Vol. 2, No. 2; Apr – Jun (2023)

Quing: International Journal of Innovative Research in Science and Engineering

Available at https://quingpublications.com/journals/ijirse

A Chat Application for Disabled using Convolutional Neural Network Deep Learning Algorithm

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ARTICLE INFO

Received: 15-05-2023
Received in revised form: 16-06-2023
Accepted: 19-06-2023
Available online: 30-06-2023

Keywords:

Convolutional Neural Networks (CNN);
Deep Learning;
Deep Learning Algorithm;
Deep Learning Techniques;
Preference.

ABSTRACT

This research paper primarily concentrates on creating a video chat application designed for individuals who are unable to speak or hear, with a specific focus on utilizing Indian Sign Language (ISL). The application employs a Deep Learning algorithm, specifically CNN, to accurately recognize various hand gestures performed by the users. Once the user begins displaying hand gestures to the camera, the algorithm promptly identifies the corresponding phrase, number, or letter, and transmits it to the front end for constructing sentences. The goal of this project is to create a tool that will allow people to communicate with individuals who are innately deaf and dumb. This project is an example of the growing research area of Sign Language Recognition, which is becoming increasingly important in helping people with disabilities to interact with others and lead more fulfilling lives.

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DOI: https://doi.org/10.54368/qijirse.2.2.0014

1.0 INTRODUCTION

Sign languages are innate communication systems utilized primarily by individuals who have hearing impairments or are deaf. However, they can also be employed by individuals with hearing capabilities who may encounter challenges in speaking or communicating through conventional means (Shin *et al.,* 2018).

It is crucial to acknowledge that sign languages are not universally standardized, and distinct countries and regions may have their own sign languages characterized by unique signs and grammatical structures (Li *et al.,* 2017). For instance, American Sign Language (ASL) and British Sign

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Language (BSL) are separate sign languages, each with its own set of signs and expressions for various words and phrases (Rajendran *et al.,* 2021).

Just like spoken languages, sign languages have their own grammar, syntax, and vocabulary. They can convey complex ideas and emotions and provide a rich and nuanced way for individuals to communicate with each other.

Benefits of learning sign language:

1. *Improved communication:* Learning sign language can provide a means of communication for individuals who are deaf or hard of hearing, as well as for those who may have difficulty speaking or communicating in other ways. It can also facilitate communication between individuals who speak different languages.
2. *Increased cultural awareness:* Learning sign language can increase cultural awareness and sensitivity to the needs of the Deaf community. It can also provide insights into the unique experiences and perspectives of individuals who are deaf or hard of hearing.
3. *Enhanced cognitive skills:* Studies have shown that learning sign language can improve cognitive skills such as memory, attention, and processing speed. This may be because sign language requires the brain to process language in a different way than spoken languages.
4. *Better academic performance:* Learning sign language can also have a positive impact on academic performance. Some studies have shown that deaf children who learn sign language from an early age perform better academically than those who do not.
5. *Improved social skills:* Learning sign language can provide opportunities to interact with individuals from different backgrounds and can enhance social skills such as empathy, patience, and communication.

Sign language recognition technology has the potential to greatly improve the quality of life for individuals who are deaf and mute, as it can enable them to communicate more effectively with others. Deep learning algorithms, such as CNNs, have shown promising results in recognizing hand gestures and signs in real time (Dong *et al.,* 2017). However, there are some challenges involved in developing a sign language recognition system, such as dealing with variations in sign language dialects, lighting conditions, and camera angles.

The ability to recognize hand gestures and signs is crucial for facilitating communication for people who are deaf and mute, and video call models that can perform this task can help bridge communication gaps. It's also important to note that training a model for sign language conversion is a complex task that requires a significant amount of data and expertise in machine learning and computer vision. However, the potential benefits for individuals who are deaf, and mute make this a worthwhile endeavour (Zhou and Zhou, 2020). Overall, the development of accurate and reliable sign language recognition technology has the potential to improve accessibility and inclusivity for people with disabilities.

The three basic components of signs in sign languages are:

1. Hand configuration refers to the shape and orientation of the hand, fingers, and palm used in making a sign. The position of the hand in relation to the body and other objects can also affect the meaning of a sign.
2. Location refers to the place in space where the sign is made, such as in front of the body, to the side, or above the head. The location of the sign can also convey information about spatial relationships, such as distance or direction.

3. Movement refers to the motion or action used to make a sign. The direction, speed, and manner of movement can all affect the meaning of a sign. Movement can also convey information about tense, aspect, or mood, similar to verb inflections in spoken languages.

2.0 PROBLEM DEFINITION

Developing a system that recognizes sign language and converts it to text and voice for communication between deaf, dumb, and normal people is a complex task that requires a combination of several technologies and approaches.

1. *Computer Vision and Image Recognition:* One of the key technologies required for this system is computer vision and image recognition. This technology can be used to capture the image of the sign language made by the person and recognize the gesture being made. There are several computer vision libraries available, including OpenCV and Tensor Flow that can be used for this purpose.
2. *Machine Learning:* Machine learning algorithms have the capability to undergo training on extensive datasets containing sign language gestures, enabling them to effectively recognize and classify these gestures. For this purpose, supervised learning algorithms like Support Vector Machines (SVMs), Random Forests, and Neural Networks can be employed. To enhance the accuracy of the system, fine-tuning the machine learning model using techniques like transfer learning can be implemented.
3. *Natural Language Processing (NLP):* After the sign language gesture has been recognized, the system needs to convert it into text and voice. This requires the use of natural language processing (NLP) techniques. NLP algorithms can be used to convert the recognized sign language gesture into text and then use text-to-speech (TTS) technology to generate the voice output. NLP techniques such as Part-of-Speech (POS) tagging, Named Entity Recognition (NER), and Sentiment Analysis can be used to improve the accuracy of the system.
4. *User Interface:* The system needs to have a user interface that allows the users to interact with it easily. The user interface can be designed as a mobile application or a web-based application that can be accessed from any device with an internet connection. The user interface should be intuitive and easy to use, with clear instructions on how to make sign language gestures and how to use the system.
5. *Testing and Evaluation:* The system should be tested and evaluated thoroughly to ensure that it meets the requirements and is reliable and accurate. The system can be evaluated using metrics such as accuracy, precision, recall, and F1 score. User testing can also be conducted to gather feedback from the users and improve the system's usability.

3.0 EXISTING SYSTEM

The existing system that aims to recognize hand gestures and convert sign language into text. However, it is unfortunate that there are still many disadvantages that make it difficult for visually impaired people to use such applications.

Some possible challenges that visually impaired people may face when using this kind of system could include:

1. *Lack of accessibility features:* The application may not have enough accessibility features, such as text-to-speech or audio descriptions, to assist visually impaired users in navigating and using the application.
2. *Difficulty in interpreting visual information:* The system may rely heavily on visual cues, such as hand gestures or facial expressions, which can be difficult for visually impaired users to interpret.
3. *Complexity of the application:* The system may be too complex or difficult to use, which can discourage visually impaired users from using it or cause frustration.
4. *Limited availability of pre-existing datasets:* The system may not have a wide enough range of pre-existing datasets to accurately recognize different sign language gestures and dialects.

4.0 PROBLEM DEFINITION

The problem statement identified is the need for sign language recognition systems to bridge the communication gap between signers and non-signers. This is a valid issue, as many individuals who rely on sign language to communicate may face barriers in everyday situations where non-signers are present. These barriers can include difficulties in accessing education, healthcare, employment, and social interactions.

Developing effective sign language recognition systems can help to address these issues and enable more inclusive communication. However, as you mentioned, one of the challenges is designing systems that can effectively recognize signs under computing power constraints. This is an active area of research and development, and there have been promising advances in recent years using machine learning and computer vision techniques.

5.0 PROPOSED SYSTEM

The proposed system Uses a proprietary video teleconferencing software program with sign language detection allows for real-time recognition of signs and gestures during video calls. It's also trains a model specifically for ISL, as different sign languages may have variations in the gestures used to convey meaning.

Using a CNN Deep Learning algorithm for sign language recognition is a common approach that has shown promising results in recent research. However, it is important to note that building an accurate and effective recognition system requires a significant amount of training data and careful algorithm design and testing.

In addition to recognizing signs and gestures, it may also be useful to incorporate other features into your system, such as translation capabilities, so that non-signers can communicate more effectively with signers who may not understand spoken or written language.

5.1 Proposed Techniques and Algorithms

The various proposed techniques and algorithms are listed below.

- *Object Detection:* Object detection is an essential computer vision task that entails the identification and localization of objects within an image or video. In the context of sign language recognition, this process plays a crucial role by allowing the system to accurately locate and track the signer's hands and gestures.

- *YOLOv5:* YOLOv5 is an object detection algorithm that has shown high accuracy and speed in recent research, making it a good choice for real-time sign language recognition. Python is a popular programming language for machine learning and computer vision tasks and is well-suited for building a sign language recognition system.
- *Deep Learning:* Deep learning is a powerful machine learning technique that has shown great success in image recognition tasks, including sign language recognition. Image recognition is an essential component of sign language recognition, as it enables the system to classify the signer's gestures into meaningful categories.
- *LabelImg:* LabelImg is an open-source graphical image annotation tool that can be used to label and annotate images for training a sign language recognition model. OpenCV is an open-source computer vision library that provides a variety of image and video processing functions and can be used for tasks like object detection and tracking.
- *NGROK:* Finally, NGROK is a tool that allows secure and encrypted tunnels to be created for secure public access to local resources, which may be useful for testing and deploying your sign language recognition system.

5.2 Advantages of Proposed System

The proposed system certainly has several advantages over existing systems and methods of communication for speech-impaired individuals.

One key advantage is that the system is secured and reliable, which is essential for any communication system. Another advantage is that the system is more convenient and user-friendly for speech-impaired individuals to operate, with the assistance of the sign language recognition technology. This can potentially increase their independence and improve their overall quality of life.

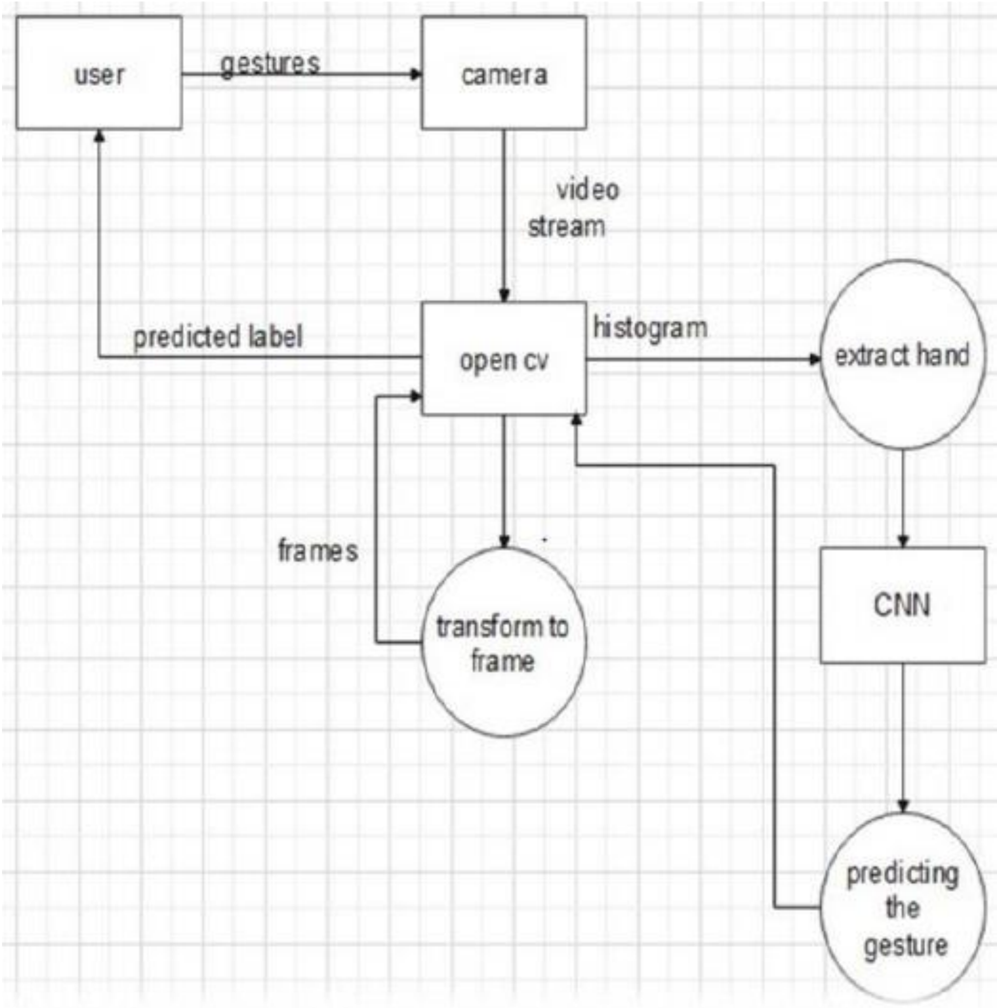
Moreover, the system can act as a bridge for speech-impaired individuals to communicate with others who may not be familiar with sign language. It can recognize sign language sentences in real-time, which can help facilitate more natural and efficient communication between speech-impaired and non-speech-impaired individuals.

Finally, the system can enable communication through online video conferencing, which can be particularly important for remote communication during times of social distancing or geographic separation.

5.3 System Structure of Proposed System

The architecture works as follows: the deaf person uses the sign language keyboard to input sign language gestures. The sign language recognition software then translates the gestures into text, which is sent to the text-to-SL video interpretation software. This software converts the text into sign language video, which is displayed to the hearing person.

Conversely, when the hearing person speaks into the microphone, the Google Speech Recognition server recognizes the speech and converts it into text. This text is then sent to the deaf person's SMS inbox, where it can be viewed and interpreted as sign language video using the same text-to-SL video interpretation software.



The proposed system consists of several components, including:

- *Sign language keyboard:* A user interface that allows the deaf person to input sign language gestures.
- *Sign language recognition software:* A deep learning algorithm that recognizes the sign language gestures and translates them into text.
- *Text-to-SL video interpretation software:* This software converts the recognized text into sign language video.
- *Microphone:* A device that captures spoken language.
- *Google Speech Recognition server:* The server that uses speech recognition technology to convert the spoken language into text.
- *SMS inbox:* A storage location for the received text messages.
- *User interface:* A graphical user interface that displays the text messages and sign language videos.

6.0 IMPLEMENTATION

6.1 Modules

The various modules that are used in the proposed system are listed below.

- Image Recognition

- Labeling images for Object Detection
- Training Sample
- Detecting Sign Language in Realtime

6.2 Image Recognition

Image recognition involves the use of computer vision techniques and machine learning algorithms to analyse and process images. The goal is to enable machines to identify and classify objects or patterns within an image accurately. This process often involves extracting relevant features from the image, such as shapes, textures, or colours, and then using those features to make predictions or comparisons with known categories or patterns.

Deep learning, specifically convolutional neural networks (CNNs), has revolutionized image recognition in recent years. CNNs are designed to mimic the visual processing mechanisms of the human brain, allowing them to effectively learn and recognize patterns in images. By training these networks on large, labelled datasets, they can learn to identify objects and recognize their corresponding categories with high accuracy.

7.0 LABELING IMAGES FOR OBJECTION DETECTION

An image labelling or annotation tool is indeed used for the process of labelling images for tasks such as bounding box object detection and segmentation. These tools enable humans to highlight and annotate objects within images, making them readable and understandable for machines.

By utilizing image labelling tools, annotators can accurately mark the objects of interest, draw bounding boxes around them, and assign appropriate labels. This process helps train machine learning models to recognize and differentiate between different objects within images. It plays a crucial role in various applications, including computer vision, autonomous driving, and object recognition.

Image labelling tools often provide functionalities for drawing precise bounding boxes, selecting object categories or labels, adjusting annotations, and ensuring the quality and consistency of the labelled data. These tools streamline the annotation process, making it more efficient and facilitating the training of accurate and reliable machine learning models.

```
# import required libraries
import torch
from pathlib import Path

# Set the YOLOv5 directory path
yolov5_dir = Path("path/to/yolov5")

# Set the dataset directory path
dataset_dir = Path("path/to/dataset")

# Set the YOLOv5 model configuration
model_config = "yolov5s.yaml"

# Set other training parameters
batch_size = 16
epochs = 50
img_size = 640

# Set the device for training
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Change to the YOLOv5 directory
os.chdir(yolov5_dir)

# Train the YOLOv5 model
train_command = (
    f"python train.py --img {img_size} --batch {batch_size} --epochs {epochs
)
os.system(train_command)
```

8.0 TRAINING YOLOv5 FOR SIGN LANGUAGE

Training YOLOv5 for sign language object detection involves several steps. Here's a high-level overview of the process:

1. *Data Collection and Annotation:* Collect a dataset of sign language images or videos and annotate them with bounding box labels around the signs you want to detect. You can use annotation tools like LabelImg or RectLabel for this task.
2. *Dataset Preparation:* Split your annotated dataset into training and validation sets. Ensure that you have a diverse range of sign language samples representing different gestures, backgrounds, lighting conditions, and camera angles.
3. *YOLOv5 Installation:* Install the YOLOv5 object detection framework by following the instructions provided in the official YOLOv5 repository on GitHub.

4. *Configuration:* Configure the YOLOv5 model settings, such as the network architecture, input image size, number of classes (sign language signs), and other parameters in the model's YAML configuration file.
5. *Training:* Start the training process by running the YOLOv5 training script on your annotated dataset. Adjust the hyperparameters, such as learning rate, batch size, and number of epochs, based on your specific requirements. Training can be time-consuming and resource-intensive, so make sure you have access to a suitable GPU for faster processing.
6. *Evaluation:* Evaluate the trained model on the validation set to assess its performance. Calculate metrics like precision, recall, and mean average precision (mAP) to measure the accuracy of object detection.
7. *Fine-tuning and Optimization:* If the model performance is not satisfactory, you can fine-tune the model by adjusting the hyperparameters or training on a larger and more diverse dataset. Consider data augmentation techniques like random cropping, rotation, and flipping to improve the model's robustness.
8. *Inference:* Once the model is trained and evaluated, you can use it for inference on new sign language images or videos. Run the trained model on unseen data to detect sign language signs and visualize the bounding boxes around them.

9.0 TRAINING SAMPLES

The training process for an object proposal and detection network typically involves two phases. Here's a breakdown of each phase and the requirements for training samples and the loss function:

Object Proposal Network Training

- *Training Samples:* For the object proposal network, you need training samples that include object classes and bounding boxes. These samples typically consist of positive samples (containing objects of interest) and negative samples (containing background regions). The positive samples are annotated with the corresponding object classes and bounding box coordinates.
- *Phase Description:* In this phase, the object proposal network is trained using the training samples. The network learns to generate proposals or regions of interest (RoIs) that have a high likelihood of containing objects.

Object Detection Network Training

- *Training Samples:* Similar to the object proposal network, the object detection network requires training samples with object classes and bounding boxes. These samples consist of positive samples (containing objects of interest) and negative samples (containing background regions). The positive samples are annotated with the corresponding object classes and bounding box coordinates.
- *Phase Description:* In this phase, both the object proposal network and the object detection network are trained. The object proposal network generates proposals, which are then used by the object detection network to classify objects and refine the bounding box locations. This joint training process helps the network learn to detect and classify objects accurately.

Loss Function

The loss function used for network training typically consists of two components: the classification loss and the bounding box regression loss.

- *Classification Loss:* This evaluates the difference between the predicted probabilities of each class and the actual class labels. Commonly used loss functions for classification include softmax loss or sigmoid loss, depending on the network architecture and the number of classes.
- *Bounding Box Regression Loss:* This quantifies the difference between the predicted coordinates of a bounding box and the actual coordinates of the ground truth bounding box. Commonly used loss functions for bounding box regression include L1 loss (mean absolute error) or smooth L1 loss.

During the training process, the network's convolution layers learn the weights and features that are necessary for accurate classification and bounding box regression. The configuration of anchors (prior boxes) helps determine the class and bounding box assignment for each proposal.

9.1 Procedure for Training

- Set up the Code
- Download the Data
- Convert the Annotations into the YOLO v5 Format o YOLO v5 Annotation Format
  - Testing the annotations
  - Partition the Dataset
- Training Options
  - Data Config File
  - Hyper-parameter Config File
  - Custom Network Architecture
  - Train the Model

10.0 DETECTING SIGN LANGUAGE IN REALTIME

The development and implementation of a real-time sign language detector using a Convolutional Neural Network (CNN) based on a Pre-Trained SSD Mobile Net V2 architecture is a significant achievement. By leveraging transfer learning on a custom dataset, the model has been trained to classify sign language gestures.

The robustness of the model is noteworthy, as it consistently performs well in the majority of cases. This is particularly beneficial for individuals learning sign language, as it provides them with a tool to practice and improve their skills. The model's accuracy ranges from 70% to 80% when recognizing selected sign language signs, even in scenarios without a controlled background and under low lighting conditions.

During the project, various human-computer interface methodologies for posture recognition were explored and evaluated. Ultimately, a series of image processing techniques combined with human movement classification were identified as the most effective approach.

The successful development of this real-time sign language detector holds great promise for improving communication between the deaf community and the general population. It opens up opportunities for more inclusive interactions and bridges the communication gap that exists.

```python
import cv2
import torch
from pathlib import Path

# Set the YOLOv5 directory path
yolov5_dir = Path("path/to/yolov5")

# Set the YOLOv5 model path
model_path = yolov5_dir / "my_model.pt"  # Path to your trained YOLOv5 model

# Load the YOLOv5 model
model = torch.hub.load(str(yolov5_dir), "custom", path=str(model_path))

# Set device for inference
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device).eval()

# Set class labels (assuming you have a class file with sign language labels
class_file = yolov5_dir / "data" / "sign_language.names"  # Path to your sig
with open(class_file, "r") as f:
    class_names = f.read().splitlines()

# Initialize the webcam or video stream
video_stream = cv2.VideoCapture(0)  # Change the argument to the video file

while True:
    # Read frame from the video stream
    ret, frame = video_stream.read()

    if not ret:
        break

    # Preprocess the frame
    img = cv2.cvtColor(frame, cv2.COLOR_BGR2RGB)  # Convert BGR to RGB
    img = torch.from_numpy(img.transpose((2, 0, 1))).float().div(255.0).unsq

    # Perform inference
    results = model(img)[0]

    # Process the detection results
    for detection in results:
        class_idx = int(detection[-1])
        confidence = float(detection[-2])
        class_name = class_names[class_idx]

        # Filter detections based on confidence threshold
        if confidence > 0.5:
            xmin, ymin, xmax, ymax = detection[:4].cpu().numpy().astype(int)

            # Draw bounding box and label on the frame
            cv2.rectangle(frame, (xmin, ymin), (xmax, ymax), (0, 255, 0), 2)
            cv2.putText(frame, f"{class_name}: {confidence:.2f}", (xmin, ymi
                        cv2.FONT_HERSHEY_SIMPLEX, 0.9, (0, 255, 0), 2)

    # Display the frame
```

```
    cv2.imshow("Sign Language Detection", frame)
    if cv2.waitKey(1) & 0xFF == ord("q"):
        break

# Release resources
video_stream.release()
cv2.destroyAllWindows()
```

11.0 CONCLUSION

A chat application for disabled using CNN deep learning algorithm can be a powerful tool for communication and social interaction. By using CNN to recognize facial expressions and gestures, the application can help disabled people to communicate more effectively with others. Additionally, the application can be used to provide social support and companionship to disabled people. One of the main benefits of using CNN for this application is that it is a very accurate and reliable method for recognizing facial expressions and gestures. CNNs have been shown to be able to recognize facial expressions with over 90% accuracy, which is much higher than the accuracy of other methods, such as human judges. This accuracy is essential for a chat application for disabled people, as it ensures that the application can accurately understand the user's intent. Another benefit of using CNN for this application is that it is a very scalable method. CNNs can be trained on large datasets of facial expressions and gestures, which allows them to learn to recognize a wide variety of expressions and gestures. This scalability is important for a chat application for disabled people, as it allows the application to be used by a wide range of users with different disabilities. Overall, a chat application for disabled using CNN deep learning algorithm has the potential to be a powerful tool for communication and social interaction. By using CNN to recognize facial expressions and gestures, the application can help disabled people to communicate more effectively with others. Additionally, the application can be used to provide social support and companionship to disabled people.

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