BIO Web of Conferences **97**, 00051 (2024) https://doi.org/10.1051/bioconf/20249700051
ISCKU 2024

Grey Wolf Optimization-based Neural Network for Deaf and Mute Sign Language Recognition: Survey

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Abstract. Recognizing sign language is one of the most challenging tasks of our time. Researchers in this field have focused on different types of signaling applications to get to know typically, the goal of sign language recognition is to classify sign language recognition into specific classes of expression labels. This paper surveys sign language recognition classification based on machine learning (ML), deep learning (DL), and optimization algorithms. A technique called sign language recognition uses a computer as an assistant with specific algorithms to evaluate basic sign language recognition. The letters of the alphabet were represented through sign language, relying on hand movement to communicate between deaf people and normal people**.** This paper presents a literature survey of the most important techniques used in sign language recognition models

1 INTRODUCTION

In the modern era of advanced technology, recognizing sign language (SL) has emerged as a significant endeavor. This is a pressing need, as it can effectively bridge the communication divide for the Deaf community. It's important to note that "Deaf" (capitalized) refers to a cultural and linguistic community that shares a common language and culture. At the same time, "deaf" (lowercase) pertains to the audiological condition of hearing impairment. Globally, virtually every country hosts Deaf communities, constituting a substantial portion of the world's population, estimated at 15% to 20% [1]. Sign language is a visual communication that conveys meaning through hand movements, arm positions, and facial expressions. It serves as a means of communication and fosters a sense of belonging and identity among individuals with Hearing impairments. Additions facilitate effective communication and support academic success[2]. However, due to sign language's primarily visual nature, it can be challenging for individuals without hearing unfamiliar and unfanned to become familiar with it to grasp its meaning. Moreover, conveying the precise nuances of sign language expressions can be easier for no-disabled individuals with expertise in sign language. Some educators working with Deaf students resort to using spoken language and struggle with sign language, leading to instances where students may not fully comprehend the content being taught. As a result, a phenomenon has emerged where students tend to align their learning preferences more with the influence of their parents, peers, and personal choices rather than relying solely on their teachers' instruction.
Sign language recognition (SL) has many applications, such as in the medical area. It is also used in the learning field of recognizing sign language (SL). This paper primarily centers on automated classification methods, combining deep learning (DL) with machine learning (ML) models and optimization techniques.

It also explores experienced Grey Wolf optimization, experienced Grey Wolf algorithms, and hybrid optimization algorithms incorporating neural networks. The structure of this paper can be summarized as follows: the first section Reviews the general introduction to sign language (SL) and outlines the specific problem statement. Section 2 provides machine learning (ML) and artificial neural network (ANN) techniques for a literature review of sign language (SL); Section 3 provides deep learning (DL) techniques for a literature review of sign language (SL). Section 4 presents a gray wolf optimization (GWO) literature review of sign language (SL). Finally, section 5 shows the conclusion about sign language (SL).

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2 MACHINE LEARNING

Machine learning (ML) is a part of artificial intelligence concerned with the study and development of statistical algorithms that can perform tasks effectively and to perform tasks without explicit instructions. It has been used in many fields (computer vision, speech recognition, email filtering, agriculture and medicine)[3].

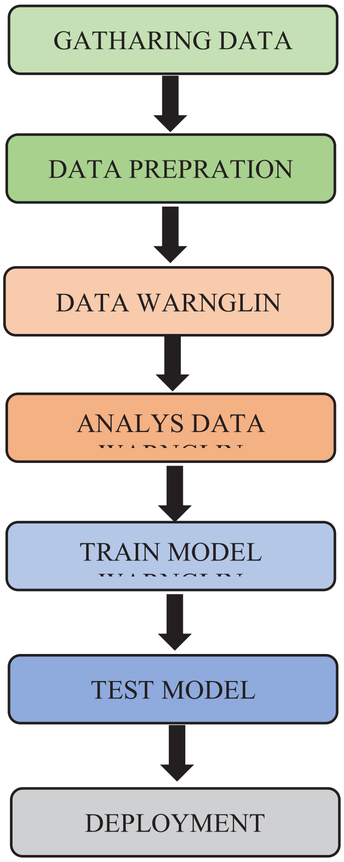

Fig. 1. The Machine Learning life cycle.

3 Artificial Neural network (ANN):

An artificial neural network (ANN) is a mathematical model inspired by the operation of biological neurons. It consists of three main layers: the input, hidden, and output layers. They communicate with each other through weights. It can modify the weights according to its actions' results, allowing it to learn and solve problems without human intervention. The input layers consist of a series of neurons containing the input signal (input), which will be transferred to the hidden layers representing the heart of the neural network, highlighting the relationships between the various variables. Then, the final result is transferred to the output layer; finally, we obtain the output [4]

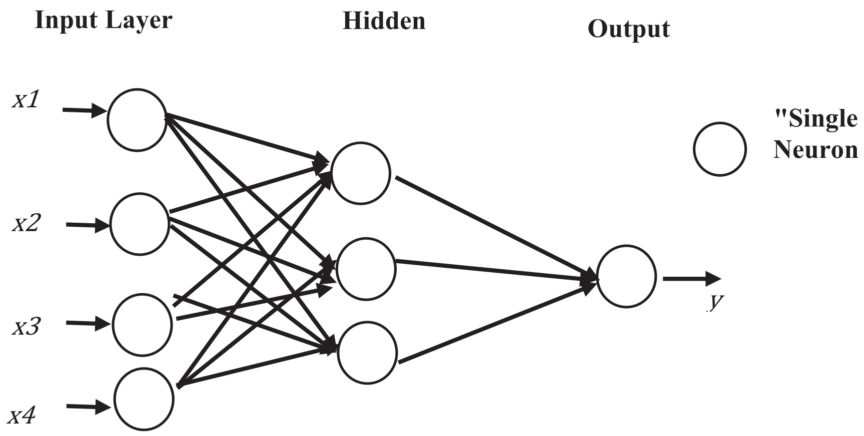

Fig. 2 The structure of ANN

In (2023), Amin & et al. proposed sensor-based assistive gloves to capture alphabet and number signs, five flexible sensors, and gyroscope sensors to capture position data, using Artificial neural network (ANN) to address the problem of sign language recognition, specifically focusing on the recognition of isolated static postures in American Sign Language (ASL), The dataset that they used consisted of three separate datasets: numeric ASL (numbers 0 to 10), alphabetic ASL (letters A to Z), and alphanumeric ASL stances (0-10 and A-Z), in this study the use a different type of activation function Relu obtained the high Training accuracy (97.7%, 95.3%, 96.5%) Testing Accuracy (94.3%, 90.7%, and 91.5%) [5].
In the same year, Hafeez, A. et al. Using CNN, KNN, ANN and SVM for sign language recognition, a recognition system using a single camera to collect data for ISL was proposed, and SVM provided an accuracy of 84%. In ANN we obtained an accuracy of 60%. ANN 41.95 and CNN algorithms show an accuracy of 88.38%, which is the most accurate among other algorithms[6].
Also In the same year, Tyagi.A. and Bansal.S. Introduced the anatomy of the hand and the artificial neural network (ANN) model for sign language recognition. FAST and SIFT feature extraction techniques are also utilized to overcome the limitations of existing detection systems based on sensing devices or gloves. To verify the performance of the proposed model, we tested it on sign language gestures consisting of ISL letters and numbers, daily life words, medical words, general uses, and home and related uses. Whether it is a uniform background or a complex background, it can achieve fast and high-precision results of 99.85%, 97.55% and 98.85%, suitable for medical use, general use, home and relatives use[7].
In 2021 Ali H. Alrubayi et al. A static gesture pattern recognition method for Malaysian Sign Language (MSL) using ANN, RF and KNN is proposed. The accuracy performance of each model for ANN, RF and K-NN techniques achieved the highest performance indicators (99%, 99% and 98.5% respectively)[8].
In the same year, Huu et al. Currently: They have been proposed algorithm uses image processing technology combined with artificial neural network (ANN) methods to help users interact with computers through common gestures, analyze and create gesture recognition algorithms suitable for smart home applications. The results show that the proposed algorithm has an average accuracy of 92.6% for images and over 91% for videos, with a processing time of about 0.098 seconds for a 10 frames per second dataset[9].
in (2020), Sahoo A et al. Applying K-nearest neighbor and naive Bayes classifiers for automatic sign language recognition. These letters are converted into text by an automated conversion system called ISL. This study used 2600 images, 100 images for each English alphabet. The results show that the model achieved a high accuracy (97%)[10].
In (2019) Candrasari et al. Current research on sign language (SL) classification using discrete wavelet transform (DWT), hidden Markov models (HMM), and K-nearest neighbors (KNN). Eigenvalues are obtained by feature extraction of DFT using two-level decomposition. The final process uses HMM and KNN. The data split for training (150) and the data split for test images (100) show the obtained HMM (58%) and ANN (100%) respectively[11].
IN (2018), Sunitha RAVI et al. A hybrid model for sign language (SL) recognition is proposed. The model needs to be divided into several stages, first applying (DWT) as a preprint of the image and then feeding the (SVM and ANN) model. In the Indian dataset used in this study, the accuracy performance shows that (WT-ANN) achieves a better high score (92.17%) than (WT-SVM)[12].
In 2018, Ashish Jasuja and Rahul D. Raj, proposed a method for detecting British Sign Language (BSL) gestures. Using artificial neural network (ANN) as classifier and graph of oriented gradients (HOG) for processing. The system's accuracy rate was a remarkable 99.01 percent[13].

In the same year, Meng Xing et al. Principal component analysis (PCA) is applied for feature factor reduction and SVM classifier reduction. To recognize sign language, they used the MSRGesture3D and SKIG datasets captured with a Kinect device. Accuracy measurements for MSRGestur3D and SKIG are 100% and 98.7%, respectively[14].
In the same year, Onamon Pinsanoh et al. An efficient feature extraction model is proposed to recognize American Sign Language letters from static and dynamic gestures. The proposed algorithm includes four different techniques: the number of white pixels at the edge of the image (NwE), the length of the finger from the center of mass point (Fcen), the angle between the fingers (AngF), and the distance between the fingers of the first and last frames. The angular difference between (delAng) is then used to extract features from the video image, and an artificial neural network (ANN) is used to classify the characters. The results of these experiments were detection rates as high as 95%, which is clearly the highest accuracy compared to other studies in this field[15].

The previous studies on sign language recognition using machine learning have demonstrated the effectiveness of machine learning algorithms, such as artificial neural networks (ANN), different activation functions, support vector machines (SVM), convolutional neural networks (CNN), and others, in accurately recognizing and classifying sign language gestures. Additionally, these studies have achieved high accuracy for various sign language gestures, both in static and dynamic contexts.

However, it is important to note that challenges and limitations still exist. Some studies have focused solely on recognizing isolated static postures, neglecting the dynamics of sign language expressions. Moreover, the scope of these studies has been limited to specific sign language variations, overlooking the broader range of sign languages. In certain cases, the accuracy of ANN models used in these studies was relatively lower compared to other algorithms like SVM and CNN. Furthermore, alternative optimization techniques and feature extraction methods were not thoroughly explored, and limited information was provided about the datasets used, their diversity, and collection methodology. Additionally, there was a lack of comparison with existing models and techniques.

To overcome these limitations, researchers should consider the following suggestions. Firstly, they should develop models capable of recognizing and interpreting the dynamic aspects of sign language, including movements, transitions, and facial expressions. Secondly, enhancing the accuracy of ANN models can be achieved through techniques such as ensemble learning, regularization methods, and hyperparameter optimization. Comparing the performance of ANN models with other algorithms can provide valuable insights for accuracy improvement. Thirdly, exploring alternative optimization algorithms and feature extraction methods can enhance the performance and representation of sign language gestures. It is important to provide comprehensive information about the datasets used and conduct thorough performance evaluations by comparing proposed models with existing techniques, while reporting relevant metrics.

4 DEEP LEARNING

Deep learning is a branch of machine learning (ML) that models structures and functions in the brain. It is a special method recently developed and used to build deep neural network models. A deep neural network is said to be deep if the input undergoes a series of nonlinear transformations before the output[16]

4.1 DEEP LEARNING TECHNIQUES

In 2023, Kim et al. Long short-term memory (LSTM) is used to design and apply wearable gloves that can recognize sign language expressions from input images and learn sign language through finger movement generation and vibration motor feedback. In this study, wearable gloves were used to teach sign language. The glove consists of direct current, joints (external finger bones) that produce finger movement, and flexible sensors. When hand coordinates are moved into the input image, sign language movements are transmitted through a vibration motor mounted on the wrist. The glove can learn 20 Korean words using sign language and learning data. The results show that the test accuracy of the LSTM model reaches 85%[17].

In the same year, Mostafa Magdy Balaha et al. A hybrid (DL) architecture is proposed. Try to solve the challenge of SLR by combining CNN and Recurrent Neural Network (RNN). The proposed architecture achieves 98% accuracy on the presented dataset. It also reached 93.4% and 98.8%. or accuracy in the UCF-101 dataset[18].

Also in the same year, Hira Hameed et al. They used radar and deep learning (DL) algorithms such as GoogLeNet, SqueezeNet, VGGNet, and (CNN) to differentiate problems in vision-based systems. Ambient lighting constraints and device privacy for DSLR cameras and BSL datasets were also used in this study. Using the VGGNet model , the proposed model achieved the highest classification accuracy of up to 90.07% at a distance of 141 cm from the subject[19].

Still in the same year, Shin Jung-pil and others. They proposed a multi-branch based CNN (CNN) and transformer to solve the cooling problem of Korean Sign Language (KSL). The main purpose of this model is to solve the problem of efficiency and performance differences between (SLR) models by leveraging the long-range transformer and feature extraction of (SLR) neural networks (CNN). They used (KLS) and their laboratory dataset. The accuracy of this model reaches 89.00% and 98.30% for KSL and laboratory datasets respectively[20].

Also in the same year, Raja'a M. Mohammed and Suhad M. Kadhem proposed a model for translating Iraqi Sign Language images into (text). They captured images from videos and then generated a dataset and then used this dataset (CNN) for sign language recognition (SLR). The measurement accuracy of this model reaches 99%[21].

Also In the same year, Devashsih Sethia et al. CNN has recognized American Sign Language (ASL). The English alphabet dataset is divided into 27,455 images for training and validation and 7172 images for testing; the model's measurement accuracy is 99.8%[22].

In 2022 Eman Aldhahri et al. Arabic Sign Language Recognition (ASLR) using convolutional neural networks (CNN) and mobile networks (2022). The proposed model was trained using the ArASL2018 dataset and achieved an accuracy of 94.46% [23].

In the same year, Adithya Venugopalan and Rajesh in (2022) used a hybrid algorithm combining (BiLSTM) and (CNN) to recognize gestures in Indian Sign Language (ISL). A novel dataset that frequently uses dynamic gestures to represent (ISL) words with an average accuracy of 83.36%.[24].

Also In the same year, Wael Suliman et al. They are a hybrid model that combines (LSTM) and (CNN) for Arabic Sign Language (ArSL) recognition and uses (CNN) as the extraction function and (LSTM) model for classification. (LSTM-CNN) the model achieves 95.9% accuracy for the signer-dependent case.[25].

In (2021), Yong Soon Tan et al. An enhanced density convolutional neural network (EDenseNet) is proposed to solve the vision (VB)-based hand gesture recognition (HGR) problem to overcome the problems of traditional (HGR) by extracting more hand-crafted features, which are included in multiple data sets, there are also two types of NUS-Hand gestures (ASL). The accuracy of this model reaches 98.50% and 99.64%, respectively [26].

In (2020), M. M. Kamruzzaman applied convolutional neural networks (CNN) to recognize and translate Arabic gesture-based letters into Arabic. This dataset uses 31 Arabic Sign Language letters for each gesture, 100 images in the training set, and 25 in the test set. The accuracy is 90% [27].

From previous studies it was shown that deep learning techniques offer several advantages in sign language recognition. Firstly, deep neural networks have shown superior performance in capturing complex patterns and relationships within sign language data. They can automatically learn hierarchical representations, allowing for more accurate and robust classification. Additionally, deep learning models can handle large-scale datasets effectively, enabling comprehensive training and improving generalization.

However, there are some challenges associated with deep learning. One limitation is the requirement for a substantial amount of labeled data for training, which may be difficult to obtain in sign language recognition tasks. Furthermore, deep neural networks are computationally intensive and often require high-performance hardware for training and inference.

To overcome these challenges, several strategies can be employed. One approach is to explore transfer learning, where pre-trained models on related tasks or datasets are leveraged to initialize the network weights. This can help mitigate the need for large amounts of labeled data. Additionally, techniques such as data augmentation can be utilized to create synthetic examples and supplement the training set. This can increase the model's ability to generalize to unseen sign language gestures.

In summary, while deep learning techniques offer significant advantages in sign language recognition, including their ability to capture complex patterns and handle large datasets, challenges such as data requirements and computational demands exist. By employing transfer learning and data augmentation techniques, these challenges can be addressed, enhancing the performance and practicality of deep learning models for sign language recognition tasks.

4.2 Grey Wolf Optimizer (GWO):

In the field of swarm intelligence, the GWO algorithm is a relatively new and highly respected optimization technology. The leadership structure and hunting strategies of gray wolves in nature are the basis of GWO and were first described by Mirjalili et al. Year 2014. The use of GWOs has increased significantly in recent years to solve various practical application problems. The social and leadership traits of gray wolves inspired the GWO algorithm. Canis lupus or gray wolves always appear in groups of 5 to 12 animals. The dominance hierarchy of gray wolf packs is their most distinctive feature. Your team will be divided into four wolf categories to maintain order within the team. The alpha wolf (alpha) is also known as the group's dominant wolf, and the decision maker falls into the first category. The second group of wolves are called beta wolves (β), and they act as messengers for the alpha wolf (α) when the alpha wolf (α) is not present. A third type of wolf is called the delta wolf (delta), responsible for caring for and protecting the group from danger. Category 4 wolves are those only allowed to eat at the end of the day. These wolves are called Omega (ω) wolves and are often used as scapegoats. Wolves are an important part of the pack because fighting and other problems would occur without them. This results from the Omega Wolves' violent and insane revenge on all Gray Wolves. These wolves also increase contentment by maintaining a dominance structure throughout the pack. Wolves also occasionally act as babysitters. An important social characteristic of gray wolves is group hunting, which involves three steps.

- Get close to prey.
- Gather around prey.
- Use force to capture prey.

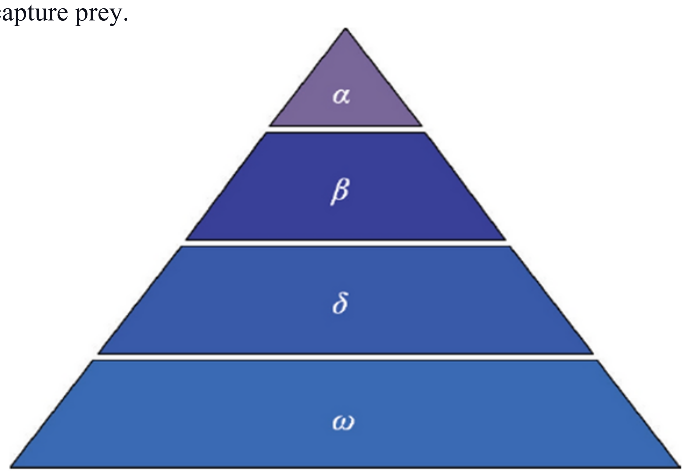

Fig.3. social hierarchy of GWO

4.2.1 Advantages of the gray wolf algorithm:

- Basically simple.
- Search speed is fast.
- High search accuracy.
- Easy to implement.

4.2.2 Disadvantages of the gray wolf algorithm:

- Slow convergence speed.
- The solution accuracy is low.
- Easy to fall into local optimum

Sign language recognition classification uses hybrid optimization algorithm, improved gray wolf optimization and empirical gray wolf optimization, as studied below.

In 2023, A. Naresh Kumar and G. Geetha proposed a technology for recognizing ancient South Indian Sign Language (SISL) by applying an artificial neural network (ANN) combined with an opposition-based gray wolf optimization algorithm (OGWA) to solve the problem due to The challenge of identifying ancient languages, symbols and writings, OGWO has an accuracy of 92.34%[28].

In the same year, Nitin Paharia et al. An enhanced gray wolf competitive optimizer (ICGWO) based on swarm intelligence (SI) was proposed to find the optimal value of the character language parameters (CNN) of English Aleph in the continuous search space. The hybrid model achieved a verification accuracy of 99.93 % [29].

In the same year, Ashish Sharma et al. They proposed a hybrid optical character recognition (OCR) model using CNN, RNN, and transcription layers and used the GWO algorithm to improve efficiency. They used the MJSynth compound word dataset from the University of Oxford. The results obtained are related to the accuracy of training data (86.28%) and test data (84.23%) [30].

In 2022, Jhansi Rani Challapalli and Nagaraju Devarakonda introduced a novel framework that applies the hybrid particle swarm and gray wolf (HPSGW) algorithm to convolutional neural network (CNN) optimization to solve the problem of (CNN) selection of optimal parameters. The proposed model (HPSGW-CNN) achieved (99.4% and 91.1%) accuracy on the MNIST and CIFAR datasets, respectively [31].

In 2020, Zhang Yiying et al. They applied a hybrid model that combines gray wolf optimization with a neural network model (GNNA) to solve global numerical optimization problems. They study the performance of the proposed GNNA algorithm using a comprehensive set of 23 well-known unconstrained benchmark functions.[32].

In 2018, HEBA M. AHMED ET AL. The hybrid model Gray Wolf Optimizer (GWO) is combined with a supervised artificial neural network (ANN) classifier to improve the effective MRI accuracy by selecting the best ultrameter of the ANN. The proposed model (GWO-ANN) achieves 98%[33].

5 CONCLUSIONS

This paper presents over 30 models for classifying sign language (SL) recognition systems, including Alpha Beta and Numeric, for various datasets. Some models use the concept of machine learning (ML) models, using popular methods such as artificial neural networks (ANN) and deep learning models such as deep convolutional neural networks (DCNN), long short-term memory (LSTM), and others. Model. Applying it to a different database and using this (DL) approach can achieve a top accuracy of 99.8%. In other models (99%). Additionally, some models using optimization algorithms were used. This study focuses on the use of improved gray wolf optimization, experienced gray wolf algorithms, and hybrid optimization algorithms.

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