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# Grey Wolf Optimization for Facial Emotion Recognition: Survey

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## ABSTRACT

Human face expression Recognition is one of the most effective forms of social communication. Generally, facial expressions are a simple and obvious way for people to express their feelings and intentions. Typically, the goal of facial expression recognition is to categorize facial expressions into specific classes of expression labels. This paper presents a survey of facial emotion expression classification based on different machine learning and deep learning mechanisms and optimization algorithms. In order to evaluate the basic emotion of a person's face, a technology called facial expression recognition employs a computer as a helper with specific algorithms. Seven basic emotions were represented by facial expressions, including a smile, sadness, anger, disgust, surprise, fear, and a natural expression. In this paper, the focus is on using the Grey Wolf algorithm for selection of the optimal features from feature extraction from input image faces to recognize human facial emotions. In most studies, the FER system was applied to popular datasets such as the JAFEE database and the Cohn-Kanade database.

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## 1. INTRODUCTION

Facial emotion recognition FER is a technique used to judge the internal emotion of human facial expressions, such as a smile, sadness, surprise, anger, fear, disgust, and neural activity. It uses specific algorithms and combines them with a computer as an aid. The facial recognition system was categorized into four categories: pre-processing, feature extraction, feature selection, and classification. Transform using scale-invariant features as the foundation of the feature extraction approach to take the features out of the facial point and to select optimal characteristics. Grey Wolf optimization was employed to classify emotions from the chosen features, a GWO-based express [1].

Facial recognition technology has many applications, including in the medical field. According to the daily follow-up of the patient's facial experiences, an accurate evaluation of the drugs can be made to know the effect of the new antidepressants. It is also used in the treatment of children with autism, where it can be used to understand their feelings and the psychological changes that affect them so that doctors can help them and build more precise treatment plans. Recognizing facial expressions and using them in the field of teaching can lead to a better understanding of the emotional changes of students and their feelings, just as the education system can build and save the emotional alterations of students in education, thus educating students according to their abilities by providing a better reference for teachers. It is also used in the field of traffic. To evaluate the stress status of pilots or drivers, as well as to prevent traffic risks from a technical point of view, and therefore we can use this technology in our daily lives a lot, and this will enhance the human and computer experience together. Automated classification methods using deep learning with machine learning strategies and optimization in this paper, the focus is on the classification of facial emotions in Asian faces using improved Grey Wolf Optimization, experienced Grey Wolf Optimization, experienced Grey Wolf algorithms, and hybrid optimization algorithms based on neural networks. The organization of this paper is as follows: Section 2 describes the literature review on FER and its respective problem statement using deep learning techniques. Section 3 describes the literature review on FER and its respective.

### Motivations and contributions

- 1-Face detection boosts productivity by raising accuracy.
- 2- Face detection provides better security.
- 3- Face detection builds face recognition technology.
- 4- Face detection makes facial motion capture possible.
- 5- Face detection makes life easier.

## 2- DEEP LEARNING

DL a combination artificial intelligence (AI), the machine learning (ml) that reflects how people accumulate information science involving data, which also includes data analysis, and forecasting, includes DL. Data scientists charged with acquiring, analyzing, and interpreting large volumes of data would benefit greatly from DL since it makes the process quicker and calmer. DL may be thought of as a way of fundamentally automate predictive analytics. Conventional algorithms for machine learning, on the other hand, are linear, but DL algorithms are organized on a ladder of increasing difficulty and concept. The following studies demonstrate face emotion recognition.

### 2.1. DEEP LEARNING TECHNIQUES

Li, M. *et al* [1] in (2018). They concentrated on a static image-based facial pattern recognition system where in some cases it is difficult to accurately classify the presentations of facial expressions in which the differences are subtle and also because of the disparity between the positions and the biometric shapes of the face identical particular facial expressions are expressed in different ways, the authors proposed using deep convolutional neural networks (CNNs) an identification and emotion joint learning strategy . They used two distinct CNNs and their associated training data began by learning the emotion and identification features individually second, they built tandem Facial Expression (TFE) feature that has been deeply ingrained, they combined two characteristics to which they fed for succeeding linked adding layers to create a new model. Lastly, to undertake collaborative education on the recently combined network. They used solely the data used to teach facial expressions they used

FER+ database and CK+. Proposed solution achieved accuracy rate of 99.31% for CK+ database and 84.29% for FER+ database.

Lee, H. J., & Hong, K.S[2] in (2017) they have been suggested a face recognition system for emotion images and developed an app that gives users with seven emotions as well as positive and negative emotion-recognition results They used deep learning to implement emotion recognition with the proposed strategy. The dataset combines public and laboratory data. They use CNN to carry out learning and testing. In seven emotions, accuracy was 50.7%, and in positive and negative emotions, it was 72.3 %.

Ninu Preetha Nirmala Sreedharan1 et al[3] in 2018 they have been provided a FER system to distinguish between the standard set of human emotions, including a smile, sadness, shock, outrage, horror, and disdain. FER system's stages included pre-processing, feature extraction, feature selection, classification. Significant features from facial point were extracted based on SIFT for feature extraction. The GWO a technique was employed to choose the best characteristics in that case. Furthermore, In the NN-GWO used for recognize relevant expression. The proposed GWO-NN has a classification accuracy For the Cohn-Kanade database, it was 91.22%, while for the JAFFE database, it was 89.79%.

Guo, J *et al* [4] in (2018) they focused on complex facial emotions, such as disgust and fear, and are more thorough than the traditional seven facial expression. The authors present methods for the challenge, which are the methods of the three winners, and in these methods, they rely on extract the characteristic using a convolutional neural network. The methods and refined as follows: The first approach is used as a graphic depiction of feelings, the displacement of landmarks, and better results are obtained as opposed to the just texture information. The following approach used with classifiers and is based on unsupervised learning. The third approach CNN Inception-v3 and a discriminative loss function were incorporated (center loss). Proposed solution attained precision rate 13.7% when applied on iCV-MEFED benchmark dataset.

Zhang, T *et al*[5].in (2018) focused on incorporating the two types of learning spatial into a single spatial-temporal dependence model the geographic and temporal information of signal sources .In order to manage EEG signal-based and facial human emotion identification using images, the authors suggested a new deep learning method architecture termed network of spatial-temporal recurrent neurons (STRNN). A bi-direction TRNN layer was nested above a multi-direction SRNN layer used to understand temporal and spatial connections in order for accurately model spatially co-occurring changes and temporal dependence variations of people expression. The accuracy rate for STRNN is 89.50%. In addition, CK+ achieves the accuracy of 95.4% when applied on the CK+ benchmark facial expression dataset and the SEED EEG dataset.

Zadeh, M. M. T. et al [6] in (2019) they have been proposed a system based on deep learning for recognizing human emotions The proposed system extracts features using Gabor filters and then classifies them using a Convolutional Neural Network (CNN). The outcome of the experiment suggest that the suggested approach improves both the velocity of CNN training and the precision of its recognition. The JAFFE database was employed. The proposed method achieves 97% accuracy

Ma, S et al [7]in 2019 they have been proposed the expression tracking technology of continuous sequences and a new better method for mini-Xception. They applied a feature extraction approach to the mini-Xception network, which allows the network to get additional features and increase the classification effectiveness of facial emotions. The public data sets CK+ and FER2013 were chosen as the data sources for this algorithm comparison experiment. The CK+ test has a 98.96% accuracy rate. Despite the algorithm's breadth of use in various circumstances.

In (2019) Zhang, H., et al [8]have been suggested a facial emotion recognition approach that extracts facial information successfully utilizing a CNN model in comparison to existing approach, The suggested technique discover patterns characteristics. Automatically eliminate a lack of completion brought on by artificially created elements. Suggested technique instantly enters image pixel range using sample image data for training. Autonomous learning can learn more abstract forms of visual feature implicitly. The instruction process for the suggested technique employ suitable weight initialization, significantly affects weight updates. The results of the experiments show that the suggested algorithm requires fewer iterations to reach an average rate of 88.56% recognition, also that it trains at the practice set at a rate that is around 1.5 times more quickly than contrast technique.

Salman, A. N., & Busso, C. [9]in (2020) The data LFW collection and the face expression database Fer-2013 were combined to create the experimental data. The LFW data set includes 13,000 portraits of people. The results of experiments show that the suggested algorithm requires fewer iterations to reach an average rate of 88.56% recognition, also that it trains at the practice set at a rate that is around 1.5 times more quickly than the contrast

technique. Particularly when the topics are conversing the conventional method of assessing pictures in a movie frame by frame without considering contextual information is flawed and has inherent limits.

Sikkandar, H., & Thiyagarajan, R. [10]in (2020) creates an efficient image retrieval system that accurately returns the facial picture from an unconstrained big scale image database When additional evidence is unavailable or untrustworthy face marks can be a powerful piece of evidence. In court. The proposed approach for leveraging soft biometric features in match faces is extremely pertinent to forensics purposes. Forensic investigators can use this method to compare the input image to the criminal history dataset that they have. Among our ongoing projects are enhancing accuracy of identification also expanding for automatically locating faces for forensic specialists' drawn images. The suggested approach was tested using datasets such as LFW, CASIA, Multi-PIE, and Color Feret accuracy rate is 92%.

Lee, J. H. et al [11]in (2020) they have been proposed Deep learning multimodal technique for classifying facial photos into seven emotional types (anger, disgust, fear, excitement, contentment, sadness, and surprise). To that goal, created database of face photographs. Dataset is comprised of the Extended CohnKanade (CK+) and the FER2013 database. There are three issues with the data. For starters, it has Asian facial expressions, which have received little attention. Second, there is an imbalance in the emotion categories. Finally, the feelings were delicately portrayed on the photographs. To overcome these issues, we created a pair of multimodal models for emotion classification utilizing images and text. Their trial results indicate that incorporating text descriptions of the characters' movements considerably improves recognition performance. The accuracy rating was less than 40%.

Ayari, N. *et al* [12] in (2020) they have been aimed at investigating Pattern recognition with data systems frequently overly depending on learning information ineffective at recognizing emotions in context The authors presented a hybrid model-based method for emotion contextual identification for use in ubiquitous contexts. This model based on two main components: Two approaches are used to recognize no directly observable emotions: 1) a hybrid-level fusion employing a multilayer perceptron (MLP) neural-network model and possibilistic logic; and 2) an expressive emotional knowledge representation and reasoning model. This model makes use of the n-ary event ontology supplied by the emotion upper ontology (EmUO). Narrative knowledge representation language NKRL language. They have used YouTube dataset and real-world conditions with 95% for accuracy.

Pons, G., & Masip, D. [13] in (2020) focused on multitasking, multi labeling, and multi dataset issues they specifically addressed one of the difficulties with discrete emotion identification in the field. To impart a similar combination of feature representation and related matters, the authors recommended using a multitask learning loss function. They show that combining detecting a model while learning it of face action units (collective muscle movements) improves emotion perception. They employed three non-controlled datasets and a program that forecasts complex face expressions of emotion. For emotion recognition, For AU detection, they employed the SFEW and Oulu-CASIA datasets, they used. The proposed method outperforms research using the conventional methods on the EmotioNet dataset, with an accuracy of 89.0% in AU identification and 54.8% in emotion recognition.

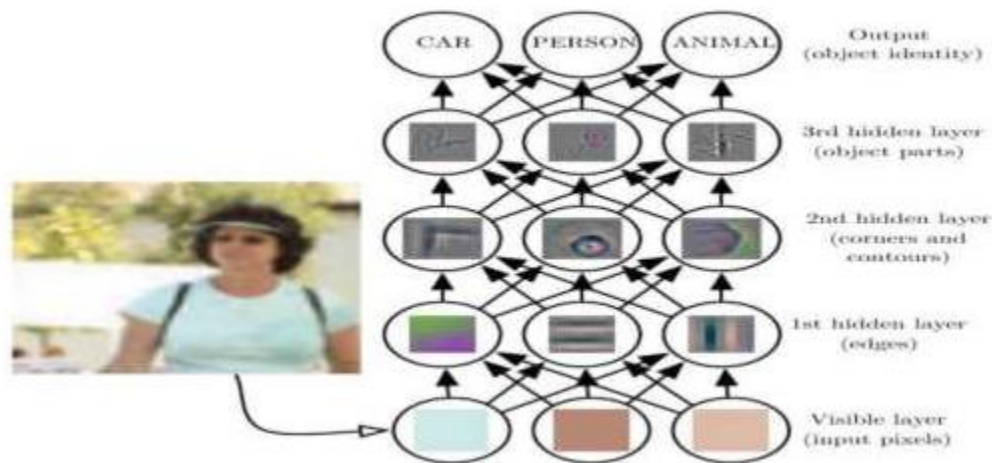
Kaviya, P., & Arumugaprasath, T.[14] in (2020) they have been proposed a convolutional neural network approach for automatically identifying collective face expressions of emotion. This is true for both static and moving pictures. Facial features are recognized and extracted using OpenCV's Haar filter. According to the proposed CNN, facial landmarks can indicate one of five emotions: happiness, sadness, rage, surprise, or neutrality. The outcome of the experiment show suggested CNN could notice the properties of facial expressions; the model's test accuracy rose to for FER-2013, 65%, and 60% for customized database. Face expressions in a group are calculated making use of the weighted average of anticipated expression.

Vulpe-Grigorași, A., & Grigore, O [15]2021 presented an automated process for creating models with different architectures and hyper parameter configurations from a discrete set of potential solutions, the Random Search algorithm, is used to generate models with improved accuracy by optimizing hyper parameters and its architecture. The experimental findings demonstrate that this approach can generate a compact model with an accuracy of 72.16% that is based only on CNN. Additionally, by limiting the search space for viable solutions to only 500 elements, the desired result was also attained. On the FER2013 database, the suggested model was trained over 750 iterations. In order to produce models with higher accuracies than the provided model.

In 2022. Jamshed, A et al [16] focused on developing identifying object movement in image frames and classifying its action label. The authors proposed feature extraction ensembles the spatial model of an image pattern using the image convolution method and the pattern model of a feature extraction technique using Convolutional Pattern of Wavelet Transform (CPWT). In the action prediction for video dataset, this type of feature extraction improved the pattern analysis model. The CNN also improves classification performance in feature analysis compared to other cutting-edge methods. That improved employing Grey Wolf Optimization method (GWO) which optimally selects the best attributes for neural network architecture arrangement. This type of

optimal feature selection and classification can be implemented in other image processing applications in the future to reduce classification time complexity while also improving performance. The suggested algorithm is implemented using the UCF Sports video dataset and the HMDB51 database for the proposed method Dice Score is 98%, accuracy is 97%, sensitivity is 97%.

Tanoy Debnath *et al.* (2022) [17] proposed a novel convolutional neural network-based facial emotion recognition model. The presented model can classify human faces using a camera in real-time. Anger, disgust, fear, happiness, neutrality, sadness, and surprise are just a few of the seven unique emotions that their "ConvNet" proposed model could identify from image data. Using training with their suggested CNN model (ConvNet), the features extracted from face expression images by the Local Binary Pattern (LBP), region-based oriented fast and rotating brief (ORB), and convolutional neural network (CNN) were combined to construct the classification model. Using the JAFFE dataset, the generalization technique yields 92.05% accuracy. the methodology and accuracy for the mentioned literature in table 1



**Fig. 1. Abstract of Deep Neural Network diagram**

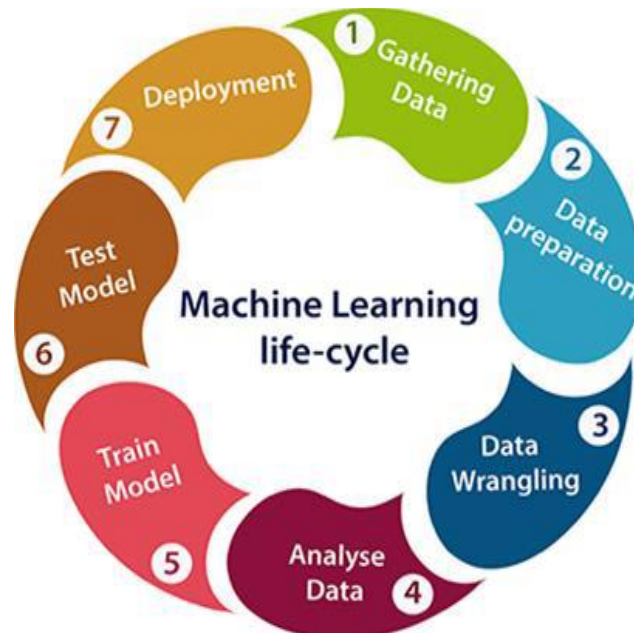
**Table 1. List of reviewed research.**

| <b>Ref No.</b> | <b>Author and year</b>  | <b>Dataset</b>             | <b>Classification methods</b> | <b>Accuracy %</b>    |
|----------------|---|----------------------------|-------------------------------|----------------------|
| 1              | Li, M., Xu, H., Huang, X., Song, Z., Liu, X., & Li, X. (2018) FER dataset                                 | CK+ and the FER+           | DCNN                          | accuracy rate 99.31% |
| 2              | Lee, H. J., & Hong, K. S (2017)   | public and laboratory data | CNN                           | accuracy 50.7%       |
| 3              | NirmalaSreedharan, N. P., Ganesan, B., Raveendran, R., Sarala, P., Dennis, B., &Boothalingam R, R. (2018) | Cohn-Kanade<br>JAFFE       | GWO-NN                        | accuracy 91.22%      |
| 4              | Guo, J., Lei, Z., Wan, J., Avots, E., Hajarolasvadi, N., Knyazev, B., ... & Anbarjafari, G. (2018)        | iCV-MEFED                  | CNN                           | accuracy rate 13.7%  |

|    |  |   |   |                                    |
|----|--|---|---|------------------------------------|
| 5  | Zhang, T., Zheng, W., Cui, Z., Zong, Y., & Li, Y. (2018)                       | CK+ and SEED EEG  | network of spatial-temporal recurrent neurons (STRNN) | accuracy rate 95.4%                |
| 6  | Zadeh, M. M. T., Majidi, B., and M. Imani (2019,February)                      | JAFFE   | CNN   | accuracy 97%                       |
| 7  | Ma, S., Cao, M., Li, J., Zhu, Q., Li, X., Shen, Y., & Wang, M. (2019,November) | CK+ and FER2013   | CNN   | accuracy 98.96%                    |
| 8  | Zhang, H., Jolfaei, A., & Alazab, M. (2019)                                    | LFW , Fer-2013  | CNN   | average recognition rate 88.56%    |
| 9  | Salman, A. N., & Busso, C (2020)   | FER   | CNN   | accuracy 88.56%                    |
| 10 | Sikkandar, H., & Thiyagarajan, R. (2020)                                       | LFW, CASIA, Multi-PIE, and Color Feret  | IGWO  | accuracy 92%                       |
| 11 | Lee, J. H., Kim, H. J., & Cheong, Y. G. (2020)                                 | CohnKanade (CK+) and the FER2013  | Deep learning multimodal technique                    | accuracy rating was less than 40%. |
| 12 | Ayari, N., Abdelkawy, H., Chibani, A., & Amirat, Y. (2020)                     | YouTube dataset and real-world conditions with the visitors of the smart devices showroom | NN  | accuracy is 95 %                   |
| 13 | Pons, G., & Masip, D.(2020)  | SFEW and Oulu-CASIA   | CNN   | accuracy is 89.0%                  |
| 14 | Kaviya, P., & Arumugaparakash, T (2020)  | FER-2013, bespoke   | CNN   | accuracy 65%                       |
| 15 | Vulpe-Grigorași, A., & Grigore, O. (2021)                                      | FER2013   | CNN   | accuracy 72.16%.                   |
| 16 | Jamshed, A., Mallick, B., & Bharti, R. K. (2022).                              | UCF Sports video and the HMDB51   | CNN   | accuracy 97%                       |
| 17 | Tanoy Debnath <i>et al</i> (2022)  | JAFFE   | CNN   | accuracy 92.05%                    |

### 3-. MACHINE LEARNING

The principles of the ability of a computer program to learn from and adjust to new data without the assistance of a human [13] Artificial intelligence's (AI's) learning subfield keeps a computer's internal algorithms current despite changes in the world economy.



**Fig.2 The Machine Learning life cycle.**

Zhang, F. *et al.* [18] in 2020 focused on proposing simultaneous pose-invariant facial expression recognition and facial image synthesis using a deep learning model from beginning to finish, utilizing the depiction of the face's shape and geometry. FER is performed by recognizing or approving individual expressions based on facial photographs taken in arbitrary poses. The proposed generative adversarial model networks (GAN) have various advantages. The proposed method's accuracy rate is 92.09%. They employed benchmark datasets from the wild, such as Multi-PIE, BU-3DFE, and SFEW.

Fu, C *et al.* [19] in 2021 have been focused on a high-resolution extreme facial alteration. The authors presented a unique framework that divides the face into two associated stages for face manipulation: border prediction and disentangled face synthesis. In the first stages, to jointly model poses and expressions, use boundary images. In particular, a network of conditional encoder-decoders is used to forecast the target photo within the boundaries of the semi-supervised manner; for faces, the introduction of pose and expression estimators increases prediction performance. In the next phase, two encoder networks encode the predicted border of the face in the input image and the image to latent arrangement and texture spaces, respectively. Accuracy rate of 87.4%.

They have used the new high-resolution database MVF-HQ, which includes 120,283 photographs at 6000 by 4000 pixels from 479 different identities varying in their positions, facial expressions, and lighting. Compared to openly accessible datasets for face manipulation in high resolution, MVF-HQ is significantly larger in both scale and resolution.

Huang, T. R., *et al.* [20] in (2021). They focused on building a system to distinguish facial patterns with mixed emotions; the authors proposed a new method for increasing the data based on the shape of the face that expresses different degrees of a designated emotion. This method collects faces expressing different degrees of specific emotions and then validates this approach successfully to distinguish face patterns in humans and machines, and these systems, when trained on additionally composite faces, showed different sensitivity to the intensity of emotions. Radboud Faces (RaFD) is used as a benchmark dataset. accuracy rate 97%.

Cao, T. *et al.* [21] in (2021) focused Faces with nonfrontal and asymmetries can readily skew our perception of an expression in the natural. Some regions of the nonfrontal face are crushed and deformed. These compressed areas may still be blurry and impair the ability to recognize facial expressions even after frontalization. Additionally, improper expression traits are produced by asymmetrical expressions, which are frequent in half or partial facial areas.

The half-face pyramid frequency conversion technique was suggested by the authors. The filters in deep learning convolutional layers can be used in this method to recognize facial expressions, and the multiscale faces' decreasing and rising faces can be used to remove inaccurate facial expression data. The wrong expressions are filtered out by this pyramid structure because they are narrow-band, while the proper expressions can be reserved since they are broadband, according to the Fourier frequency conversion theory. Two half-faces are processed individually in order to remove the asymmetrical half-faces. With the following possible recognition, outcomes produced contrasting two half-faces in a row over various ranges for frequency conversion. Over 80% of people can typically distinguish between pleasant and unpleasant things. When applied to the SFEW and FER 2013 benchmark datasets.

Zhang, X et al. [21]. in (2021) The two half-faces are processed individually in order to remove the asymmetrical half-faces, and the final recognition outcome may be produced by contrasting the two half-face emotion outcomes over various ranges for frequency conversion. Over 80% of people can typically distinguish between pleasant and unpleasant things. (Multi-PIE, MMI, and RAF-DB.

**Table 2. List of reviewed research.**

| Ref No. | Author and year  | Dataset   | Classification methods                           | Accuracy %                                 |
|---------|--|---|--|--|
| 18      | Zhang, F., Zhang, T., Mao, Q., & Xu, C. (2020)               | wild benchmark using BU-3DFE, Multi-PIE, and SFEW | GAN  | accuracy rate 92.09%                       |
| 19      | Fu, C., Hu, Y., Wu, X., Wang, G., Zhang, Q., & He, R. (2021) | (MVF-HQ)  | Face manipulation                                | accuracy rate 87.4%                        |
| 20      | Huang, T. R., Hsu, S. M., & Fu, L. C. (2021)                 | Radboud Faces (RaFD)                              | face morphing                                    | accuracy rate 97%                          |
| 21      | Cao, T., Liu, C., Chen, J., & Gao, L. (2021)                 | SFEW and FER 2013                                 | ( half-face pyramid frequency conversion method) | average recognition rates larger than 80%. |
| 22      | Zhang, X., Zhang, F., & Xu, C. (2021)                        | (Multi-PIE, MMI, and RAF-DB)                      | GAN  | accuracy rate of 93.66%                    |

#### 4- OPTIMIZATION

Optimize is an approach used to find the best combination of inputs to achieve the best possible output, subject to satisfying certain prespecified requirements.

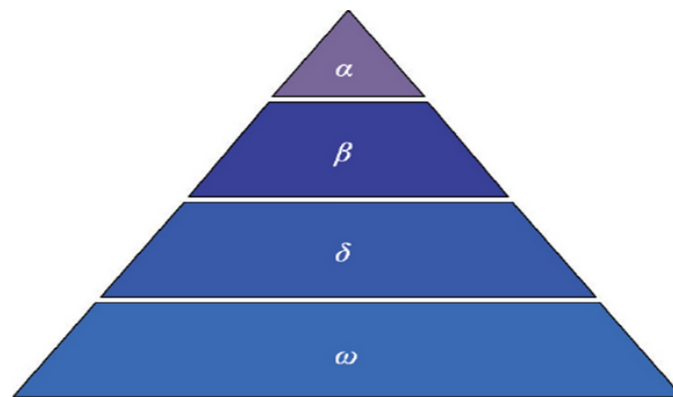
##### 4.1 Grey Wolf Optimizer (GWO)

In the area of swarm intelligence, the GWO algorithm is a relatively new and well-respected optimization technique. The leadership structure and hunting strategy of grey wolves in nature served as the basis for the GWO, which was first proposed by Mirjalili et al. in 2014. GWO has seen a substantial increase in use in recent years to address a variety of practical application issues. The social and leadership features of grey wolves serve as inspiration for the GWO algorithm. *Canis lupus*, or grey wolves, always exist in groups of between 5 and 12 animals. A grey wolf pack's dominant hierarchy is its most distinguishing characteristic. Their group is separated into four categories of wolves to keep order within the group. The alpha wolf ( $\alpha$ ) is also known as the dominant wolf of the group, and the decision-maker belongs to the first class. The second group of wolves are known as the beta ( $\beta$ ) wolves, which serve as messengers for the alpha ( $\alpha$ ) wolves when they are not present. The wolves in the third category are known as delta ( $\delta$ ) wolves, who look after the group and defend it from danger. The wolves in the fourth category are those who are only allowed to eat at the very end of the day. These wolves are known as



omega ( $\omega$ ) wolves, and they frequently serve as scapegoats. The wolves are a crucial component of the pack because without them, there may be fighting and other issues within the wolf pack. This is a result of the omega wolves' violent and angry retaliation against all grey wolves. These wolves also help with satisfaction by preserving the dominance structure throughout the pack. Wolves occasionally serve as babysitters. A significant social characteristic of grey wolves is group hunting, which involves three steps in the hunting process.

- 1-Close to the prey.
- 2- Swarming around the prey.
- 3- Taking the prey by force.



**Fig.3 social hierarchy of GWO**

#### **GREY WOLF ALGORITHM PROS:**

- 1- Simple in principle.
- 2- Fast seeking speed.
- 3- High search precision.
- 4- Easy to realize.

#### **GREY WOLF ALGORITHM CONS:**

- 1- Slow convergence speed.
- 2- Low solution accuracy.
- 3- Easy to fall into the local optimum.

To classify face emotion recognition using hybrid optimization algorithms, improved grey wolf optimization, and experienced grey wolf optimization, as in the following studies.

Joshi, H., Arora, S. [23] (2017) introduced a Grey Wolf Optimizer improvement modeled after how grey wolves hunt in nature. The proposed algorithm modifies the first three steps involved in the method of hunting existing GWO, namely tracking, pursuing, and a predator assault. The suggested Enhanced GWO algorithm (EGWO) seeks to optimize exploration and exploitation, increasing its stability and rate of convergence, and it is effective at resolving problems involving global optimization. The benchmark test problems' simulation results showed the suggested method performs better than other examined algorithms in terms of improved search space exploration and utilization. With regard to accuracy, the simulation results indicate that the suggested approach is quite effective for node localization. Results showed that the EGWO method has the potential to be a useful tool for dealing with actual optimization problems.

Zheng-ming Gao et al. [24] in 2019 have proposed an enhanced GWO algorithm as a consequence of the PSO method to improve the ratio of convergence and error reduction. The results of studies and validations reveal that it outperforms the

traditional GWO method and various other popular meta-heuristic algorithms. An empirical investigation was conducted, and it was discovered that the minimum number of swarm populations should be  $>20$ . Benchmark function solving experiments were conducted, and the enhanced GWO method was determined to have more capabilities than the PSO algorithm with the original GWO algorithm.

Emary, E et al. [25]. In 2017, they suggested a form of GWO that takes each agent's particular exploration rate into account (Wolf). The seasoned GWO (EGWO) gains knowledge of the activities that should be conducted at various optimization phases and in various areas of the search space, employing reinforcement-learning concepts. To store the experience data, it made use of a neural network model for two major applications of optimization: feature allocation and ANN weight adaptation. The traditional GWO, PSO, and GA contrasted with the suggested EGWO. When compared to the other approaches, we see that EGWO performs significantly better. EGWO is capable of quickly adapting to the varied terrains of space and avoiding hasty convergence. Furthermore, the beginning of the search agent starting positions for the optimization process affects EGWO performance, with uniform and MR initialization giving greater diversity in agents for searching, allowing the skilled model to be easily trainable. Their approach is more of a demonstration of the idea that determining the parameters of learning algorithms automatically rather than manually (by trial and error) is more efficient, and it may be adapted to other comparable algorithms. The UCI machine-learning repository's 21 data sets the accuracy rate is 72%.

In 2019, Al-Tashi, Q. et al. [26] proposed using grey wolf optimization (GWO) and particle swarm optimization (PSO) in binary form to resolve feature selection issues. They used an existing technique called BGWOPSO to address the feature selection problem. 18 common UCI benchmark datasets were used to confirm the usefulness and effectiveness of the suggested technique. The suggested approach evaluated using a set of evaluation measures. The suggested hybrid compared to GWO2, BPSO, BGA, and the hybrid WOASAT-2 selected features algorithms. Regarding accuracy and quantity of characteristic chosen, the findings showed that the recommended technique outperformed several different techniques on most datasets. Furthermore, to put the proposed binary algorithm to the test, a calculation period comparison performed between the hybrid WOASAT-2 and the binary hybrid technique, and the findings revealed that the proposed approach has a faster running time. The proposed method achieves a 93% accuracy rate.

IN (2019), Wei Liu et al. [27] they have investigated and presented a classification method based on a feedforward neural network based on an improved grey wolf optimizer. The data sets iris, heart, cancer, and wine were utilized to evaluate the provided approach, and the results were compared to those of PSO, GSA, and GWO. The experimental results suggest that evolutionary algorithms, group intelligence algorithms, and physical algorithms are excellent choices for tackling training challenges such as updating link weights and biases in feed-forward neural networks. NGWO offers the highest classification accuracy and lowest error among the four algorithms, making it a better training approach. In general, the proposed technique can balance classification accuracy with MSE. Reduce the dimension of log data and improve the feed-forward neural network's learning capabilities to achieve an accuracy rate of 99%.

Kihel, B. K., & Chouraqui, S [28] (2020). Suggested For feature subset selection, a new stochastic search method inspired by Grey Wolf optimization theory. The proposed strategy formulates as an optimization issue; the feature selection algorithm seeks an ideal with the fewest characteristics in a feature space and the highest efficiency. The study's aim is to strike a compromise between the size of the feature subsets and the classification accuracy chosen. The suggested approach was examined with ten identical databases from the UCI repository and verified on two large databases from the literature.

In 2020. Zhang, Y. et al. [29] have proposed an orthogonal frequency division multiplexing signal identification for OFDM approach that depends on an optimization technique for hybrid grey wolves since the fundamental Grey Wolf Optimization (GWO) is a deep neural network model to be improved and is prone to stalling when performing operations involving prey attack differences in Evolution (DE), which is merged with GWO to drive GWO to leap from the standstill using the DE's powerful searching capabilities. In a multipath channel, this approach can differentiate between complicated signals like the OFDM modulation signal, single-carrier signals, wavelet packet signals (WPM), and OFDM signals. First, we extract the modulation signal's characteristics as the classifier's input, and then we apply the HGWO approach to enhance the DNN's thresholds and weights. For overall data set eigenvectors of 3900. The accuracy rate is 87%.

Bansal, J. C., and Singh, S. [30] in 2021 have proposed an upgraded version of the traditional GWO that incorporates two techniques. The first is an exploratory equation, and the second is opposition-based learning. GWO's exploration capabilities have improved thanks to the explorative equation. Opposition-Based Learning (OBL) has aided in preventing GWO stagnation and has accelerated convergence. Statistical, diversity, and convergence analyses were used to evaluate the proposed IGWO on 23 recognizable benchmark test issues. A statistical analysis was performed, and it was discovered that IGWO is a better optimizer with greater exploration capabilities while maintaining a high convergence speed. In addition, done based on a collection of 23 common benchmark test problems to use to tackle a variety of real-world application problems.

M. Ashok Kumar et al. [31] reported that they implemented an intelligent FER model in 2021. The suggested design consists of a few stages (a): extracting the face,(b) image filtration , (c)facial component extraction ,(d) attribute

selection, (e) classification are a few of the procedures. The Viola-Jones method, which frequently employed for object allocation, initially used to remove the face from the input images. Gabor filtering is then used to reduce the image's noise. Then the facial features taken from the components. Using the enhanced SIFT technique known as the ASIFT, or Affine-Scale-Invariant Feature Transform, because the ASIFT-generated descriptions are long, the optimal descriptor selection approach employs an algorithm using an integrated meta-heuristic known as MV-WOA to reduce the number of the descriptors. The extracted descriptors are processed using a neural network (NN). The 48x48 pixel grayscale portraits of people make up the set. The projected MV-WOA-accuracy NN's is 92 %.

**Table 3 List of reviewed research**

| Ref No. | Author and year   | Dataset   | Classification methods                       | Accuracy %      |
|---------|---|---|--|-----------------|
| 23      | Joshi, H., & Arora, S. (2017)   | twenty-five benchmark functions                     | EGWO algorithm                               | Accuracy 80.07% |
| 24      | Emary, E., Zawbaa, H. M., & Grosan, C. (2017)                                     | UCI machine learning repository's 21 data sets      | EGWO algorithm                               | Accuracy 72%    |
| 25      | Gao, Z. M., & Zhao, J. (2019)   | seven UCI benchmark                                 | EGWO algorithm                               | Accuracy 93%    |
| 26      | Al-Tashi, Q., Kadir, S. J. A., Rais, H. M., Mirjalili, S., & Alhussian, H. (2019) | 18 common UCI benchmark                             | BGWOPSO                                      | Accuracy 93%    |
| 27      | Liu, W., Hu, M., Ye, Z., Tang, Y., Wang, Z., Zhang, L., & Wei, M. (2019)          | iris, heart, cancer, and wine                       | NGWO   | Accuracy 99%.   |
| 28      | Kihel, B. K., & Chouraqui, S. (2020)  | UCI repository                                      | new Genetic Grey Wolf Optimization algorithm | Accuracy 88%    |
| 29      | Zhang, Y., Liu, D., Liu, J., Xian, Y., & Wang, X. (2020).                         | 3900 eigenvectors                                   | HGWO   | Accuracy 87%    |
| 30      | Bansal, J. C., & Singh, S. (2021)   | set of 23 standard benchmark test problem           | IGWO   | Accuracy 94%    |
| 31      | Ashok Kumar, P. M., Maddala, J. B., & Martin Sagayam, K. (2021).                  | photographs of faces in gray scale, 48 by 48 pixels | MV-WOA-NN                                    | Accuracy 92 %   |

## 5. CONCLUSIONS

In conclusion, this paper has presented forty-five models to classify system for recognizing facial emotions (FER) that includes normal, sad, surprised, angry, fearful, and disgusted human face expressions. Some models used deep learning concept by using the popular approach deep convolution neural network (DCNN). Where it was applied to various databases and the highest accuracy was obtained by using this method, which is 99.31%. In other models, the concept of machine learning was used to determine facial expressions and was applied to various databases, and the average rates of recognition of this method was surpasses 80% in size. In addition, some models where optimization algorithms were used. In this paper, the focus was on the use of the Grey -Wolf algorithm, which simulates the mechanism of hunting in nature, and was used to come up with the best solution, where it used to choose optimal features. This study concentrates of using Improved Grey wolf optimization and experienced grey wolf algorithms and hybrid optimization algorithms.

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