A
Project Report
on

Real Time Sign Language Gesture Recognition with Text and Audio Output

Submitted in partial fulfilment of the requirement for the award
Of
BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE ENGINEERING

Under the Guidance
Of

Dr. Devendra Kumar Singh

(Asst. Prof., Dept. of Computer Science & Engineering)

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DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING
SCHOOL OF STUDIES, ENGINEERING & TECHNOLOGY
GURU GHASIDAS VISHWAVIDYALAYA
KONI, BILASPUR, CHHATTISGARH

OCTOBER 2023-2024

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CERTIFICATE

This is to certify that the Project entitled **"Real Time Sign Language Gesture Recognition with Text and Audio Output"** presented by **Yatindra Deo** and **Abhishek Kumar Singh** of **DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING** in **School of Studies, Engineering & Technology, GGV** has been completed successfully between month of July to October 2023-2024. This is in partial fulfilment of the requirements of Bachelor Degree in Department of Computer Science & Engineering under Institute of Technology, Guru Ghasidas Vishwavidyalaya, Koni, Bilaspur, Chhattisgarh, 495009.

I wish him success in all future endeavours.

Signature of students

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We must acknowledge the faculties and staff of the Department of Computer Science & Engineering for their help.

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DECLARATION

I hereby declare that the project "**Real Time Sign Language Gesture Recognition with Text and Audio Output"** which we have submitted in the partial fulfilment for the requirement for the award of the Degree of Bachelor of Technology in Computer Science & Engineering, School of Studies Engineering & Technology, Guru Ghasidas Vishwavidyalaya, Bilaspur, Chhattisgarh is an authentic work done during the session 2023-2024(July - Oct) Under the supervision of Dr. Devendra Kumar Singh (Assistant Professor), Department of Computer Science & Engineering, School of Studies Engineering & Technology, Guru Ghasidas Vishwavidyalaya, Bilaspur, Chhattisgarh. I further declare that the work which have done in this project has not been submitted either in part or in full, for the award of any other degree or diploma in this institute

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ABSTRACT

Inability to speak is considered to be true disability. People with this disability use different modes to communicate with others, there are number of methods available for their communication one such common method of communication is sign language.

Developing sign language application for deaf people can be very important, as they'll be able to communicate easily with even those who don't understand sign language. Our project aims at taking the basic step in bridging the communication gap between normal people, deaf and dumb people using sign language.

The main focus of this work is to create a vision-based system to identify sign language gestures from the video sequences. The reason for choosing a system based on vision relates to the fact that it provides a simpler and more intuitive way of communication between a human and a computer. In this report, 46 different gestures have been considered

In this project, we employed a Random Forest Classifier to capture both spatial and temporal features in static sign language images. To extract spatial features, we leveraged the power of the MediaPipe Hand Landmark library to detect and locate key hand landmarks within the images. The dataset used was meticulously curated, comprising a diverse range of sign language gestures, each meticulously captured in static images.

For spatial feature extraction, the MediaPipe Hand Landmark model was applied to each image to detect and represent the positions of significant hand landmarks. These landmark positions were then fed into the Random Forest Classifier for training. The Random Forest Classifier is an ensemble learning method that effectively captures spatial patterns and relationships in the sign language images.

To enhance the temporal understanding of sign language communication, we associated each image with an audio output corresponding to the recognized sign. The Random Forest Classifier, after learning from the spatial features, determined the most likely sign

represented by the static image. Upon identification, the classifier triggered an audio output, allowing for effective communication in sign language.

The custom dataset used in this project comprised a wide array of static sign language images, encompassing various gestures and signs, with a focus on accuracy and diversity. Through the use of the Random Forest Classifier and the integration of audio output for static images, our system achieved an impressive accuracy rate of 93.3%, making it a valuable tool for sign language communication and interpretation."

Introduction

Sign language is a rich and expressive mode of communication used by deaf and hard-of-hearing individuals to convey their thoughts and feelings. For many, sign language is not just a means of communication, but an integral part of their culture and identity. However, sign language interpretation remains a complex and challenging task, requiring real-time recognition and understanding of the intricate hand movements, facial expressions, and body language that form the basis of this unique language.

In recent years, advancements in computer vision and machine learning have opened up exciting possibilities for sign language recognition and interpretation. One promising approach involves the use of hand landmark detection and categorization techniques. Hand landmark detection refers to the process of precisely identifying the key points or landmarks on a person's hand as it articulates sign language gestures. These landmarks provide essential spatial information that is central to understanding the sign being conveyed.

Mediapipe, an open-source library developed by Google, offers an efficient and accurate solution for hand landmark detection. With the capability to track multiple hands in real-time and provide the 3D coordinates of key landmarks, it has become a valuable tool in the field of sign language gesture recognition. The accurate spatial data obtained from Mediapipe can serve as a foundation for recognizing and categorizing sign language gestures.

In this context, we explore the fusion of two powerful technologies: hand landmark detection using Mediapipe and categorization using a Random Forest Classifier. The synergy between these technologies enables the development of a system capable of recognizing and interpreting sign language gestures with remarkable accuracy.

The Random Forest Classifier, an ensemble learning method, excels at capturing complex spatial relationships and patterns. By training this classifier on spatial features extracted from the detected hand landmarks, we can build a robust model for recognizing individual signs. The Random Forest Classifier's versatility allows it to adapt to various sign language dialects and regional variations, making it a versatile tool for sign language recognition.

This research aims to harness the potential of hand landmark detection and the Random Forest Classifier to create a comprehensive system for sign language gesture recognition. By leveraging the spatial features extracted from hand landmarks and the classifier's decision-making capabilities, we strive to bridge the communication gap between the deaf and hearing communities. Our work not only contributes to the development of assistive technologies for the deaf and hard-of-hearing but also offers a deeper understanding of the intricate language of sign, fostering inclusivity and communication on a global scale.

Python: Python is a high-level, versatile, and widely-used programming language known for its readability and simplicity. It was created by Guido van Rossum and first released in 1991. For machine learning Python is the best suited and widely used programming language.

Library Used:

Different libraries and algorithms used in our project:

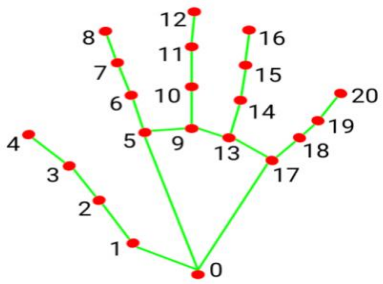
A. OpenCV: A collection of Python bindings called OpenCV-Python was created to address issues with computer vision. An image is loaded using the cv2.imread () method from the given file. This method produces an empty matrix if the picture cannot be read (due to a missing file, poor permissions, an unsupported or invalid format, etc.).

B. Numpy: A general-purpose array processing package is called Numpy. It offers a multidimensional array object with outstanding speed as well as capabilities for interacting with these arrays. It is the cornerstone Python module for scientific computing. In addition to its apparent scientific applications, Numpy is a powerful multi-dimensional data container.

C. OS: Python's OS module offers tools for communicating with the operating system. OS is included in the basic utility modules for Python. This module offers a portable method of using functionality that is dependent on the operating system. There are numerous functions to deal with the file system in the **os** and **os.path** modules.

D. Mediapipe hand: It is a component of Google's MediaPipe framework, which provides real-time, high-fidelity hand tracking and hand landmark recognition. It's designed to detect and track hands in images and videos, making it a valuable tool for various applications, including sign language recognition, gesture control, and augmented reality. It is capable of tracking multiple hands in real time, making it suitable for applications that require tracking hand movements and gestures.

Key Hand Landmarks: The system identifies and tracks a set of key landmarks on the hand. These landmarks include the tips of each finger, the base of the palm, and other key points on the hand. The system can track up to 21 hand landmarks in total.

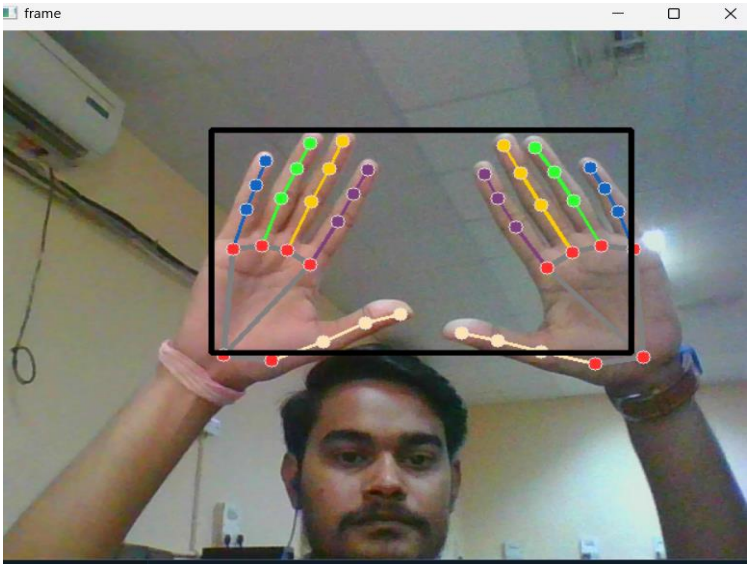


0. WRIST
1. THUMB_CMC
2. THUMB_MCP
3. THUMB_IP
4. THUMB_TIP
5. INDEX_FINGER_MCP
6. INDEX_FINGER_PIP
7. INDEX_FINGER_DIP
8. INDEX_FINGER_TIP
9. MIDDLE_FINGER_MCP
10. MIDDLE_FINGER_PIP
11. MIDDLE_FINGER_DIP
12. MIDDLE_FINGER_TIP
13. RING_FINGER_MCP
14. RING_FINGER_PIP
15. RING_FINGER_DIP
16. RING_FINGER_TIP
17. PINKY_MCP
18. PINKY_PIP
19. PINKY_DIP
20. PINKY_TIP

In addition to 2D landmarks, It also provides 3D coordinates for each landmark. This allows for precise tracking and understanding of the hand's position in 3D space. It can determine whether the detected hand is a left hand or a right hand.

This information can be useful for various applications, such as recognizing gestures that are specific to the left or right hand. It can work with various hand sizes, orientations, and lighting conditions, making it adaptable to different scenarios and environments.

MediaPipe Hand is used in sign language recognition systems to detect and interpret hand gestures for communication with the deaf and hard-of-hearing community for which we used it.



E. Pickle: The pickle library in Python—quite the versatile tool for serializing and deserializing Python objects. It's like a magical preservation spell for your data, allowing you to take your complex Python objects and transform them into a byte stream that can be easily stored or transmitted. Pickle plays a crucial role in data persistence, helping you save the state of your program or share information between different Python scripts or even across different platforms.

One of the coolest things about pickle is its ability to handle a wide variety of Python objects, from simple data types like integers and strings to more complex structures like lists, dictionaries, and even custom objects. It's like a universal translator for Python data, ensuring that you can seamlessly convert your in-memory Python objects into a format that can be stored or shared and then bring them back to life when needed.

However, like any powerful tool, pickle should be used with caution. It's not meant for secure data interchange with untrusted sources, as loading pickled data from untrusted or unauthenticated sources could potentially execute arbitrary code.

F. Matplotlib: matplotlib is a comprehensive 2D plotting library that produces static, animated, and interactive visualizations in Python. It is often used in conjunction with pyplot, a module in matplotlib that provides a convenient interface for creating various types of plots and charts. pyplot simplifies the process of creating visualizations by providing a set of functions that allow users to quickly generate common types of plots, such as line plots, scatter plots, bar plots, histograms, and more. It is particularly useful for tasks like data exploration, data analysis, and presentation of results.

   One of the key strengths of matplotlib and pyplot is their flexibility and customization options. Users can finely control the appearance of plots, adjust colors, labels, titles, and other elements to suit their specific needs. This makes these libraries suitable for a wide range of applications, from simple data exploration to the creation of publication-quality figures. Whether you are a beginner looking to create basic plots or an advanced user seeking intricate visualizations, matplotlib and pyplot provide the tools and flexibility to meet your requirements.

G. Scikit-learn (sklearn): It is a machine learning library in Python that provides simple and efficient tools for data analysis and modeling. It includes a wide range of tools for tasks such as classification, regression, clustering, dimensionality reduction, and more. `scikit-learn` is built on NumPy, SciPy, and Matplotlib, and it is designed to integrate well with other scientific computing libraries.

H. Ensemble: The `ensemble` module in `scikit-learn` is focused on ensemble learning techniques, where multiple models are combined to improve the overall performance. Ensemble methods, such as random forests, bagging, and boosting, can often provide more robust and accurate predictions compared to individual models. The `RandomForestClassifier` is a popular ensemble learning method in `scikit-learn` that creates a forest of decision trees during training and outputs the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

I. Model_selection: The `model_selection` module in `scikit-learn` provides tools for model selection and evaluation. One essential function in this module is `train_test_split`, which is used to split a dataset into training and testing sets. This is crucial in machine learning to assess how well a model trained on one set of data generalizes to new, unseen data.

J. Metrics: The `metrics` module in `scikit-learn` offers a variety of metrics for evaluating the performance of machine learning models. One commonly used metric is `accuracy_score`, which calculates the accuracy of a classification model by comparing the predicted labels to the true labels. It's a simple and intuitive metric that represents the ratio of correctly predicted instances to the total instances.

K. Train_test_split: 'train_test_split' is a function in scikit-learn that facilitates the process of splitting a dataset into training and testing sets. This is crucial for assessing the performance of machine learning models. By randomly dividing the data, it helps prevent overfitting and provides a more realistic evaluation of the model's generalization to new, unseen data.

L. Accuracy_score: accuracy_score is a metric in scikit-learn used to evaluate classification models. It measures the accuracy of the model by comparing the

predicted labels to the true labels of the test set. The accuracy score is the ratio of correctly predicted instances to the total instances in the test set, providing a quick and intuitive way to assess the model's overall performance.

M. Pyttsx3: `pyttsx3` is a Python library that allows text-to-speech conversion with various voice and rate settings. It provides a simple interface to integrate speech synthesis into applications, making it useful for creating voice-based applications, accessibility features, and more.

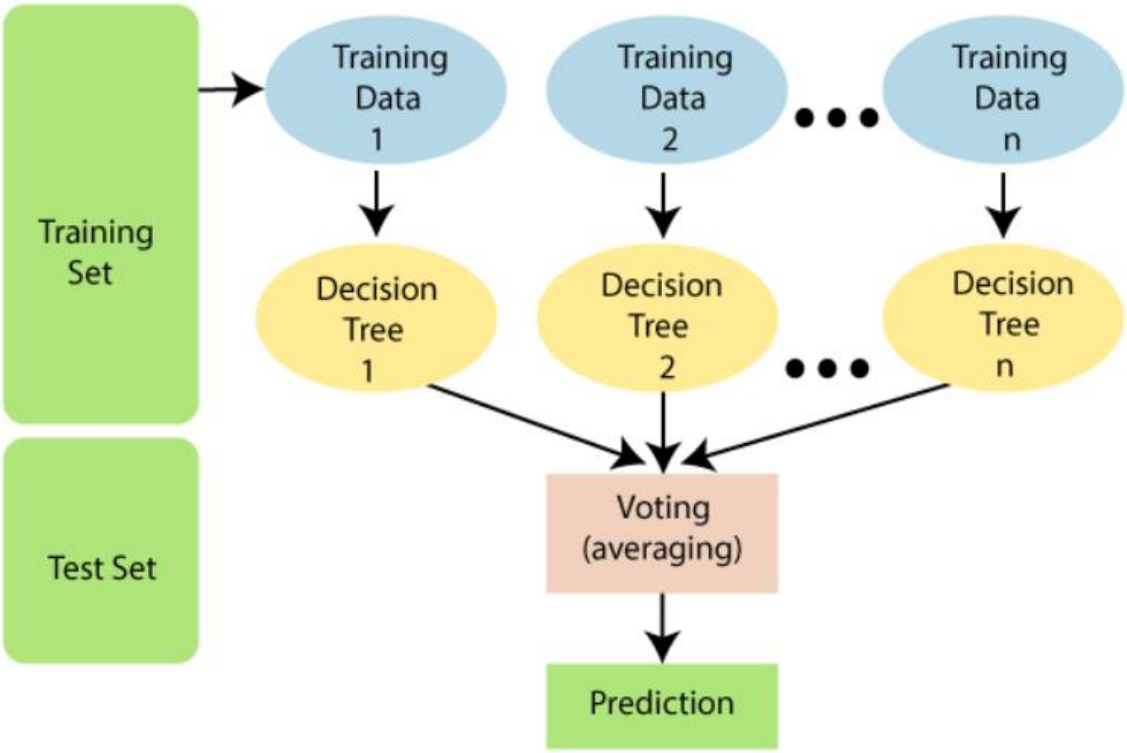
N. Threading: `threading` is a module in Python that enables concurrent execution, allowing multiple threads to run simultaneously. It is particularly useful for tasks that can be performed independently, improving program efficiency. Threading is essential for handling parallel operations, such as simultaneous data processing or managing multiple tasks concurrently.

O. Playsound: `playsound` is a Python library for playing sound files. It provides a straightforward way to incorporate audio playback into applications, making it useful for creating games, multimedia applications, or any scenario requiring sound output. The library supports various sound file formats and simplifies the process of playing sounds with a single function call.

Random forest classifier:

A Random Forest Classifier is a versatile and powerful machine learning algorithm that is part of the ensemble learning family. It is widely used for both classification and regression tasks in various domains, including data science, machine learning, and artificial intelligence. The algorithm derives its name from the "forest" structure, which consists of multiple decision trees. Random Forest is

known for its robustness, scalability, and ability to handle high-dimensional data with ease.



Random forest flow diagram

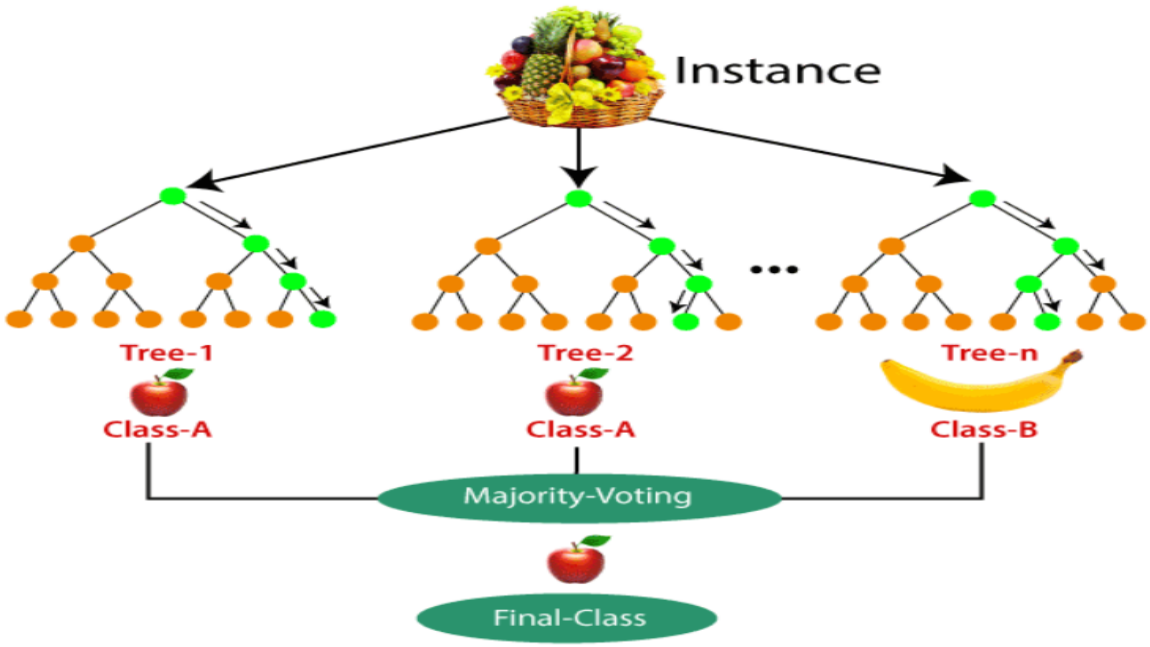
Random Forest works by aggregating the predictions of multiple decision trees, each trained on a different subset of the data and features. This ensemble approach helps mitigate overfitting, enhance generalization, and improve predictive accuracy. During training, the algorithm randomly selects subsets of data points and features for each tree, ensuring diversity in the individual models. Once trained, Random Forest combines the predictions of the constituent trees through a voting or averaging process for classification and regression, respectively.

One of the key advantages of Random Forest is its capability to handle noisy and high-dimensional data. It can identify important features, making it useful for feature selection and ranking. Additionally, the algorithm provides measures of feature importance, which can aid in understanding the factors that drive the predictions. Random Forest is also resilient to outliers and can effectively deal

with imbalanced datasets. Its versatility, robustness, and accuracy make it a popular choice for a wide range of applications, including medical diagnosis, financial modeling, image classification, and more.

Example:-

Let's say there is a dataset with several fruit photos. Therefore, the Random forest classifier receives this dataset. Each decision tree is given a portion of the whole dataset. Each decision tree generates a prediction result during the training phase, and the Random Forest classifier predicts the outcome based on the majority of outcomes when a new data point is encountered.



Problem Statement

The problem at hand is to develop a real-time sign language gesture recognition system that can accurately interpret and translate dynamic sign language gestures into text or speech. This project seeks to address the communication barriers faced by the deaf and hard-of-hearing community by enabling seamless interaction with the hearing world. The system must accurately detect and categorize sign language gestures using computer vision techniques and machine learning models. It should be capable of recognizing a wide range of gestures and adapting to different sign language dialects. The goal is to create an accessible and inclusive communication tool that empowers individuals with hearing impairments to engage effectively with the world around them.

Various datasets used in earlier similar projects were inefficient in low light conditions and un-uniform background but since we used custom dataset in this project, it resulted in higher accuracy with high efficiency in almost all conditions. In different dataset available, number of sign language is fixed but in our custom dataset we can add any number of sign language as we want.

Objective

The primary objective of the Real-time Sign Language Gesture Recognition project is to develop an innovative and practical system capable of recognizing and interpreting sign language gestures in real time. The project aims to bridge the communication gap between deaf and hard-of-hearing individuals and the broader community by providing a reliable and intuitive means of sign language interpretation.

Enhancing Accessibility: The project's central focus is to make the world more accessible to individuals who use sign language as their primary means of communication. By recognizing and translating sign language gestures in real time, we aim to facilitate seamless communication for the deaf and hard-of-hearing community in various contexts, including educational, professional, and social settings.

Real-time Recognition: Our project prioritizes real-time recognition, ensuring that sign language gestures are interpreted with minimal latency. The system will be capable of instantaneously detecting and understanding gestures, providing immediate feedback to both sign language users and their communication partners.

The Real-time Sign Language Gesture Recognition project represents a significant step forward in assistive technology, promoting accessibility and empowering individuals who use sign language to communicate effectively in a hearing world. The overarching goal is to provide a valuable and practical tool for both sign language users and their communication partners, ultimately fostering a more inclusive and connected society.

DATASET

For training our model we used custom dataset which we made by taking our own images. We used custom dataset as it has many advantages over pre-existing dataset. In pre-existing dataset number of sign is fixed we cannot change according to our needs but in custom dataset we can change according to our need.

For audio output we also used our custom data using our own voice.

Custom datasets, tailored to specific research or application requirements, offer several advantages over regular or pre-existing datasets. These advantages stem from the unique characteristics and relevance of custom datasets to the problem at hand. Here are some of the key advantages of custom datasets:

Relevance to Research or Application: Custom datasets are curated to address specific research questions or application needs. This relevance ensures that the dataset is precisely aligned with the goals and objectives of the project.

Domain-Specific Information: Custom datasets often contain domain-specific information that may not be available in regular datasets. This data can be critical for specialized applications or niche research areas.

Control Over Data Collection: Researchers have full control over the data collection process when creating a custom dataset. This control enables them to design experiments, choose data sources, and ensure data quality, which is not always possible with regular datasets.

Data Annotation: Custom datasets allow for manual annotation, which is particularly valuable for supervised learning tasks. High-quality annotations can enhance model training and evaluation.

Task-Specific Labels: Custom datasets allow for the creation of task-specific labels or annotations, enhancing the dataset's utility for a particular application. For instance, a custom dataset for sign language recognition can include sign language gloss annotations.

Improved Model Performance: Models trained on custom datasets are often better optimized for the specific task or problem, leading to improved model performance and accuracy.

Innovative Research: Custom datasets encourage innovative research and experimentation by allowing researchers to explore new ideas and hypotheses in a controlled data environment.

Changing Needs: Custom datasets can be adapted and expanded over time to accommodate changing research or application requirements.

While custom datasets offer numerous advantages, it's essential to recognize that they require significant time, effort, and resources for collection, annotation, and maintenance. Additionally, they may have limited generalizability outside the specific context for which they were created. Careful consideration of the trade-offs between custom and regular datasets is crucial when choosing the appropriate dataset for a particular project.

Custom image Dataset:






Custom Audio dataset:


Make a call.wav


I.wav


five.wav


Need food.wav


Make a call.wav


Need food.wav

Hardware & Software Requirements:

Hardware:

Computer system:

Configuration: intel i3 processor (5 gen or above), 4gb RAM, 2 gb free disk space

Cameras- 1

Flash Light

Software:

Windows 10/11

Visual studio code, Python and its IDE

Libraries & Modules:

OpenCV

NumPy

Mediapipe

OS

Multiprocessing

SciPy

Threading

Play sound etc.

Methodology

Sign language recognition using the MediaPipe Hand Landmark model and Random Forest classifier is a complex process that combines computer vision, machine learning, and human-computer interaction. This methodology outlines the steps involved in building a sign language recognition system, highlighting key components, and explaining the approach in detail. While the explanation provided here is concise, it provides an overview of the primary methods and techniques involved in the process.

1. Data Collection:

The first step in developing a sign language recognition system is to gather a comprehensive dataset of sign language gestures. This dataset should cover a wide range of signs, including letters, words, and phrases. It's crucial to capture signs from various sign languages, as there are different sign languages used worldwide. Collecting data can be done through video recordings of signers performing the gestures. It's essential to ensure that the dataset is diverse and representative.

2. Data Preprocessing:

Once the data is collected, it needs to be preprocessed to make it suitable for model training. Preprocessing steps may include video frame extraction, background subtraction, hand segmentation, and noise reduction. The goal is to isolate the hand and relevant features in each frame.

3. Hand Landmark Detection:

The MediaPipe Hand Landmark model is employed to detect and track the landmarks of the hand in each frame. This model provides the coordinates of 21 key points on the hand, such as finger joints and the palm. These landmarks serve as the basis for feature extraction and sign gesture representation. The accuracy and robustness of this landmark detection model are critical for the success of the sign language recognition system.

4. Feature Extraction:

From the landmark data, features are extracted to represent the sign gestures effectively. Feature extraction techniques can include calculating distances between landmarks, angles between fingers, and the movement trajectory of the hand. These features help characterize the unique aspects of each sign gesture and provide meaningful input to the classifier.

5. Labeling and Annotation:

Each frame of the dataset needs to be accurately labeled with the corresponding sign gesture. Manual annotation is often required to ensure that the data is correctly tagged, associating each frame with the appropriate sign. This annotated data serves as the ground truth for training and evaluating the machine learning model.

6. Training Data Split:

The dataset is split into training, validation, and test sets. The training set is used to train the Random Forest classifier, while the validation set helps fine-tune hyperparameters. The test set is reserved for evaluating the model's performance.

7. Random Forest Classifier:

The heart of the sign language recognition system is the Random Forest classifier. Random Forest is a machine learning algorithm that is well-suited for classification tasks. It is an ensemble learning method that combines multiple decision trees to make predictions. Each tree is trained on a subset of the data and features, and the final decision is made by aggregating the results of individual trees. In this context, Random Forest takes the extracted features from the hand landmarks as input and predicts the corresponding sign gesture.

8. Model Training:

The Random Forest classifier is trained on the labeled dataset. During training, the algorithm learns the relationships between the hand landmark features and the sign gestures. This process involves the creation of decision trees, feature selection, and handling any missing or noisy data. The classifier aims to build a robust model capable of recognizing a wide range of sign gestures accurately.

9. Model Evaluation:

After training and hyperparameter tuning, the model's performance is assessed using the test dataset. Common evaluation metrics for sign language recognition systems include accuracy, precision, recall, and F1 score. The model's ability to correctly classify sign gestures is critical, and its performance is often compared to baseline models to gauge its effectiveness.

10. Real-Time Sign Language Recognition:

To create a real-time sign language recognition system, the trained Random Forest classifier is integrated with a video input stream from a camera. Each frame of the video is processed using the MediaPipe Hand Landmark model to detect the hand landmarks. These landmarks are then used to extract features, which are fed into the Random Forest classifier for prediction. The system continuously monitors the video stream, recognizing sign gestures in real time.

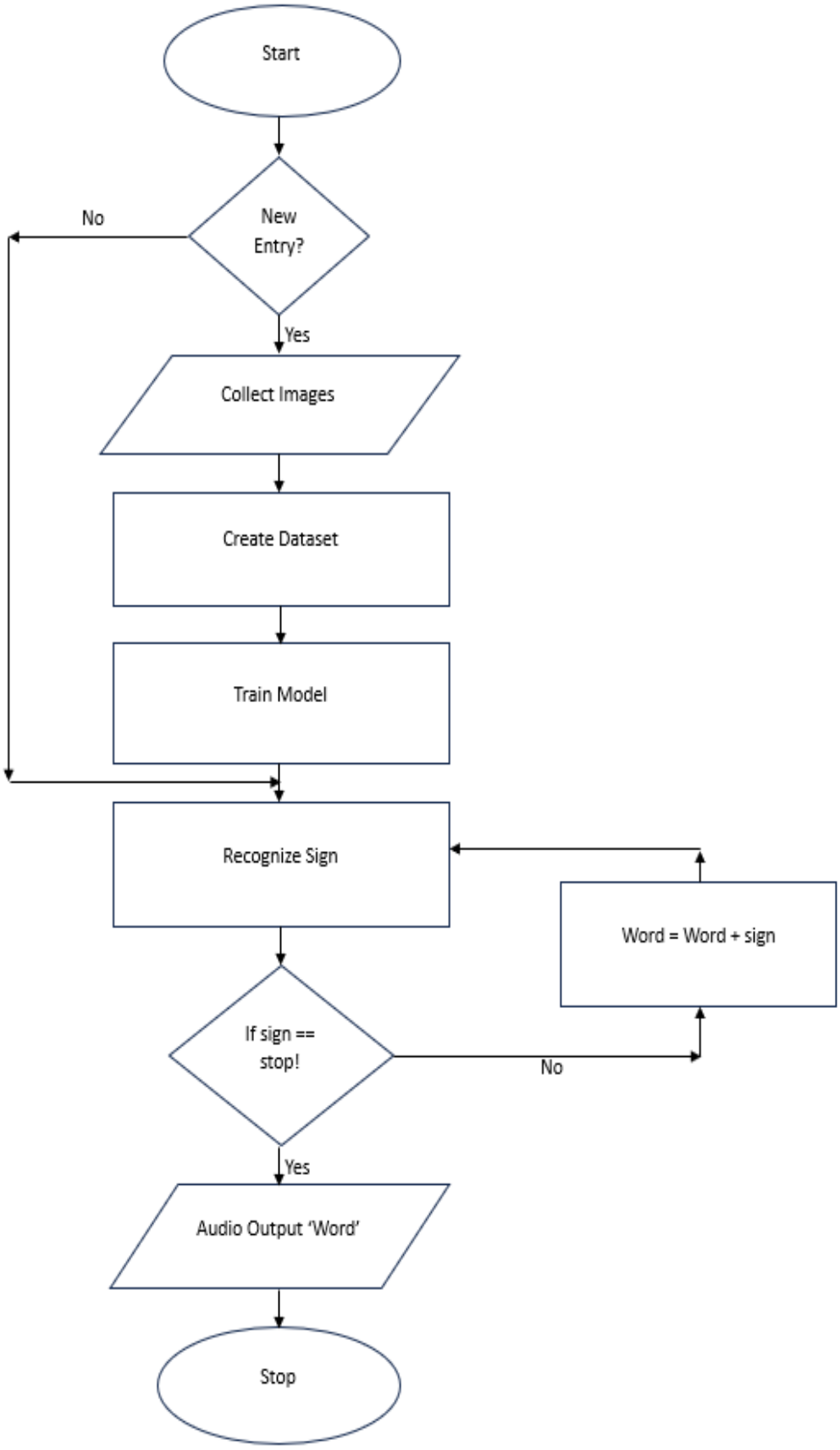
11. Accessibility and Inclusivity:

Sign language recognition systems have the potential to enhance accessibility and inclusivity for deaf or hard-of-hearing individuals. They can be integrated into various communication tools and devices, such as sign language interpretation apps, educational platforms, and smart devices, to facilitate communication and interaction.

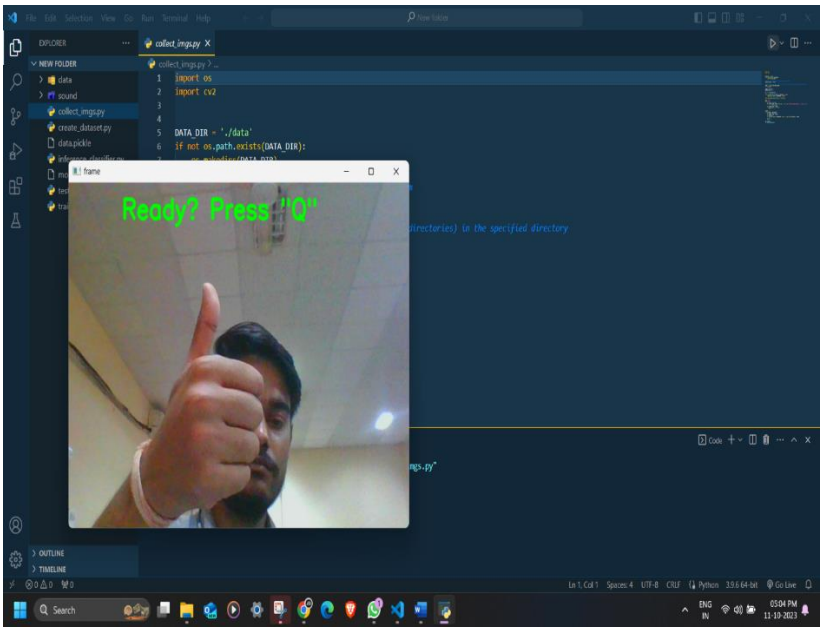
14. Continuous Improvement:

Developing a sign language recognition system is an ongoing process. Continuous data collection, model retraining, and refinement are necessary to improve accuracy, expand the vocabulary of recognized signs, and adapt to different signing styles and languages.

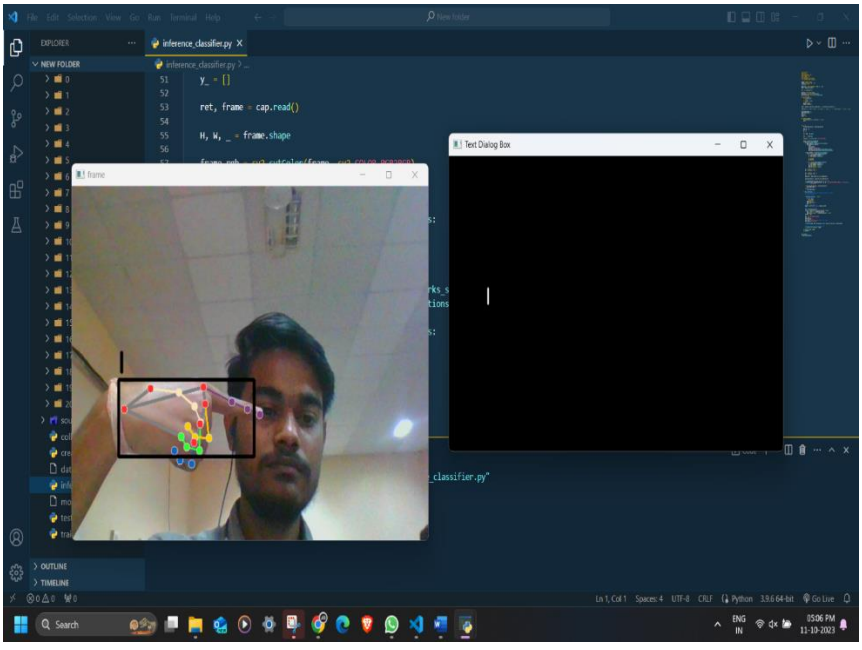
FLOW CHART


Start
New Entry?
No
Yes
Collect Images
Create Dataset
Train Model
Recognize Sign
Word = Word + sign
If sign == stop!
No
Yes
Audio Output 'Word'
Stop

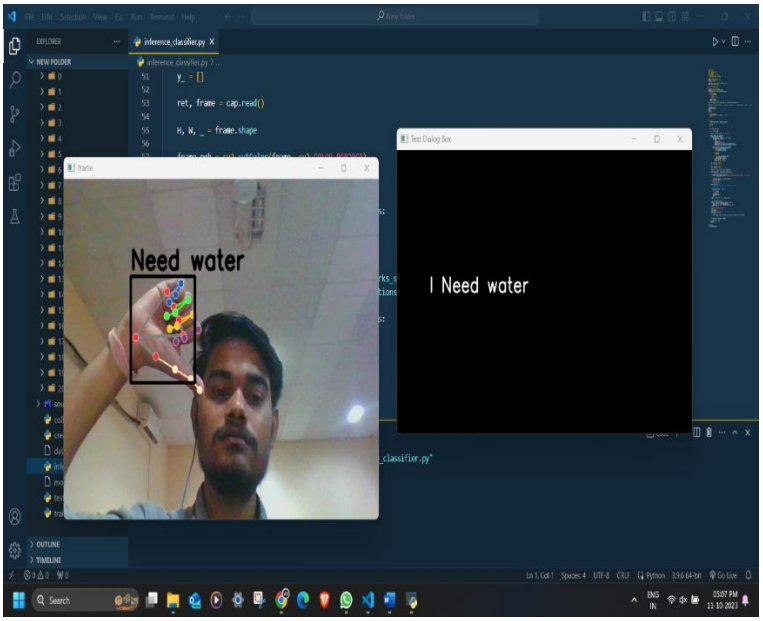
Implementation and Result



In this step, we are required to analyze the best hand position to be captured by pressing ‘Q’

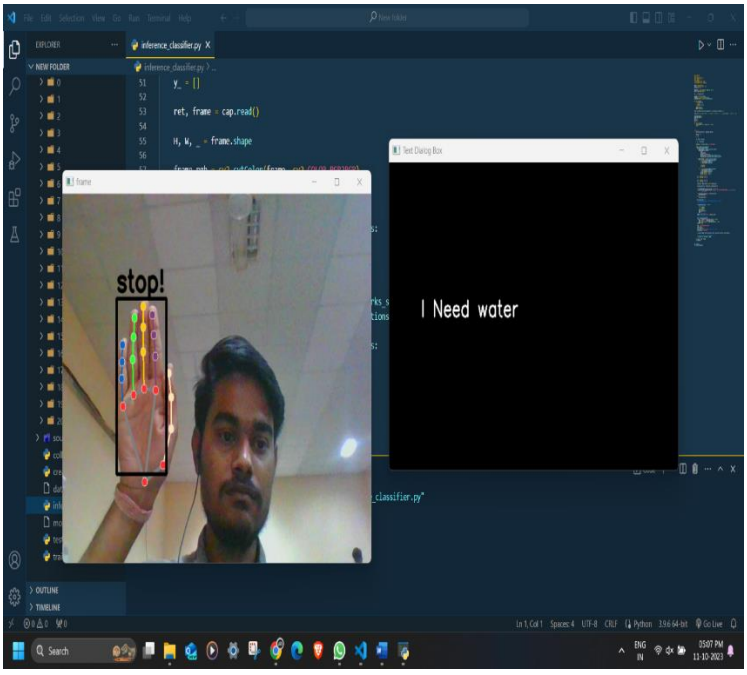


The user is pointing towards himself i.e., he is trying to tell ‘I”

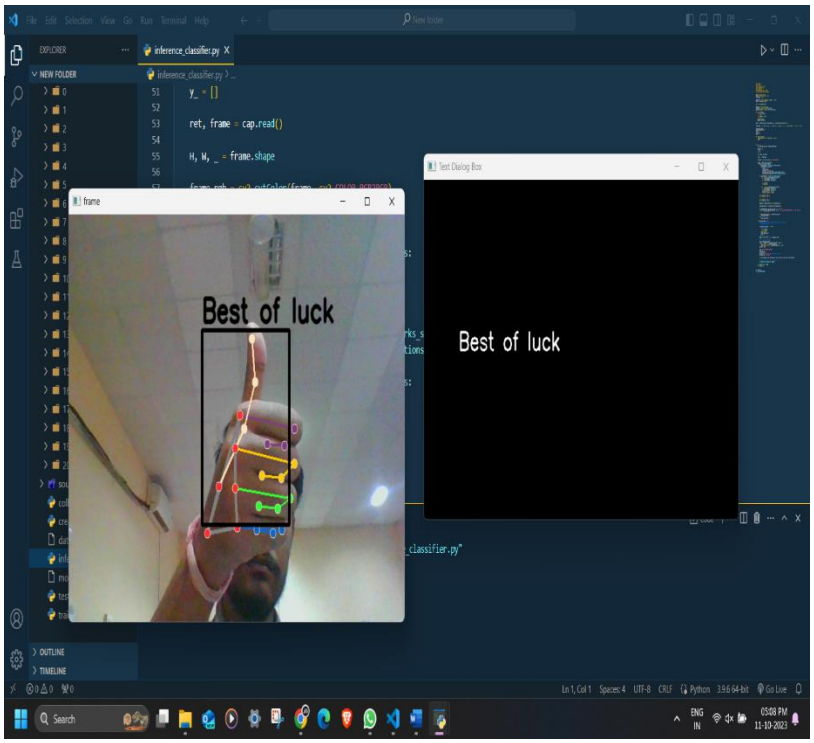


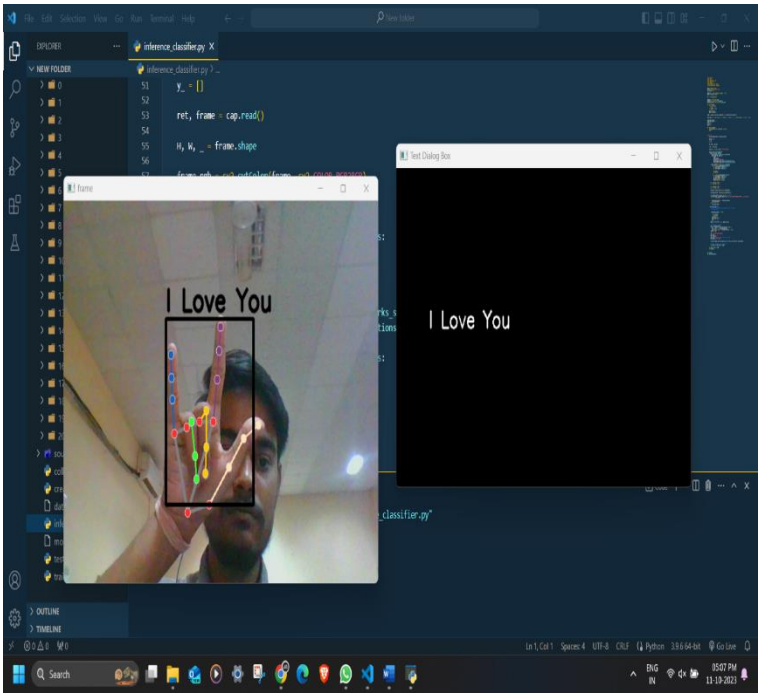
Next the user signals to have to water as what is displayed on the screen

Finally as the user signals to stop recognizing the audio output can be heard



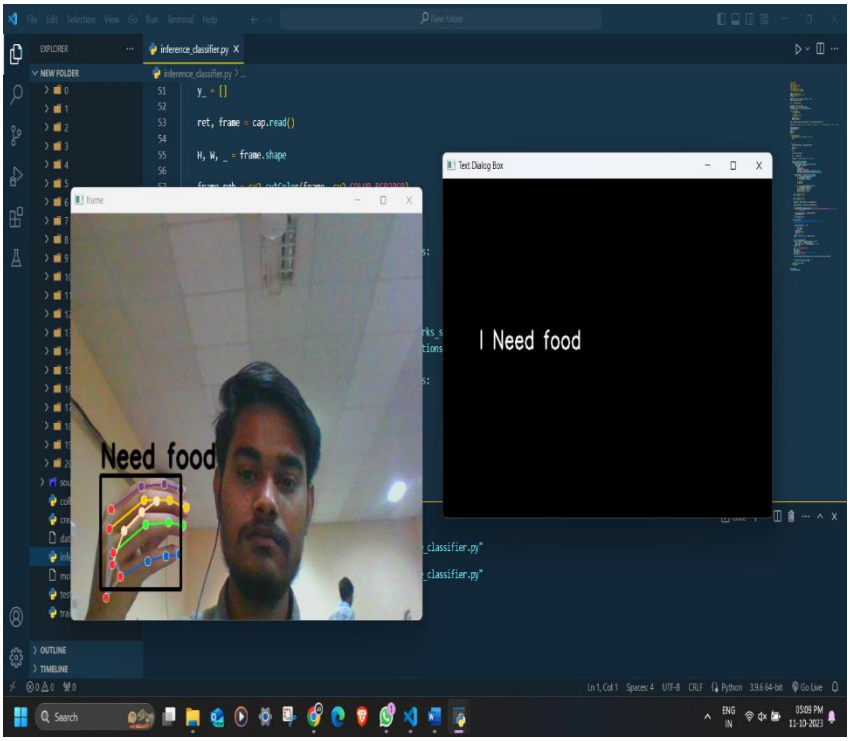
User is showing thumb to signal ‘Best of Luck’





Index, thumb and pinky finger open while others closed to signal ‘I Love You’

All five fingers pointing to mouth to gesture that the user needs food



Conclusion and Future work

Wrapping up our report on sign language gesture recognition is an exciting journey. We've ventured into uncharted territory by creating a custom dataset and integrating a unique audio output for the recognized signs. Through meticulous research and experimentation, we have witnessed the fusion of visual and auditory elements, enhancing accessibility and inclusivity for the deaf and hard of hearing community.

The custom dataset not only addressed the limitations of existing datasets but also paved the way for more accurate and context-aware recognition. The inclusion of static images in the gesture recognition process has opened doors to a new dimension, enabling more nuanced and expressive communication through sign language.

Furthermore, the incorporation of custom audio output is a game-changer, transcending the boundaries of visual recognition. This innovative approach goes beyond mere translation, providing an immersive and dynamic experience for users. The synergy of visual and auditory cues enriches the communication process, fostering a deeper connection between individuals using sign language and those who may not be familiar with it.

As we conclude, our pioneering work in sign language gesture recognition contributes significantly to the advancement of assistive technologies. The journey doesn't end here; there's potential for further refinement, expansion, and real-world applications. Our report serves as a testament to the power of technology in fostering inclusivity, breaking communication barriers, and making strides toward a more accessible future.

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