19}$$

Based on the target matrix $\text{Tar}_M$, the recognition label can be produced by the output layer of classifier.

Based on the target matrix $\text{Tar}_M$, the recognition label can be produced by the output layer of classifier. Figure 3 shows some sample segmentation results taken for the Sebastian Marcel dataset, which include the input image, binary segmented region, region detection, boundary localized image, and final segmentation output.

## 4 Result and Discussion

This section evaluates the performance of both conventional and proposed classification techniques by using various measures such as accuracy, sensitivity, specificity, precision, recall, error rate, F1-score, Area Under Curve (AUC), and Receiver Operating Characteristics (ROC). For evaluating the performance of these techniques, there are different types of datasets such as Sebastian Marcel and ASL fingerprint digits used in this system. They are calculated as follows:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{20}$$

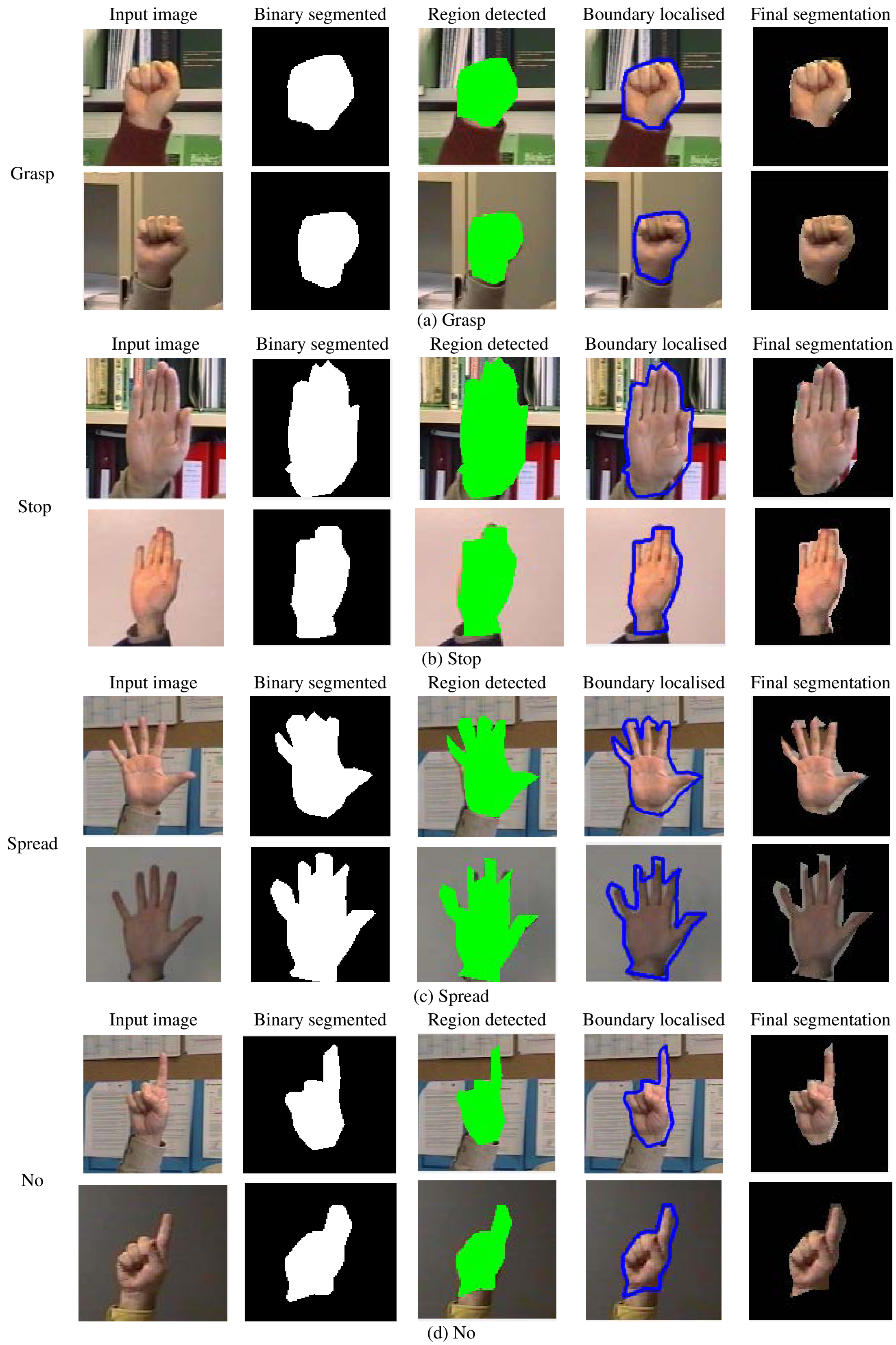



**Fig. 3 Sample segmentation results taken for the Sebastian Marcel dataset with four different classes.**

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{21}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{22}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{23}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{24}$$

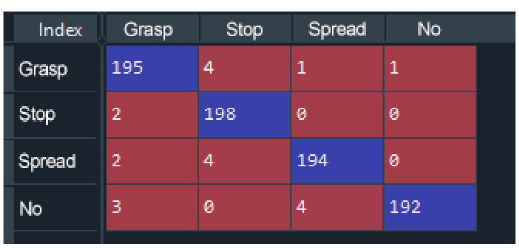
$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{25}$$

$$\text{Error rate} = 1 - \text{Accuracy} \tag{26}$$

where TP is the true positives, TN indicates the true negative, FP denotes the false positive, FN indicates the false negative, $P_o$ is the percentage of trials when the judges concur, and $P_e$ is the percentage of trials where agreement would be anticipated from chance.

### 4.1 Performance analysis of the proposed system

Here, the performance of proposed HMFO-AELM based hand gesture recognition system is validated by using both the Sebastian Marcel dataset and ASL-finger dataset. As shown in Fig. 4, the confusion matrix has been generated for the proposed HMFO-AELM technique with respect to four different classes such as grasp, stop, spread, and no. Similar to that, the confusion matrix of the proposed system is also constructed for the ASL-finger dataset. Typically, the performance and effectiveness of classifier is validated based on the confusion matrix analysis. Based on this evaluation, it is observed that the proposed HMFO-AELM technique could efficiently detect the hand gestures for all classes of datasets by using the optimal set of features.



| Index | Grasp | Stop | Spread | No |
|---|---|---|---|---|
| Grasp | 195 | 4 | 1 | 1 |
| Stop | 2 | 198 | 0 | 0 |
| Spread | 2 | 4 | 194 | 0 |
| No | 3 | 0 | 4 | 192 |

**Fig. 4 Confusion matrix for Sebastian Marcel dataset.**

Then, the performance of conventional SVM and proposed HMFO-AELM techniques are validated and compared based on the measures of correct classification, incorrect classification, accuracy, and time, as shown in Table 1. Here, the results are estimated for all number of classes in the Sebastian Marcel dataset. Figure 4 depicts the confusion matrix for Sebastian Marcel dataset, and similar to that, the confusion matrix of the proposed system also constructed for the ASL-finger dataset is depicted in Fig. 5. From the evaluation, it is analyzed that the proposed HMFO-AELM outperforms the SVM technique with improved performance measures by accurately recognizing the hand gestures. The proposed HMFO-AELM techniques are validated by using Sebastian Marcel dataset. Consequently, Tables 2 and 3 evaluate the overall performance of the proposed recognition system by using the Sebastian Marcel dataset and ASL-finger dataset, respectively. According to these evaluations, it is clearly evident that the proposed HMFO-AELM provides an improved results in terms of increased accuracy, precision, recall, sensitivity, specificity, F1-score, AUC, Postive Prediction Value (PPV), and reduced error rate.

Figure 6 validates the performance of the proposed HMFO-AELM based recognition system with and without optimization by using the Sebastian Marcel dataset. Then, Fig. 7 shows the results of the proposed mechanism with and without optimization by using the ASL-finger dataset. Typically, the sensitivity, specificity, accuracy, precision, and recall are the widely used measures in many prediction systems for evaluating the performance and effectiveness of classifier. Similarly, the other measures such as PPV, AUC, F1-score, and error rate are also used for testing the efficiency of classification. Moreover, the improved values of these measures assure an increased system performance. Based on this analysis, it is identified that the proposed model provides increased performance values, when it integrates with the HMFO technique, because the

**Table 1 Comparative analysis between the conventional SVM and proposed HMFO-AELM techniques using Sebastian Marcel dataset.**

| Hand gesture | Number of correct classifications | | Number of incorrect classifications | | Accuracy (%) | | Time (ms) | |
|---|---|---|---|---|---|---|---|---|
| | SVM | HMFO-AELM | SVM | HMFO-AELM | SVM | HMFO-AELM | SVM | HMFO-AELM |
| Stop | 188 | 198 | 12 | 2 | 94 | 96.5 | 0.024 | 0.018 |
| No | 196 | 192 | 4 | 8 | 98 | 96.5 | 0.024 | 0.018 |
| Spread | 192 | 194 | 8 | 6 | 96 | 98.5 | 0.024 | 0.018 |
| Grasp | 196 | 195 | 4 | 5 | 98 | 99.0 | 0.024 | 0.018 |

| Index | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 199 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 2 | 198 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 199 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 2 | 0 | 0 | 198 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 1 | 0 | 0 | 199 | 0 | 0 | 0 | 0 | 0 |
| 5 | 1 | 0 | 3 | 0 | 0 | 196 | 0 | 0 | 0 | 0 |
| 6 | 1 | 1 | 0 | 1 | 0 | 0 | 197 | 0 | 0 | 0 |
| 7 | 1 | 0 | 0 | 2 | 0 | 0 | 0 | 197 | 0 | 0 |
| 8 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 198 | 0 |
| 9 | 1 | 1 | 2 | 3 | 0 | 0 | 0 | 0 | 0 | 192 |

**Fig. 5 Confusion matrix for ASL finger dataset.**

**Table 2 Performance analysis of the proposed HMFO-AELM for Sebastian Marcel dataset.**

| Hand gesture | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | Recall (%) | F1-score | AUC | Error rate | PPV |
|---|---|---|---|---|---|---|---|---|---|
| Grasp | 99.0 | 100 | 98.030 | 98 | 100 | 0.9899 | 0.9902 | 0.0100 | 0.98 |
| Spread | 98.5 | 100 | 97.087 | 97 | 100 | 0.9848 | 0.9854 | 0.0150 | 0.97 |
| Stop | 96.5 | 100 | 93.450 | 93 | 100 | 0.9637 | 0.9673 | 0.0350 | 0.93 |
| No | 96.5 | 100 | 93.450 | 93 | 100 | 0.9637 | 0.9673 | 0.0350 | 0.93 |

**Table 3 Performance of the proposed HMFO-AELM for ASL-finger dataset.**

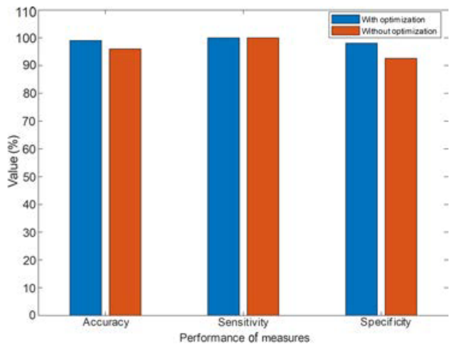
| Index value | Accuracy (%) | Sensitivity (%) | Specificity (%) | Precision (%) | Recall (%) | F1-score | AUC | Error rate | PPV |
|---|---|---|---|---|---|---|---|---|---|
| 0 | 97.75 | 100 | 95.69 | 95.50 | 100 | 0.97 | 0.97 | 0.022 | 0.95 |
| 1 | 98.06 | 100 | 96.26 | 96.12 | 100 | 0.98 | 0.98 | 0.019 | 0.96 |
| 2 | 97.81 | 100 | 95.80 | 95.62 | 100 | 0.97 | 0.97 | 0.021 | 0.95 |
| 3 | 98.25 | 100 | 96.61 | 96.5 | 100 | 0.98 | 0.98 | 0.017 | 0.96 |
| 4 | 98.25 | 100 | 96.61 | 96.5 | 100 | 0.98 | 0.98 | 0.017 | 0.96 |
| 5 | 98.56 | 100 | 97.20 | 97.12 | 100 | 0.98 | 0.98 | 0.017 | 0.97 |
| 6 | 96.8 | 100 | 97.68 | 97.62 | 100 | 0.98 | 0.98 | 0.014 | 0.97 |
| 7 | 99.18 | 100 | 98.40 | 98.37 | 100 | 0.99 | 0.99 | 0.019 | 0.98 |
| 8 | 99.31 | 100 | 98.64 | 98.62 | 100 | 0.99 | 0.99 | 0.008 | 0.98 |
| 9 | 99.37 | 100 | 98.76 | 98.75 | 100 | 0.99 | 0.99 | 0.006 | 0.98 |

optimization helps to reduce the dimensionality of features for increasing the efficiency of classification. Moreover, the increased number of features can produce the misclassification results with high positives, hence it affects the performance of entire system. Then, these parameters are also validated for the proposed technique using the ASL-finger dataset. The obtained results of this validation also show that the proposed HMFO-AELM provides improved performance values, when compared to that without optimization models.

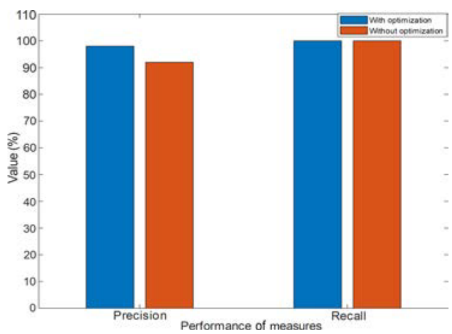
Figures 8a and 8b validate the Receiver Operating Characteristics (ROC) of the proposed system for Sebastian Marcel and ASL-finger datasets, respectively. In Fig. 8b, 0 to 9 represents the image index of ASL dataset. In general, the ROC is plotted with respect to the True Positive Rate (TPR) and False Positive Rate (FPR) for the different classes in the dataset. This analysis shows that the ROC of the proposed model is improved for both datasets with increased TPR.

### 4.2 Comparative analysis

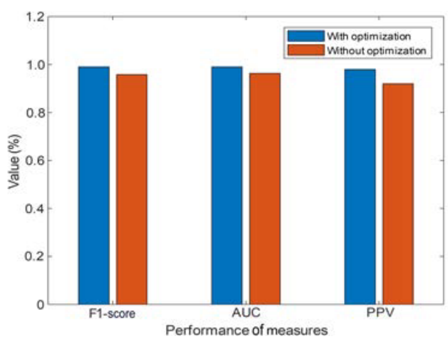
Figure 9 and Table 4 compare the performance of existing and proposed techniques based on the measures of sensitivity, specificity, and accuracy. Here, the feature extraction based classification techniques are compared with the proposed recognition approach. This analysis shows that the proposed HMFO-AELM technique provides an increased performance value, when compared to the other techniques, because the proposed model MFE and HMFO techniques help




(a) Accuracy, sensitivity, and specificity of proposed mechanism for Sebastian Marcel dataset

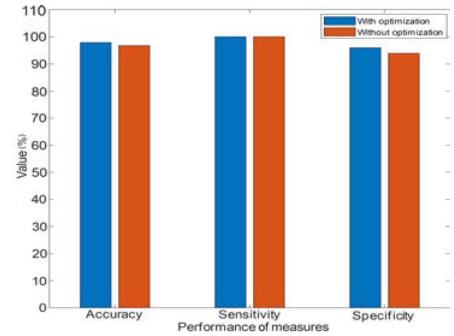



(b) Precision and recall of proposed mechanism for Sebastian Marcel dataset

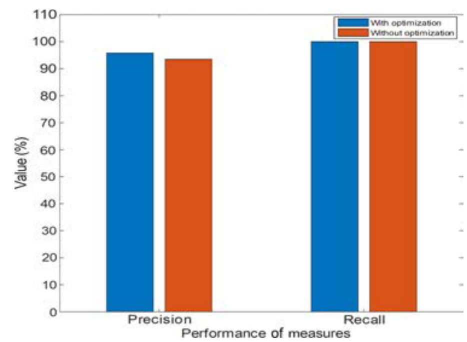



(c) F1-score, AUC, and PPV of proposed mechanism for Sebastian Marcel dataset

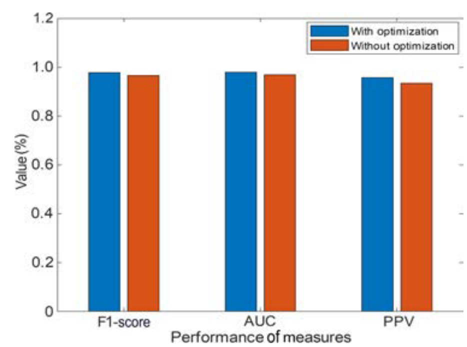
**Fig. 6 Performance analysis using Sebastian Marcel dataset.**




(a) Accuracy, sensitivity, and specificity of proposed mechanism for ASL-finger dataset




(b) Precision and recall of proposed mechanism for ASL-finger dataset



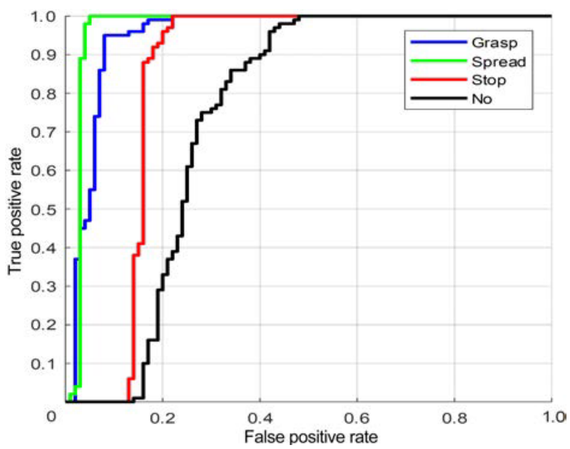

(c) F1-score, AUC, and PPV of proposed mechanism for ASL-finger dataset

**Fig. 7 Performance analysis using ASL-finger dataset.**

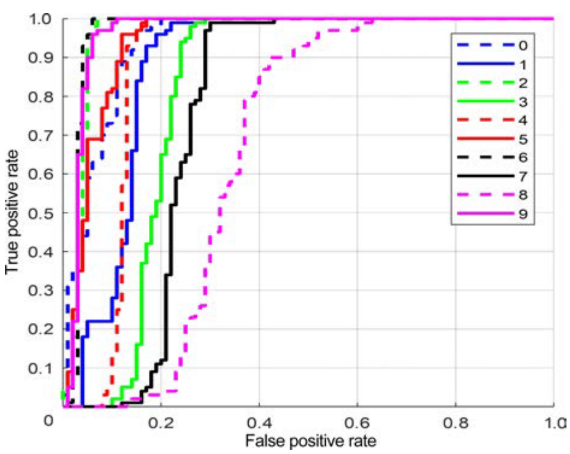
to extract and select the suitable number of features for training the models of classifier, which helps to obtain an increased accuracy performance value. Figure 10 compares the training and testing accuracy of conventional[37] and proposed HMFO-AELM techniques by using the ASL-finger dataset. According to the obtained results, it is observed that the proposed model outperforms the other techniques with increased accuracy in both training and testing processes.

## 5 Conclusion

This paper presented an advanced detection framework for accurately recognizing the hand gesture from the given dataset by using intelligent image processing techniques. For validating and testing, there are two different datasets such as Sebastian Marcel and ASL-finger utilized. Initially, the input image segmentation is performed for segmenting the hand gesture region from the original image by suppressing the backgrounds. During this process, skin color detection and morphological operations are applied for improving the segmentation. Then, a multiple numbers of features are extracted from the segmented portion of the hand image by using the MFE model. To reduce the dimensionality of features and to increase the overall accuracy of recognition, the HMFO technique was employed, which helps to select the optimal




(a) ROC for Sebastian Marcel dataset




(b) ROC for ASL-finger dataset

**Fig. 8 ROC analysis.**

features based on the best fitness value. Finally, the AELM based classification technique is employed for accurately predicting the classified label of the hand gesture of a given image. The major benefits of the proposed HMFO-AELM techniques are reduced complexity of operations, minimal time consumption, optimal performance efficiency, high convergence speed, and reduced error value. During performance analysis,

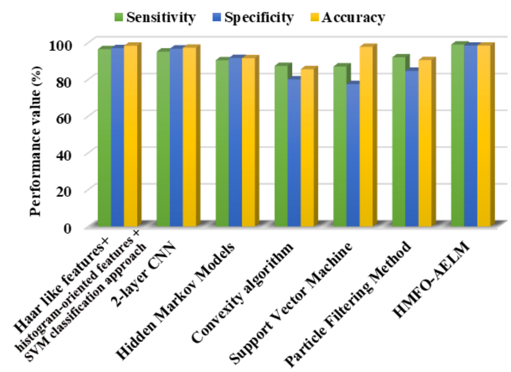



**Fig. 9 Comparative analysis between existing and proposed techniques.**

various measures have been used to test the results of these techniques.

## Acknowledgment

The authors like to express their gratitude to their colleagues and friends for their unwavering support and assistance throughout the study and in obtaining the results.

## References

[1] H. N. Saha, S. Tapadar, S. Ray, S. K. Chatterjee, and S. Saha, A machine learning based approach for hand gesture recognition using distinctive feature extraction, in *Proc. 2018 IEEE 8$^{th}$ Annual Computing and Communication Workshop and Conference* (*CCWC*), Las Vegas, NV, USA, 2018, pp. 91–98.

[2] M. Oudah, A. Al-Naji, and J. Chahl, Hand gesture recognition based on computer vision: A review of techniques, *Journal of Imaging*, vol. 6, no. 8, p. 73, 2020.

[3] G. Devineau, F. Moutarde, W. Xi, and J. Yang, Deep learning for hand gesture recognition on skeletal data, in *Proc. 2018 13$^{th}$ IEEE International Conference on Automatic Face & Gesture Recognition* (*FG 2018*), Xi'an, China, 2018, pp. 106–113.

[4] A. Jaramillo-Yánez, M. E. Benalcázar, and E. Mena-Maldonado, Real-time hand gesture recognition using surface electromyography and machine learning: A systematic literature review, *Sensors*, vol. 20, no. 9, p. 2467,

**Table 4 Comparative analysis between existing and proposed recognition techniques.**

| Reference | Methodology | Performance evaluation parameter | | |
|---|---|---|---|---|
| | | Sensitivity (%) | Specificity (%) | Accuracy (%) |
| [31] | Haar like features+ histogram-oriented features + SVM classification approach | 96.5 | 97.1 | 98.4 |
| [32] | 2-layer CNN | 95.2 | 96.8 | 97.28 |
| [33] | Hidden Markov models | 90.5 | 91.7 | 91.6 |
| [34] | Convexity algorithm | 87.4 | 80.1 | 85.6 |
| [35] | Support vector machine | 87.1 | 77.5 | 97.8 |
| [36] | Particle filtering method | 92.1 | 84.7 | 90.6 |
| – | Proposed methodology | 99 | 98.5 | 98.5 |

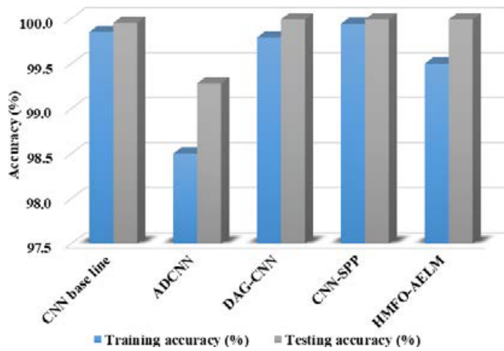



**Fig. 10 Analysis of training and testing accuracy.**

2020.

[5] F. Zhan, Hand gesture recognition with convolution neural networks, in *Proc. 2019 IEEE 20$^{th}$ International Conference on Information Reuse and Integration for Data Science* (*IRI*), Los Angeles, CA, USA, 2019, pp. 295–298.

[6] S. Skaria, A. Al-Hourani, M. Lech, and R. J. Evans, Hand-gesture recognition using two-antenna Doppler radar with deep convolutional neural networks, *IEEE Sensors Journal*, vol. 19, no. 8, pp. 3041–3048, 2019.

[7] X. Y. Wu, A hand gesture recognition algorithm based on DC-CNN, *Multimedia Tools and Applications*, vol. 79, pp. 9193–9205, 2020.

[8] Y. He, G. Li, Y. Liao, Y. Sun, J. Kong, G. Jiang, D. Jiang, B. Tao, S. Xu, and H. Liu, Gesture recognition based on an improved local sparse representation classification algorithm, *Cluster Computing*, vol. 22, pp. 10935–10946, 2019.

[9] G. Li, H. Tang, Y. Sun, J. Kong, G. Jiang, D. Jiang, B. Tao, S. Xu, and H. Liu, Hand gesture recognition based on convolution neural network, *Cluster Computing*, vol. 22, pp. 2719–2729, 2019.

[10] W. -J. Li, C. -Y. Hsieh, L. -F. Lin, and W. -C. Chu, Hand gesture recognition for post-stroke rehabilitation using leap motion, in *Proc. 2017 International Conference on Applied System Innovation* (*ICASI*), Sapporo, Japan, 2017, pp. 386–388.

[11] J. -H. Kim, G. -S. Hong, B. -G. Kim, and D. P. Dogra, DeepGesture: Deep learning-based gesture recognition scheme using motion sensors, *Displays*, vol. 55, pp. 38–45, 2018.

[12] G. Benitez-Garcia, L. Prudente-Tixteco, L. C. Castro-Madrid, R. Toscano-Medina, J. Olivares-Mercado, G. Sanchez-Perez, and L. J. G. Villalba, Improving real-time hand gesture recognition with semantic segmentation, *Sensors*, vol. 21, no. 2, p. 356, 2021.

[13] M. Al-Hammadi, G. Muhammad, W. Abdul, M. Alsulaiman, M. A. Bencherif, T. S. Alrayes, H. Mathkour, and M. A. Mekhtiche, Deep learning-based approach for sign language gesture recognition with efficient hand gesture representation, *IEEE Access*, vol. 8, pp. 192527–192542, 2020.

[14] M. Luo, F. Nie, X. Chang, Y. Yang, A. G. Hauptmann, and Q. Zheng, Adaptive unsupervised feature selection with structure regularization, *IEEE Transactions on Neural Networks and Learning Systems*, vol. 29, no. 4, pp. 944–956, 2018.

[15] B. Remeseiro and V. Bolon-Canedo, A review of feature selection methods in medical applications, *Computers in Biology and Medicine*, vol. 112, p. 103375, 2019.

[16] Y. Hu, Y. Wong, W. Wei, Y. Du, M. Kankanhalli, and W. Geng, A novel attention-based hybrid CNN-RNN architecture for sEMG-based gesture recognition, *PLoS ONE*, vol. 13, no. 10, p. e0206049, 2018.

[17] S. Jadooki, D. Mohamad, T. Saba, A. S. Almazyad, and A. Rehman, Fused features mining for depth-based hand gesture recognition to classify blind human communication, *Neural Computing and Applications*, vol. 28, pp. 3285–3294, 2017.

[18] H. Badi, A. Hamza, and S. Hasan, New method for optimization of static hand gesture recognition, in *Proc. 2017 Intelligent Systems Conference* (*IntelliSys*), London, UK, 2017, pp. 542–544.

[19] Suharjito, M. C. Ariesta, F. Wiryana, and G. P. Kusuma, A survey of hand gesture recognition methods in sign language recognition, *Pertanika Journal Science and Technology*, vol. 26, no. 4, pp. 1659–1675, 2018.

[20] Y. Chen, L. Zhao, X. Peng, J. Yuan, and D. N. Metaxas, Construct dynamic graphs for hand gesture recognition via spatial-temporal attention, arXiv preprint arXiv: 1907.08871, 2019.

[21] M. J. Cheok, Z. Omar, and M. H. Jaward, A review of hand gesture and sign language recognition techniques, *International Journal of Machine Learning and Cybernetics*, vol. 10, pp. 131–153, 2019.

[22] D. Chen, G. Li, Y. Sun, J. Kong, G. Jiang, H. Tang, Z. Ju, H. Yu, and H. Liu, An interactive image segmentation method in hand gesture recognition, *Sensors*, vol. 17, no. 2, p. 253, 2017.

[23] C. Bhuvaneshwari and A. Manjunathan, Advanced gesture recognition system using long-term recurrent convolution network, *Materials Today: Proceedings*, vol. 21, pp. 731–733, 2020.

[24] R. F. Pinto, C. D. B. Borges, A. M. A. Almeida, and I. C. Paula, Static hand gesture recognition based on convolutional neural networks, *Journal of Electrical and Computer Engineering*, https://doi.org/10.1155/2019/4167890, 2019.

[25] A. Mujahid, M. J. Awan, A. Yasin, M. A. Mohammed, R. Damaševičius, R. Maskeliūnas, and K. H. Abdulkareem, Real-time hand gesture recognition based on deep learning YOLOv3 model, *Applied Sciences*, vol. 11, no. 9, p. 4164, 2021.

[26] H. I. Mohammed, J. Waleed, and S. Albawi, An inclusive survey of machine learning based hand gestures recognition systems in recent applications, *IOP Conf. Ser.: Mater. Sci. Eng.*, vol. 1076, p. 012047, 2021.

[27] K. Rzecki, Classification algorithm for person identification and gesture recognition based on hand gestures with small training sets, *Sensors*, vol. 20, no. 24, p. 7279, 2020.

[28] K. M. Sagayam and D. J. Hemanth, ABC algorithm based optimization of 1-D hidden Markov model for hand gesture recognition applications, *Computers in Industry*, vol. 99,

pp. 313–323, 2018.
[29] Y. -L. Chung, H. -Y. Chung, and W. -F. Tsai, Hand gesture recognition via image processing techniques and deep CNN, *Journal of Intelligent and Fuzzy Systems*, vol. 39, no. 3, pp. 4405–4418, 2020.
[30] T. Ozcan and A. Basturk, Transfer learning-based convolutional neural networks with heuristic optimization for hand gesture recognition, *Neural Computing and Applications*, vol. 31, pp. 8955–8970, 2019.
[31] S. Sharma, S. Jain, and Khushboo, A static hand gesture and face recognition system for blind people, in *Proc. 2019 6th International Conference on Signal Processing and Integrated Networks* (*SPIN*), Noida, India, 2019, pp. 534–539.
[32] P. S. Neethu, R. Suguna, and D. Sathish, An efficient method for human hand gesture detection and recognition using deep learning convolutional neural networks, *Soft Computing*, vol. 24, no. 20, pp. 15239–15248, 2020.
[33] T. Chaikhumpha and P. Chomphuwiset, Real-time two hand gesture recognition with condensation and hidden Markov models, in *Proc. 2018 International Workshop on Advanced Image Technology* (*IWAIT*), Chiang Mai, Thailand, 2018, pp. 1–4.
[34] A. Marium, D. Rao, D. R. Crasta, K. Acharya, and R. D'Souza, Hand gesture recognition using webcam, *American Journal of Intelligent Systems*, vol. 7, no. 3, pp. 90–94, 2017.
[35] M. H. Rahman and J. Afrin, Hand gesture recognition using multiclass support vector machine, *International Journal of Computer Applications*, vol. 74, no. 1, pp. 39–43, 2013.
[36] Z. Wang, B. Chen, and J. Wu, Effective inertial hand gesture recognition using particle filtering based trajectory matching, *Journal of Electrical and Computer Engineering*, vol. 2018, pp. 1–9, 2018.
[37] Y. S. Tan, K. M. Lim, C. Tee, C. P. Lee, and C. Y. Low, Convolutional neural network with spatial pyramid pooling for hand gesture recognition, *Neural Computing and Applications*, vol. 33, pp. 5339–5351, 2021.

**Seetharam Khetavath** received the PhD degree in image processing from CMJ University, Shilong, Meghalaya in 2012, the ME (electronics & communication engineering) degree in systems and signal processing from Osmania University, Hyderabad in 2004, and the BTech (electronics & instrumentation engineering) degree from Kakatiya University, Warangal in 2000. He is currently working as a professor and head of the Department of Electronics and Communication Engineering, Chaitanya (Deemed to be University), Warangal, India. He has more than 25 publications in various reputed journals and conferences and two book publications. He is a reviewer and editorial board member for reputed journals. His research interests include image processing, wireless sensor networks, machine learning, Internet of Things, etc.

**Navalpur Chinnappan Sendhilkumar** received the PhD degree in electronics and communication engineering from St Peters University, Chennai, the master degree of technology in communication engineering from VIT University, Vellore, and the bachelor degree of engineering in electronics and communication engineering from Priyadarshini Engineering College, Vaniyambadi, University of Madras, Chennai. He is a professor in the Department of Electronics and Communication Engineering at Sri Indu College of Engineering & Technology, Sheriguda, Hyderabad, Telangana, India. He has more than 18 years of experience in teaching UG and PG engineering students. His research interests include computer networks, VLSI, high speed networks, internet of things, and digital communication. He has published more than 25 refereed publications in journals and conferences.

**Lakshmanan Malliga** received the diploma (DECE) in 1986 and AMIE (ECE) from Indian Institute of Engineers, Calcutta in 2006. She received the ME degree in applied electronics from Anna University, Trichirappalli in 2009. She has done the PhD thesis on "Optimization of CBMIR System Performance Using Fuzzy Clustering with Random Forest Classifier" in 2018, Anna University, Chennai, India. She is working as a professor in the Department of Electronics and Communication Engineering, Malla Reddy Engineering College for Women (Autonomous), India. She has published more than 18 research papers in international journals and 20 papers in international conferences proceedings. She has attended/participated in more than 30 conferences and workshops. Her special areas of interest are content-based image retrieval, bio medical imaging, bio-signal processing, and applications of soft computing techniques in image analysis. She is a life member of ISTE and IASTE.

**Pandurangan Mukunthan** received the PhD degree in electronics and communication engineering from Pondicherry University, Puducherry, the master degree of engineering in applied electronics from University of Madras, and the bachelor degree of engineering in electronics and communication engineering from University of Madras, Chennai. He is a professor in the Department of Electronics and Communication Engineering, Sri Indu College of Engineering & Technology, Sheriguda, Hyderabad, India. His research interests include wireless communication and networks, wireless sensor networks, high speed networks, internet of things, and cellular mobile communications. He has published more than 40 publications in journals and conferences.

**Yousef Farhaoui** received the PhD degree in computer security from Ibn Zohr University of Science. He is a professor at Faculty of Sciences and Techniques, Moulay Ismail University of Meknès, Morocco. He is the chair of IDMS Team and the director of STI laboratory. He is a local publishing and research coordinator of Cambridge International Academics in United Kingdom. His research interests include learning, e-learning, computer security, big data analytics, and business intelligence. He has three books in computer science. He is a coordinator and member of the organizing committee, a member of the scientific committee of several international congresses, and a member of various international associations. He has authored 7 books and many book chapters with reputed publishers such as Springer and IGI. He serves as a reviewer for IEEE, IET, Springer, Inderscience, and Elsevier journals. He is also the guest editor of many journals with Wiley, Springer, Inderscience, etc. He has been the general chair, session chair, and panelist in several conferences. He is a senior member of IEEE, IET, ACM, and EAI research group.

**Subburayalu Gopalakrishnan** received the PhD degree in information and communication engineering from Anna University, Chennai, the master degree of engineering in embedded system technology from Anna University affiliated institution, and the bachelor degree of engineering in electronics and communication engineering from Anna University affiliated institution, Chennai. He is working as an associate professor at the Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Chennai, India. He also has additional responsibility in R&D in charge of Siddhartha Institute of Technology and Sciences. His research interests include wireless networks, embedded systems, internet of things, and mobile ad-hoc networks. He has published more than 40 publications in journals and conferences. He is the editor-in-chief of *Recent Trends in Electronics & Communication Systems* Journal. He has successfully completed a special issue in *IJEER*–Scopus-indexed Journal with an acceptance ratio 28%. He is also an editorial board member in many reputed journals, and a guest editor in an ongoing special issue in Scopus-indexed Journal named *International Journal of Electrical and Electronic Engineering & Telecommunications*.

**Sankuru Ravi Chand** received the PhD degree in electronics and communication engineering from JNTU University Kakinada, the master degree of technology in digital systems and computer electronics from JNT University, and the bachelor degree of technology in electronics and communication engineering from Acharya Nagarjuna University. He is a senior member of IEEE and a life member in IST. He is currently working as a professor and head in the Department of Electronics and Communication Engineering, Nalla Narasimha Reddy Education Society's Group of Institutions-Integrated Campus, India. His research interests include wireless sensor networks, network security, embedded systems, internet of things, and digital computing. He has more than 25 publications in various reputed journals and conferences and two book publications. He is a reviewer and editorial board member for reputed journals. He is part of academic council, BoS member, faculty advisor for ISTE students' chapter, coordinator IQAC, in-charge examination section, college academic committee member, governing body member, etc.

**Selvaganesan Jana** received the BE degree in electronics and communication engineering from Bharathidasan University, the ME degree in communication systems from Anna University Chennai, and the PhD degree in information and communication engineering from Anna University. She has over 25 years of academic experience and is currently working as a professor in the Department of Electronics and Communication Engineering, Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology. She is a member of ISTE and IEEE Signal Processing Society. She has published over 25 papers in national and international conferences and journals. Her research interests include artificial intelligence, machine learning, deep learning, signal processing, and computer vision.