International Journal of Advances in Engineering and Management (IJAEM)
Volume 6, Issue 08 Aug. 2024, pp: 604-616 www.ijaem.net ISSN: 2395-5252

An Optimistic Featured-GWO with CNN Algorithm Used For Hand Gesture Recognition System

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Date of Submission: 25-08-2024 Date of Acceptance: 05-09-2024

ABSTRACT- Nowadays, one of the most famous issues faced by our society is that hearing-impaired and deaf people are searching it tough to come up with the progressive moving technology. The SL (sign language) plays a significant role for these people as only through the SL they can communicate with each other. SL normally includes several movements of hands, palms, and other human body parts. Sign or Gesture shows an image of particular body part. GR (gesture recognition) is a progressive technology that is utilized to recognize the posture of human body parts. . The main objective of this category of software is to provide a medium between the human body movements with CS (Computer system). In GR mainly HGR gives a much more efficient and natural way for non-verbal information exchange when working with HCI (human-computer interaction) system. The research work defines a real-time vision method for detecting HG based on DL (deep learning) using MATLAB. Data collection is the main phase is a research method where it developed a dynamic HG database of SL. The next phase it has defined the original research structure to depict HGR with the help of hand shape and several motion descriptors. This 2nd phase has applied the pre-processing steps: (i) conversion (ii) attack image (iii) filtration, and (iv) edge detection. The 3rd phase has developed a feature extraction method using the KPCA algorithm. It has extracted the reliable feature sets in the form of eigenvalues and eigenvectors. After that 4th phase has implemented to select the feature sets using the GWO method and then classify or recognize the hand gestures. The proposed work has implemented a optimized featured-based grey wolf optimizer-CNN (OFGWO-CNN) classification model to recognize the hand gestures. The proposed model achieved the accuracy value of 98.0 per cent and MSE value of 0.0144. It calculated the performance metrics such as accuracy rate, MSE, etc. and compare it with the existing model. The proposed method has better attained the accuracy as compared with the existing models such as YOLO, Naïve Bayes, Decision Tree, etc.

Index – Hand Gesture Recognition, Optimized Featured-based Grey Wolf Optimization-CNN, Convolutional Neural Network, Kernel Principal Component Analysis.

I. INTRODUCTION

Recent, research exposed hand gesture recognition (HGR) as the most popular area of research direction. This field of research fascinates more scholars using machine learning (ML) and vision-based model [1]. For some decades, spoken language has been one of the more critical ways of conveying information between human beings. This process is genetic from the generations, and the human languages vary significantly with human communities among them. Some people face problems such as loss of hearing and deaf etc., due to this cause. They are not able to understand human language for communication. So, the population who face a disability of hearing require support to stay living. According to the statement of the WHO for 2020, around 466 million people worldwide are affected by the disability of deafness. This defective population may be increased up to 900 million by 2050. The recognition of gestures is an essential form of computer technology to provide the facility to recognize human gestures using methods. The main benefit is that low sensitivity to environmental conditions. A human being can communicate through a computer anytime. Various gestures are reliable, flexible, bright, pictorial, and intuitive in human-computer interaction (HCI). [2]. Sign languages (SL) convey information using expressions, hand gestures (HG), and body movements. It is defined as the conversion of SL into the alphabets of fundamental languages. So, the conversion of SL into words using the technique, model, or method can link the gap among the population with disabilities such as hearing loss. The computer-vison-based recognition of gesture is a domain of existing dynamic research in computer-vison and ML. The main motive of HGR is to develop systems or models that can provide identification of human gestures individually and utilize them to communicate data. Computer-vison-based HG interfaces want fast and very robust real-time detection of hand and GR. So, HGs are a powerful communication mode for humans using bags of possible applications [3]. The gestures provide better human interaction; mostly, face and hand movements are widely used to communicate with others. It is one of the wide-ranging methods most required in recognizing sign language (SL) and video games. The gesture recognition system (GRS) has two types or subcategories such as static and dynamic gesture recognition. In static gestures, the actor is static or stable in form, whereas non-static or unstable actors include dynamic gestures. Static gesture is also called direct gesture recognition, and dynamic gestures are called to as indirect gesture recognition. The best suitable example of static, such as saying "Thankyou" to somebody and requesting water, is an example of a dynamic gesture. Gesture recognition has some critical challenges, such as latency, limitation of gesture language and performance, etc. several people type gestures contrarily due to issues in recognizing motions.Different applications may find it problematic to execute on source constraints [4]. This proposed work uses construct hand images as input for gesture recognition.Real-time hand gesture dataset is used, and features are extracted using the KPCA method and GWO method are used to optimize and classification of proposed model is done with CNN model.This work enhances hand gesture of images.

The 1stsection represents an introduction of hand gestures recognitions, process, benefits, and drawbacks.The 2ndsection describes the study of several kinds of literature related to hand gesture, sign languages and other methodologies, models, and other research directions.The 3rd section describes the problem in the current study.Section 4threpresents the methodology of the proposed work then section 5th presents the proposed work's output with parameter evaluations, tables, and graphs.Section 6thdisplays the conclusion of our proposed work and further extends direction.

II. RELATED WORK

Naoto lenaga et al.(2022)[5] proposed gesture research explored speech recognition and the mechanism used for communication convey. Both intermediate terms of gesture and speech were used as the syntax, alignment, semantic, phonemics, pragmatics, etc. The gestures were used in medical, social interaction for communication and human perceptions and used evaluation of learning languages for children. Th e development of video data was manually time-consuming, and the RGB video data was applied to the proposed semi-automatic gesture tool input as video data. The proposed technique elaborated the estimation and dynamic learning. The proposed process of the videos automatically uses an F-Score of 0.85. The proposed used two datasets and achieved accuracy for both datasets were more than 98%. **Xiao Yan Wu (2020)[6]**proposed gesture research explored speech recognition and the mechanism used for communication convey. Both intermediate terms of gesture and speech were used as the syntax, alignment, semantic, phonemics, pragmatics, etc. The gestures were used in medical, social interaction for communication and human perceptions and used evaluation of learning languages for children. The development of video data was manually time-consuming and was applied the RGB video data to the proposed semi-automatic gesture tool input as video data. The proposed technique elaborated the estimation and dynamic learning. The proposed process of the videos automatically uses an F-Score of 0.85. The proposed used two datasets and achieved accuracy for both datasets were more than 98%.**PavelA.Popov et al. (2022)[7]**proposed recognition and evaluation of human hand motions in the video was research fields of Hand Gesture recognition. The gesture recognition enabled humans to use hands for communication and understanding other languages and enhanced the state of HCI. The proposed used two stages of a real-time approach for hand gesture recognition. The ML (machine learning) used to train this approach for detection combined with RGB processing curve shape authentications. The HOG feature was used by Adaboost Cascades or SVM (support vector machine) for detection. The proposed approach achieved robust real-time

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performance enhancement with an efficient true positive rate and low false positive rate.**RaziehRastgoo et al.(2022)[8]**proposed hand gesture detection of hand movements used for communication and sign language understanding based on HCI based on linguistic rules. The sign languages for gesture recognition were used to convey the language to hearing communities and applied hard linguistic rules to phonemic mechanisms. The sign languages and their various types were based on different cultures or nations of countries and regions. Real-time recognition was the main issue in HCI models, specifically for sign language. The proposed efficient and low complexed model to eliminates issues in sign language. The proposed used SVD (singular value decomposition) for efficient, compressed to achieve more discriminated features. The proposed achieved better recognition time and accuracy.**Thippa Reddy Gadekallu et al.(2021)[9]** proposed HCI and gesture detection approaches developed for the execution of communicating computational structures. The HCI research highlights the structure used, the development of new techniques to support human activities, information accessed and confirmed continuous communication. The AI (artificial intelligence) and DL (deep learning) based approaches were wide-ranging across different areas of state-of-art results. The proposed development of a crow search-based CNN technique implemented for gesture recognition referred to the HCI domains. The proposed performed experiments using the Kaggle dataset of hand gestures. The proposed used one hot training technique to convert classified data values to binary form. The proposed CSA (crow search algorithm) for extracting optimal parameters and datasets with CNN techniques. The accurate parameters were evaluated from the proposed CSA algorithm to enhance the accuracy of hand gesture classification.**Shivashankara S et al(2022)[10]** proposed real-time hand gesture words into human recognising English text. The proposed ASL (American sign language) hand gesture used for understanding and detection was completely scalable, luminance, complex background location and gender. The proposed viola-Jones algorithm, canny approximation and CIE lab colour performed hand segmentation properly. The proposed algorithm extracted various features, such as entropy, boundary, filtering, etc., for understanding and recognising hand gestures. The proposed used various classification methods such as KNN, M-SVM, and DT for hand gestures. The KNN classifier achieved a better recognition rate of 92.71% and an average recognition time of 0.48 seconds per gesture. **Sakshi Sharma et al (2021) [11]** proposed hand gesture detection or recognition research area. Hand gestures were a significant element of communication. The hand gesture developed sign language, which provides a pictorial form of communication. The proposed DL (deep learning) based on the CNN technique was developed for gesture-based sign language recognition. The proposed compact vision technique achieved better performance accuracy over the other CNN models considering two datasets. The efficiency of the proposed model was evaluated by VGG-11 and VGG-16 to train and test the functionality of the proposed model. The proposed massive collection of ISL (Indian sign language) gestures included 2150 images through an RGB camera with ASL (American sign language) dataset. The proposed model achieved a performance accuracy of 99.96% for ISL. **Ming Jin Cheok (2019) [12]** proposed hand gestures and sign language techniques for communication. The hand gesture recognition was significant for various issues resolved by human beings. The ability of machines to recognize the human activities and meaning utilized. The proposed analysis of state-of-the-art approaches for hand gesture and sign language recognition research. The proposed survey of hand gesture and sign language recognition techniques was properly categorized into various phases: data gaining, pre-processing, separation, feature extraction and sorting. The proposed survey elaborated on various algorithms, issues, and qualities compared to hand gesture recognition and sign language. **P.S Neethu et al. (2020) [13]** proposed efficient methods for hand gesture recognition to detection of automation of human activities such as HCI. The proposed recognition of human hand gestures was distinguished and recognized by the CNN classification approach. The proposed segmented the interest hand region using mask images, finger segmentation, normalization and recognition of fingers segmented images with a CNN classifier. The proposed improving the contrast of pixels with an adaptive histogram equalization method. The proposed connected component analysis algorithm for segmenting fingertips from hand images. These images were delivered to the CNN classification algorithm for image classification into various classes. The proposed achieved better performance through state-of-the-art methods. **Srinivasa Rao K et al. (2021) [14]** proposed elaborating the

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communication with hand gestures using CNN approaches. A hand gesture was the activities of the human hand widely used in daily life for communication and understanding policies. The physical interaction of human hand gestures was used to recognize in HCI for automation of systems. The proposed gesture recognition model uses a transfer learning technique trained with the CNN approach. The proposed approach highly provides modularisation and quickly moved gesture recognition to other system applications. The proposed approaches for image processing were hand gesture recognition, pattern, thresholding and detection. The proposed hand gesture recognition and detection technique improved performance based on DL and CNN.

III. PROBLEM FORMULATION

Gestures are a basic manifestation of the human that is utilized for communicating with one another. Perhaps the most popular mode of communication is the hand sign. It is defined as a series of gestures made over a while. Gestures are thought to be employed in two-thirds of all interactions. Hand signals can be classified into two groups: Static-at any given time, there is a clearly defined dominating hand. A succession of motions that occur over a lengthy period is referred to as dynamic. The outcomes of gesture recognition algorithms are used in interaction, human-machine interface, interpersonal behavior, and augmented reality.

In this context, gesture recognition is a challenge that consists of two parts: feature extraction and pattern classification. Integrating a variety of represented labels, each label signifying an identifiable action, is what hand gesture identification entails. It's also critical to specify the exact instant when the action is performed. Data collection, pre-processing, feature extraction, classifications, and post-processing are steps in developing a hand gesture detection system. If obtaining a statistical equation is difficult or impossible, machine learning could be utilized to build the categorization component.

There are various existing hand gesture recognition techniques but still suffer from various challenges. Several challenges occur in hand gesture recognition techniques such as Data augmentation and Generalization issues, and gestures diversity increases the computational time of the system, etc.

Table 3.1. Existing techniques of hand gesture recognition

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Author's and Year	Year	Proposed technique	Research gap
Mujahid, A., et al., [15]	2021	Deep learning based YOLOv3 model	Low precision rate of the proposed technique
Tan, Y. S., et al., [16]	2021	Convolutional neural network-based technique for HAND GESTURE Recognition	Data augmentation and Generalization issues
Peng, F., et al., [17]	2021	Extreme learning-based forest-dependent approach for gesture identification	Limited dataset, need to add more samples for the reliability of the system
Rahimian, et al., [18]	2021	Few SHOT Learning-based Hand Gesture Recognition	Gestures diversity increases the computational time of the system
Abhishek, et al., [19]	2020	Hand position identification through the Machine learning approach	Complex background degrades the performance of the proposed model

IV. PROPOSED METHODOLOGY

4.1 Proposed Methods

In this section discussed the proposed methods such as KPCA, GWO, and CNN model. Each algorithm is explained as;

4.1.1 Kernel Principal Component Analysis (KPCA) Using Feature Extraction

The pixel values in the form of a matrix are accessed as a grid matrix of the sampling window and sorted in ascending order of which the middle-valid pixel is selected as the pixel to be replaced. The boundary pixel is to be replaced. At the grayscale levels of an image, pixel values represent ascending order in matrix form. The pixel's mean value is chosen to replace known as KPCA because that is the latest variety of PCA. Whereas PCA is an LFE (linear feature extraction) technique widely used in various classification approaches such as pattern classification. The KPCA provides different application areas [20] [21]. This method is used directly to represent the features as a minimum to maximum measurement space; due to this, features are displayed in linear form individually. It evaluates the eigenvectors of the matrix known as kernel-matrix, that is, the conversion of the covariance matrix. This matrix makes the renewal of predictable PCA straightforward, and multiple similarity-based features are highly dimensional spaces. The kernel function constructs it. The main advantage of this method is that it provides the facility to develop non-linear plotting. The KPCA evaluates the matrix of the Kernel (K) of features in eq. (i). It is represented as

$$K_{xy} = k\,(f_{x,}\ f_y) \quad \text{……………………………………………………………………(i)}$$

Eq (ii) represents k is kernel fn(). , with xy conversion attributes.

$$k_{xy}=k_{xy} - {}^{1}/_{n}\textstyle\sum_{l}k_{xl} - {}^{1}/_{n}\sum_{l}k_{yl} + {}^{1}/_{n}{}^{2}\sum_{ln} k_{ln} \quad \text{……………………………………………(ii)}$$

Centralized process of finding the mean in conventional principle component analysis for features. It provides the surety that features are highly measurement space elaborated by Kernel funs() are 0 mean. The principle of eigenvectors "Ev" is evaluated at the centre of the kernel matrix. That is represented in eq. iii, eigenvectors of the covariance matrix "Cv" is mapped from the eigenvectors of the **kernel matrix.**

Cv =……………………………………………………… ……………….. (iii)

4.1.2 Grey Wolf Optimization (GWO) Using Feature Selection

This optimization technique is based on the Canadian family's grey wolf members. It is a more dangerous hunter family at the highest place in the food chain. They primarily like to live in parks. The average group limit is 5 to 12[22]. The significant feature of these consists of a hard dominant hierarchical mode represented. It provides the experimental structure of community hierarchy, tracking, surrounding and attacking, etc.. Community or social structure consists of mathematical functions performed as the community of wolves during the construction of GWO. Alpha is considered a perfect solution, and beta and delta represent the 2nd and 3rd solutions, respectively, and the remaining members are considered omega. That is used for optimization.

1. Initialize the population of grey wolfs. Such as Xi (1,2,3…….n)
2. Initialize d(distance), A (agent), and C (co-variance) and calculate the distance between the grey wolf and the Prey.
3. Construct the individual location of the search agent.
4. Find the Xalpha, Xbeta, and Xgamma as the 1^{st}, 2^{nd}, and 3^{rd} agent search.
5. Increment the location of the current search agent.
6. Increment in d, A, C.
7. Calculates the fitness value for all search agents.
8. Update the position of Alpha, Xbeta, and Xgamma.
9. If updating the position of Alpha, Xbeta, and Xgamma is valid, then return Xalpha; otherwise, repeat steps 5 to 8.
10. End

4.1.3 CNN (Convolutional Neural Network)

A convolution Neural Network (CNN) is multiple layers Neural Network (NN) using a unique model required for deep learning (DL) [23]. It consists of three effective layers convolution layer (CL), pooling layer (PL), and Fully Connected Layer (FCL), represented in figure 11. It is mainly required for identifying an object, viewing, and handling various functions such as detection, analysis, classification, etc. Multiple aspects are responsible for its importance and are deployed significantly. These aspects are: CNN is widely used for direct feature extraction learning of data compared to image processing (IP) tools. It is beneficial for the recognition process and provides the renewal of this process. It can be quickly developed from an existing network.

4.2 Methodology

The proposed work is divided in different steps and flow chart as defined in figure 1.Initially, the dataset is collecting from the online UCI machine learning repository site. Secondly, the image preprocessing steps are described such as (i) Conversion color to gray scale image (ii) Noise (iii) Filtration, and (iv) edge detection. This process has been developing feature extraction using KPCA (kernel principle component analysis). KPCA method is a nonlinear dimensionality reduction method. It is an addition of PCA that is linear dimensionality optimized method using KFn (kernel functions). GWO is an novel meta heuristic optimization and rule is to reproduce the nature of GWs in behaviour to hunt in a co-operative path. It selects the extracted unique feature sets with fitness function. The classification CNN model that has been measured in this proposed work to identify HG is collected of 2 CLs (Convolution layers), 2 max PL (pooling layers), 2 FN layers, and OL (output layer). CNNs are world widely utilized for IC (image classification), and detection. CNN deep learning method is evaluated for several reasons like easy to implementation, easy to use, minimum evaluation time, and recognizes gestures precisely. After that, it evaluated the proposed parameters such as accuracy, precision, recall, f1-score, etc.

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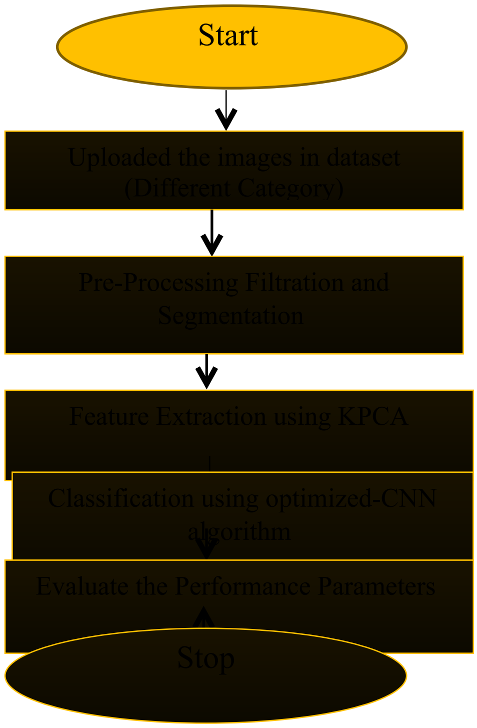

Figure 1. Proposed Work Flow Chart

V. EXPERIMENTAL RESULT ANALYSIS

Simulation tool is used MATLAB 16a and KPCA and GWO methods used for features extraction and optimization and CCN model is required for classification.MATLAB stands for MATrix LABoratory. It was initially written to deliver informal entrance to matrix software invented by the linear system package (LINPACK) and Eigen system package (EISPACK) tasks. MATLAB is an extraordinary performance semantic for procedural computing. It incorporates computation, graphics, and a program design environment.

5.1 Performance Metrics

5.1.1 MSE (Means Square Error)

The MSE is calculated by taking the average of the squared differences between the predicted and actual values across all the test samples. A lower MSE indicates a better accuracy of the system. The formula for calculating the MSE is:

MSE = (1/n) * Σ(y_pred - y_actual)^2 ……… (i)

where n is the number of test samples, y_pred is the predicted value, and y_actual is the actual value.

5.1.2 FAR (False Acceptance Rate)

FAR (False Acceptance Rate) represents the probability of an unauthorized person being incorrectly accepted by the system. It is calculated as the ratio of the number of false acceptances to the total number of identification attempts. The formula for FAR is:

FAR = (Number of False Acceptances) / (Number of Identification Attempts) . ……. (ii)

5.1.3 FRR (False Rejection Rate)

FRR (False Rejection Rate) represents the probability of an authorized person being incorrectly rejected by the system. It is calculated as the ratio of the number of false rejections to the total number of identification attempts. The formula for FRR is:FRR = (Number of False Rejections) / (Number of Identification Attempts) …. (iii)

5.1.4 Accuracy

Accuracy represents the overall effectiveness of the system in correctly identifying individuals. It is calculated as the ratio of the number of correct identifications to the total number of identification attempts. The formula for accuracy is:

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Accuracy = (Number of Correct Identifications) / (Number of Identification Attempts) ……. (iv)

5.2 Simulation Result

It shows the different categories of the hand gesture images, create training model which is knowledge domain. It trains the gesture images to the machine. It stores the extracted features in the database. It applies the segmentation technique to detect the ROI (region of interest), filtration method to calculate the smooth images. So, that it recognize the exact gesture. After that, the classification model has been used to validate the gesture images, recognize the gestures and enhance the accuracy rate with the CNN model.

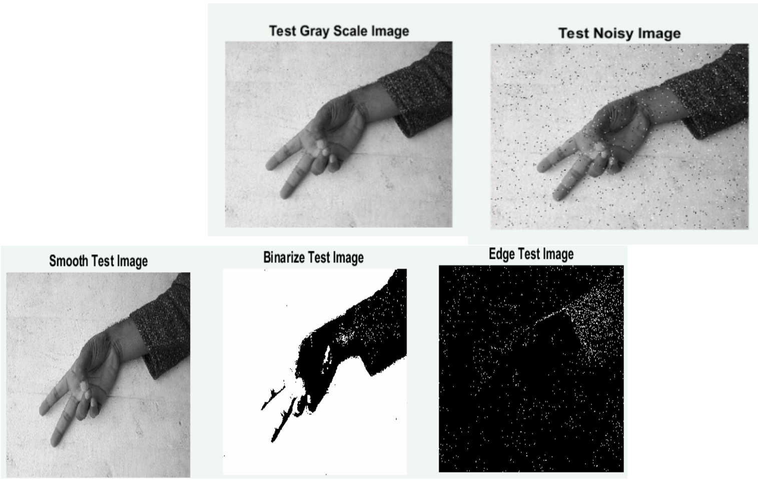

Figure 2. (i) Test Image (ii) Grayscale Image (iii) Noise Image (iv) Smooth Test Image (v)Noisy Image (vi) Smooth Image (v) Binaries, and (vi) Edge Detection

Figure 2 (i),(ii),(iii), (iv),(v), and (vi) defines that the upload the test input image which is gesture or sign image. It uploaded the color or RGB format image. It converts the RGB format to grayscale format image. It reduces the dimensionality size of the image. After that, it added the attacks in the converted image. Because of RGB format image is not easy to identify the attacks in the images. That’s why we applying this process. After the attack image has applied the filtration method to reduce the attacks effects in the noisy image. It applied the binarize process which converts the image into 1,0 format. After that, it applied the edge detection method to calculate the ROI (Region of interest) or edges of the binaries gesture image.

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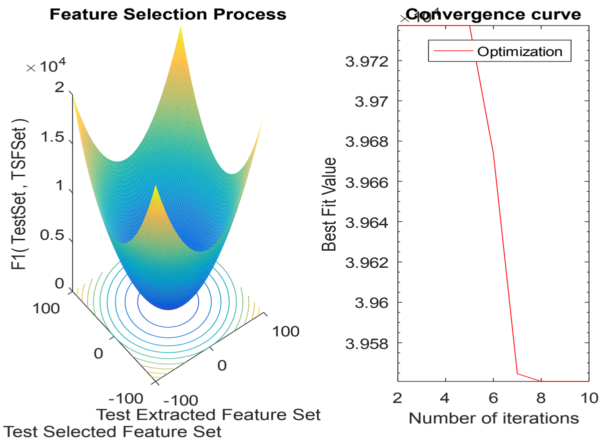
TestFeatureSet

1x700 double

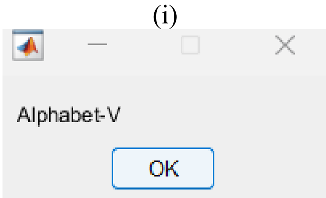
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	2.9023e+03	2.8857e+03	2.8659e+03	2.8414e+03	2.8055e+03	2.7787e+03	2.7567e+03	2.7603e+03	2.7682e+03	2.7689e+03	2.7824e+03	2.8002e+03	2.7878e+03	2.7916e+03	2.8319e+0
2															
3															

Figure 3. Feature Extraction using KPCA

Figure 3 defines the feature extraction process using KPCA method. The KPCA provides different application areas. This method is used directly to represent the features as a minimum to maximum measurement space; due to this, features are displayed in linear form individually. It evaluates the eigenvectors of the matrix known as kernel-matrix, that is, the conversion of the covariance matrix. This matrix makes the renewal of predictable PCA straightforward, and multiple similarity-based features are highly dimensional spaces. The kernel function constructs it. The main advantage of this method is that it provides the facility of developing non-linear plotting.



(i)



(ii)

Figure 4. (i) Feature Selection Using GWO Optimization, and (ii) Recognition

Figure 4 (i) shows the graphical representation of the feature selection process. This proposed method is used to remove the irrelevant features and redundant by exploring for best feature in the HGR system. Initially, GWO create in the initial positions of population, and so update the recent positions of population in the discrete searching speac (DSS). CNN classifier is showed depends on the optimal feature set gained in the initial phase. GWO is utilized to efficient search the feature-space for best feature. The best feature and optimal outcome is the one with maximum classification accuracy rate and minimum no. of chosen features. figure (ii) represents the recognize the hand gesture categories recognized. It created a knowledge domain in the training phase, and testing phase recognized the features and compared it category wise.

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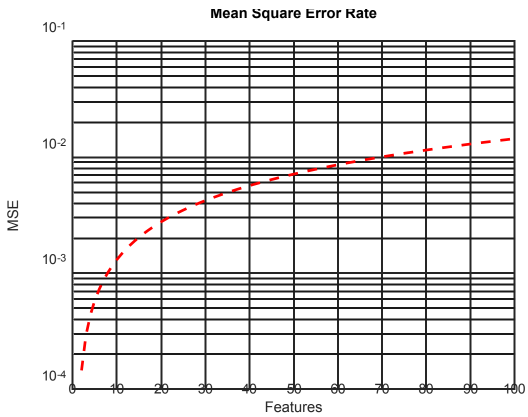

Figure 5 MSE with OFGWO-CMM Model

Figure 5 shows the proposed model performance in the for MSE parameter. The proposed model has mitigated the error rate value as compared with the existing one. In Hand Gesture Recognition Systems, Mean Square Error (MSE) is a commonly used performance metric to evaluate the accuracy of the system. The MSE measures the average squared difference between the predicted and actual values. In the context of hand gesture recognition, the predicted values are the positions of the hand keypoints or the angles of the hand joints, while the actual values are the ground-truth positions or angles. The MSE is calculated by taking the average of the squared differences between the predicted and actual values across all the test samples. A lower MSE indicates a better accuracy of the system.

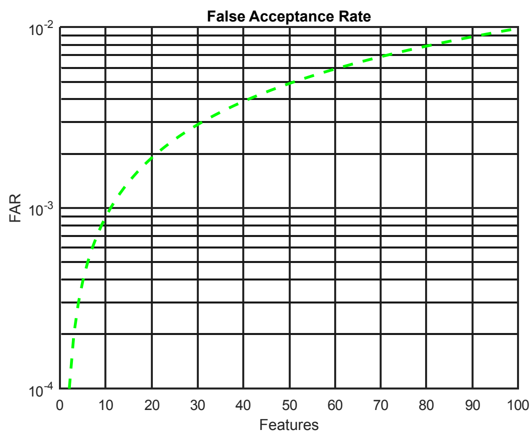

Figure 6. False Acceptance Rate (FAR)

Figure 6.shows the False Acceptance Rate (FAR) is a parameter used to measure the accuracy of a Hand Gesture Recognition System. FAR refers to the percentage of times the system incorrectly accepts an impostor (i.e., a user who is not authorized to use the system) as an authorized user

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(i.e., a user who is authorized to use the system). In other words, the FAR measures the probability of a false positive identification. In the context of Hand Gesture Recognition, FAR is particularly important when the system is used for security or authentication purposes. If the FAR is too high, it means that unauthorized users can easily gain access to the system, compromising its security. To calculate the FAR, the system is typically tested with a set of impostors who attempt to mimic the gestures of authorized users. The system's response to these impostors is then compared to its response to the authorized users. The FAR is calculated as the ratio of the number of false acceptances to the total number of impostors tested.

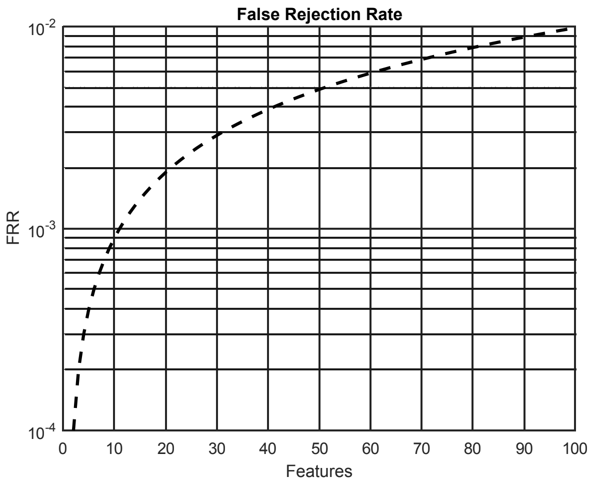

Figure 7. False Rejection Rate

Figure 7 shows the False Rejection Rate (FRR) is a parameter used to measure the accuracy of a Hand Gesture Recognition (HGR) System. FRR refers to the percentage of times the system incorrectly rejects an authorized user (i.e., a user who is authorized to use the system) as an impostor (i.e., a user who is not authorized to use the system). In other words, the FRR measures the probability of a false negative identification. In the context of HGR, FRR is particularly important when the system is used for security or authentication purposes. If the FRR is too high, it means that authorized users may have difficulty accessing the system, which can be frustrating and time-consuming. To calculate the FRR, the system is typically tested with a set of authorized users who attempt to mimic the gestures of other users. The system's response to these authorized users is then compared to its response to the true authorized users. The FRR is calculated as the ratio of the number of false rejections to the total number of authorized users tested.

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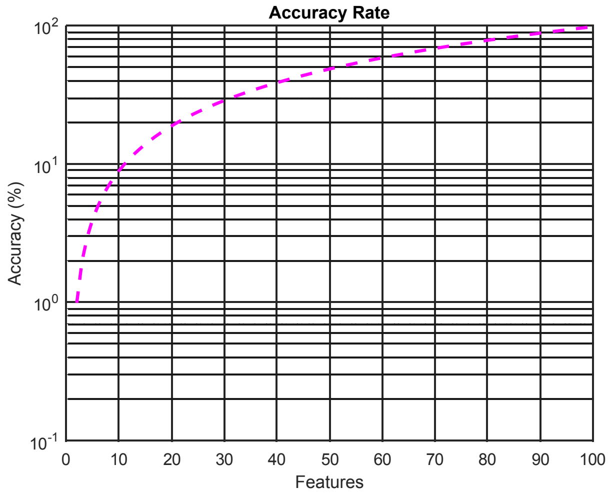

Figure 8. Accuracy Rate

Figure 8, shows accuracy is one of the most important metrics used to evaluate the performance of Hand Gesture Recognition (HGR) systems. Accuracy refers to the ability of the system to correctly identify the hand gestures performed by a user. It is typically measured as the percentage of correctly identified gestures out of the total number of gestures performed. To evaluate the accuracy of an HGR system, it is typically tested with a set of hand gesture samples. These samples are often captured in controlled conditions with specific lighting, background, and camera settings to ensure consistency across the dataset. The system is trained on a subset of the data and tested on the remaining samples to evaluate its performance. In general, a high accuracy rate is desirable for HGR systems, especially for applications that require precise and reliable hand gesture recognition, such as sign language recognition or gesture-based control systems. The accuracy of an HGR system can be affected by various factors such as the complexity of the gesture, variability in lighting and background, and variations in hand position and orientation.

5.3 Comparative Analysis

International Journal of Advances in Engineering and Management (IJAEM)
Volume 6, Issue 08 Aug. 2024, pp: 604-616 www.ijaem.net ISSN: 2395-5252

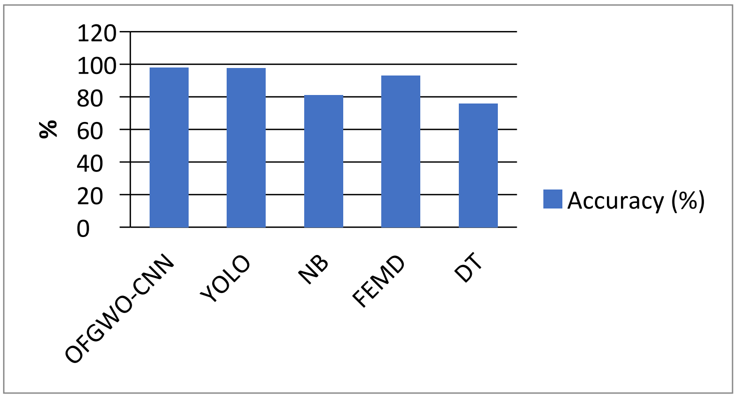

Figure 9. Comparison Analysis : Accuracy Rate (%)

Figure 9 shows the comparative analysis with different methods; OFGWO-CNN, YOLO, FEMD, Naïve Bayes, and Decision Tree with accuracy parameter. Each of these methods has its own strengths and weaknesses, and the best method for a particular application depends on various factors such as the size of the dataset, the complexity of the problem, the available computational resources, and the desired level of accuracy.YOLO is a popular object detection algorithm that is known for its fast processing speed and high accuracy. FEMD is a feature extraction method that can be used to extract discriminative features from a dataset, while Naive Bayes and Decision Tree are classification algorithms that can be used to classify data based on a set of pre-defined rules. The OFGWO-CNN proposed model is a relatively new approach that combines the Grey Wolf Optimizer (GWO) algorithm with Convolutional Neural Networks (CNN) for image classification. It has shown promising results in terms of accuracy and computational efficiency, especially for large-scale image datasets. The proposed model which is OFGWO-CNN model has achieved value of 98.0 percent, YOLO model accuracy value of 97.6 percent, Naïve Bayes value of 81.2 percent, FEMD model value of 93.2,and Decision tree value of 76 percent. The minimum accuracy rate has achieved by decision tree as compared to the proposed model using OFWGO-CNN model.

Table 1 shows the proposed model performance metrics are MSE value of 0.014, FAR value achieved by 0.009, FRR value of 0.009, and accuracy rate value of 98.0 percent. The proposed model has attained high accuracy rate and overcome the error rate. Table 2 shows the comparative analysis with different deep learning models such as OFGWO-CNN, YOLO, Naïve Bayes, FEMD, and DT. The high accuracy value of 98.0 percent has achived by proposed model as compared with the existing deep learning models.

Table 1 Proposed Metrics

Parameters	MSE	FAR	FRR	Accuracy
OFGWO-CNN	0.014	0.009	0.009	98.0

Table 2. Comparative Analysis

Models	OFGWO-CNN	YOLO	NB	FEMD	DT
Accuracy (%)	98.0	97.6	81.2	93.2	76

VI. CONCLUSION AND FUTURE SCOPE

In conclusion, Hand Gesture Recognition systems have a wide range of potential applications, and with further research and development, they could revolutionize the way we interact with machines and devices. As the technology continues to evolve, we can expect to see even more advanced HGR systems that are more accurate, reliable, and user-friendly, making them an essential tool for various industries and domains. The research work has collected the dataset from the real-time hand gesture images. It is a static gesture images. It has applied the pre-processing steps such as conversion, noise, attacks free or filtered image, and edge detection image. After that, it developed the KPCA method to extract the features. It is used to reduce the dimensionality of the feature sets in the form of Eigen Values (E), and Eigen Vectors (V). Thus, the feature has extracted has introduced the novel approach which is OFGWO-CNN (optimized featured-based grey wolf optimizer-Convolutional Neural Network) model.This model has extracted the optimized feature with help of fitness function and CNN model has classify the different hand gestures in the form of alphabets. The proposed model (OFWGO-CNN) has achieved the maximum accuracy rate of 98.0 percent, and optimized the error rate value of 0.0144.

The future scope of HGR using deep learning models is immense. Here are some potential areas of development: (i) Real-time gesture recognition: One of the key challenges of HGR is real-time recognition, especially in dynamic environments such as virtual reality or robotics. Further research and development of deep learning models could improve the real-time performance of HGR systems. (ii) Multi-modal gesture recognition: Multi-modal HGR systems that can recognize hand gestures along with other cues such as voice, gaze, or facial expressions could enhance the interaction and communication between humans and machines.

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