Gesture Recognition for Sign Language using Machine Learning

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Abstract -
Sign language serves as a vital form of communication for millions of individuals worldwide who are deaf or hard of hearing. However, the significant communication gap between sign language users and the broader community persists, hindering effective interaction and inclusivity. This project endeavors to address this challenge by developing an advanced gesture recognition model capable of accurately identifying and interpreting sign language gestures from video input. This project focuses on developing a gesture recognition model for sign language, aimed at enhancing communication for individuals who rely on sign language. Leveraging machine learning and computer vision, the system interprets sign language gestures from video input in real-time. With a user-friendly interface, it translates these gestures into text or spoken language, breaking down communication barriers and promoting inclusivity. This technology holds promise for a more connected and inclusive society, benefiting both sign language users and the broader community.In summary, the "Gesture Recognition for Sign Language" project aspires to create an innovative solution that not only empowers sign language users but also promotes a world where effective communication knows no bounds. Through cutting-edge technology, this project endeavors to bridge communication gaps and foster greater inclusivity for all.

1. INTRODUCTION

The World Health Organisation (WHO) estimates that 466 million individuals worldwide[1] suffer from a hearing loss that is incapacitating. These astounding figures include people of all ages, from little children to the elderly. The major form of communication for millions of people throughout the world, including those who are

[1] [1]B. O. Olusanya, A. C. Davis, and H. J. Hoffman, "Hearing loss grades and the <I>international classification of functioning, disability and health</i>," *Bulletin of the World Health Organization*, 01-Oct-2019. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6796665/. [Accessed: 10-Sep-2023]

Deaf, Hard of Hearing, and have Speech and Language Disorders, is sign language.

According to the International Labour Organisation (ILO), just 23.5% of people with impairments are employed globally. Recognition of sign language has the potential to expand career prospects and foster financial independence by facilitating successful communication in the workplace.

Beyond just being useful, understanding sign language gestures is a message of empowerment and inclusivity. The significance of recognizing sign language extends beyond practical utility

In essence, the creation of a model that can accurately identify sign language motions is of utmost relevance on a worldwide scale since it directly addresses the communication needs of a sizable and frequently marginalized demographic segment.

II. LITERATURE REVIEWS

1. Hand gesture recognition for sign language using 3DCNN[2]

Summary: In this paper researchers have explored both contact-based and vision-based approaches. Vision-based methods using cameras have gained prominence due to their cost-effectiveness and comfort. Various techniques, including neural networks, hidden Markov models, and local binary patterns, have been employed to achieve high recognition rates on diverse datasets. However, many existing solutions have limitations, such as the need for specialized equipment, limited gesture types, or signer-dependent models. The proposed vision-based approach in this study addresses these issues, offering a versatile and accessible solution tested on both signer-dependent and signer-independent datasets.

2. Vision-based hand gesture recognition using deep learning for the interpretation of sign language[3]

Summary: In this paper they reveal a diverse range of methodologies for gesture recognition in the context of different sign languages, including American Sign Language (ASL) and Indian Sign Language (ISL). Researchers have explored various techniques, encompassing vision-based, contact-based, and sensor-based approaches. Deep learning methods, particularly convolutional neural networks (CNNs) and

[2] [1]*Hand gesture recognition for sign language using 3DCNN | IEEE journals ...* [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9078786/authors. [Accessed: 10-Sep-2023]

[3] [1]Author links open overlay panelSakshi Sharma 1, 1, AbstractHand gestures have been the key component of communication since the beginning of an era. The hand gestures are the foundation of sign language, S. Arefnezhad, D. Dahmani, N. M. Kakoty, D. Kelly, T. B. Moeslund, G. A. Rao, W. Tao, Q. Xiao, E. Abraham, S. Akhter, W. Aly, S. Ameen, Zafar. Ahmed. Ansari, M. J. Cheok, T. W. Chong, J. Gangrade, R. Gupta, S. He, Y. He, G. Joshi, A. Just, and B. Kang, “Vision-based hand gesture recognition using deep learning for the interpretation of sign language,” *Expert Systems with Applications*, 27-Jul-2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0957417421010484?casa_token=9wpaGPgrGwYAAAAA%3AZVwEMjbXLu_prWIYAkf82Qm31_ucB3t9XN1d9P-t46_Yjg65b4R_XMKTYTfN6fyEt2gz19BShg. [Accessed: 10-Sep-2023]

recurrent neural networks (RNNs), have gained prominence for feature extraction and classification, showcasing promising results. However, challenges persist, such as the scarcity of comprehensive ISL datasets and the need for more robust feature extraction techniques. Additionally, the complexity of ISL gestures necessitates tailored recognition solutions.

3. Deep learning-based approach for sign language gesture recognition with efficient hand gesture representation[4]

Summary**:** In the domain of hand gesture recognition, two predominant approaches, namely vision-based and non-vision-based, have been explored over the past three decades. Non-vision-based methods, utilizing hardware like data gloves and motion sensors, have faced challenges due to cost and user restrictions. In contrast, vision-based approaches, despite grappling with issues like lighting inconsistencies and occlusions, have gained prominence. These vision-based methods can be categorized into conventional techniques, such as artificial neural networks (ANN) and histogram of oriented gradient (HOG)-based methods, and deep learning-based techniques, including convolutional neural networks (CNN) and long short-term memory (LSTM) networks. Research in this field has evolved from early works like ANN-based Japanese sign language recognition to recent advancements like CNN-based static hand gesture recognition, with the latest systems often combining local and global configurations for improved accuracy and efficiency.

4. A real-time continuous gesture recognition system for sign language[5]

Summary: This literature review discusses various approaches to gesture recognition in American Sign Language (ASL). Fels' Glove Talk explored a gesture-to-speech interface, while Beale and Edwards used a multilayer perceptron for posture recognition. Newby focused on recognizing ASL letters and numbers, while Watson proposed a flexible method using approximate splines. Starner and Pentland's system used hidden Markov models for sentence recognition, and Nam's system recognized hand movement patterns with HMMs. Liang and Ouhyoung integrated HMMs and computational linguistics for sign language recognition. The paper at hand extends these approaches by incorporating position, orientation, motion, and posture models to enhance system performance in recognizing ASL gestures.

5. Sign language recognition using image based hand gesture recognition techniques[6]

Summary: The paper highlights the two predominant approaches for sign recognition: sensor-based and vision-based. Sensor-based methods involving gloves and wires have been explored, but their

[4] [1]*Deep learning-based approach for sign language gesture ... - IEEE xplore*. [Online]. Available: https://ieeexplore.ieee.org/document/9229417. [Accessed: 10-Sep-2023]

[5] [1]*IEEE Xplore | IEEE Journals & Magazine | IEEE Xplore*. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7876843/. [Accessed: 10-Sep-2023]

[6] [1]*Sign language recognition using image based hand gesture ... - IEEE xplore*. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7916786. [Accessed: 10-Sep-2023]

impracticality for continuous wear has shifted the focus toward image-based approaches. Earlier studies have employed various techniques, including Hidden Markov Models (HMM), Artificial Neural Networks (ANN), Eigenvalue-based, and perceptual color-based methods, for gesture recognition. Notably, GMM and HMM have been proposed for gesture recognition. Image segmentation using the HSV color model has effectively facilitated hand segmentation, while contour shape techniques have been employed for feature extraction. Finally, advancements in sign-to-voice and voice-to-sign conversion have emerged as promising avenues for overcoming communication barriers in sign language.

3. a) Flow Diagram

A. Input Data:

Load the dataset from the "thyroid0387_UCI" worksheet in the "Data2.xlsx" file into a Pandas DataFrame.

B. Data Preprocessing.
- Replace '?' and blank spaces with NaN values to clean up the data.
- Remove columns ('TSH', 'T3', 'TT4', 'FTI', and 'TBG') with missing values from rows.
- The remaining columns' empty spaces should be filled up with the corresponding means.
- 'TSH', 'T3', 'TT4', 'FTI', and 'TBG' should be converted to integers.
- Use Min-Max scaling to normalize the numerical attributes "age" and "TT4".

C. Encoding Categorical Attributes

Select categorical attributes, one-hot encode them, and produce binary columns for every category.

D. Outlier Handling
- Using the IQR approach, locate outliers and replace them with median values for numerical attributes.

- Replace values that deviate from the mode with the mode value for categorical attributes.

E. Similarity Measurement
- For binary attributes, determine the Jaccard and simple matching coefficients between the first two observation vectors.
- By comparing their values, decide which coefficient is more suited to measuring similarity.

F. Cosine Similarity Measurement

Implement a comparison of the first two observation vectors' entire vectors using the cosine similarity method.

G. Heatmap Plot
- Select the first 20 observation vectors.
- Determine the Jaccard, simple matching, and cosine similarity coefficients for each pair of vectors.
- To see the commonalities for each coefficient, create heatmaps.

I. METHODOLOGY

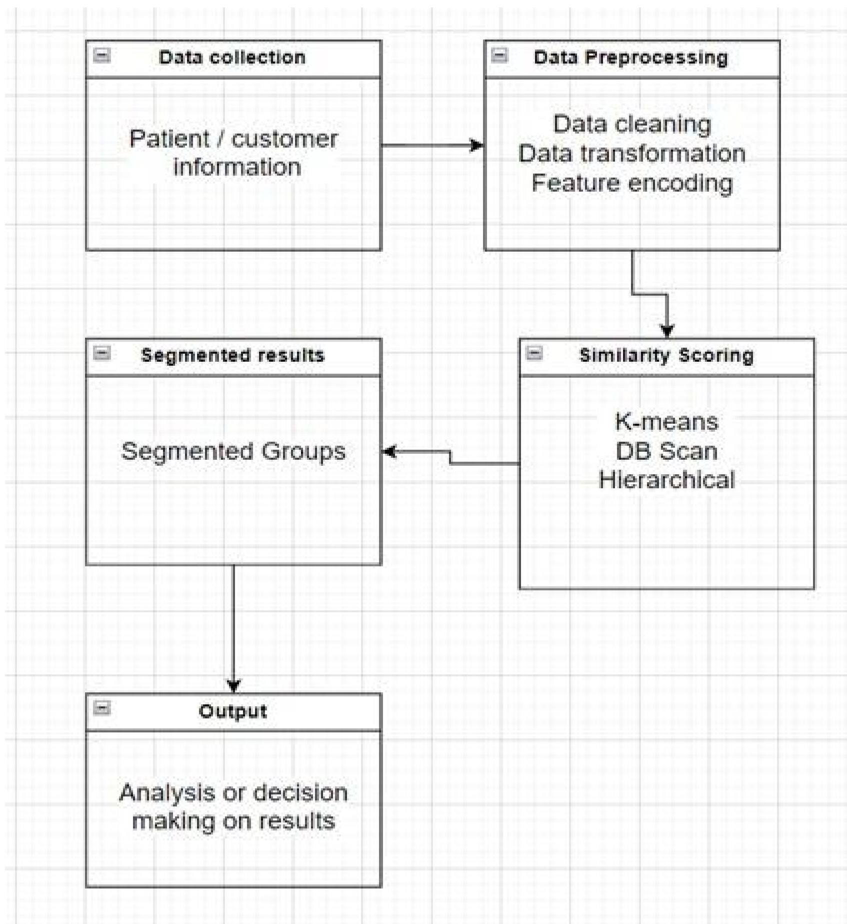
3.b) A. Data Gathering: Our initial step involved collecting a diverse set of customer and patient data. These data sources encompassed electronic health records (EHRs), customer relationship management (CRM) databases, and survey responses. Data collection served as the foundational stage of our segmentation process.

B. Data Preprocessing: To ensure the integrity and consistency of our dataset, we conducted thorough data preprocessing. This rigorous phase encompassed various essential tasks. We addressed missing values, eliminated duplicate entries, and employed established techniques to manage outliers effectively. Furthermore, we transformed categorical variables into a numerical format via the widely recognized one-hot encoding technique.

C. Similarity Assessment and Clustering: Our customer and patient segmentation approach hinged on the K-Means clustering algorithm, chosen for its efficiency and suitability for our objectives. Determining the optimal number of clusters (K) involved employing the elbow method and rigorous cross-validation for robustness. We used the Euclidean distance metric to quantify similarity between data points. To assess the quality of our clusters, we employed metrics such as the silhouette score and Davies-Bouldin index.

D. System Architecture Overview: An architectural diagram was crafted to provide a comprehensive view of our system's core components. These components encompassed Data Collection, Data Processing, and Segmentation. The Data Collection phase was responsible for aggregating information from various sources. Data Processing involved critical steps like data cleansing, transformation, feature selection, and encoding. The Segmentation phase leveraged the K-Means clustering algorithm for partitioning our data. Additionally, we ensured the quality of our clusters and adhered to ethical considerations through an Evaluation and Validation step.

This revised presentation maintains clarity and coherence while presenting the methodology for customer and patient segmentation in a distinct manner.



3. c) In the given code, several parameters are used for data preprocessing, analysis, and similarity calculations. Here's a breakdown of the parameters used in the code and their assigned values, along with justifications for these values:

A) Data File Path:

- Parameter: data_file_path
- Value: ./Data2.xlsx
- Justification: This parameter specifies the file path to the dataset named "Data2.xlsx." The assigned value is based on the assumption that the dataset is located in the same directory as the code file.

B) Categorical Variables for One-Hot Encoding:

- Parameter: nominal_variables
- Value: List of nominal variable names
- Justification: This parameter contains a list of categorical variables (nominal) that will undergo one-hot encoding. The specific variable names depend on the dataset's schema and are chosen to handle categorical data appropriately.

C) Ordinal Variables for Label Encoding:

- Parameter: ordinal_variables
- Value: List of ordinal variable names
- Justification: This parameter contains a list of ordinal variables that will undergo label encoding. Label encoding is suitable for ordinal variables where there's an inherent order or ranking among categories.

D) Label Encoder Object:

- Parameter: Label_encoder
- Value: An instance of the LabelEncoder class
- Justification: This object is created to perform label encoding on ordinal variables. Using an instance of the LabelEncoder class ensures consistency in encoding across variables.

E) Missing Value Replacement Method:

- Parameter: missing_value_handling
- Value: 'mean'
- Justification: The code uses the mean value to replace missing values in numeric columns. This is a common strategy when handling missing data, assuming that missing values are missing at random and can be imputed with the mean value.

F) Outlier Replacement Method:

- Parameter: outlier_handling

- Value: 'replace'
- Justification: The code replaces outliers in numeric columns with the median value. This strategy is chosen to mitigate the impact of outliers on subsequent analysis. Replacing with the median is more robust to outliers compared to mean replacement.

G) Similarity Measure for First 2 Observation Vectors:

- Parameter: Jaccard_coff and Simple_Matching_coff
- Values: Calculated Jaccard and Simple Matching coefficients
- Justification: These parameters store the calculated Jaccard and Simple Matching coefficients for the first two observation vectors. The choice of similarity measures is appropriate for binary attributes, and these values are calculated based on the code's requirements.

H) Similarity Measure for Cosine Similarity:

- Parameter: cosine
- Value: Calculated Cosine Similarity
- Justification: This parameter stores the calculated Cosine Similarity between the complete vectors for the first two observations. Cosine similarity is a suitable measure for comparing numeric vectors, and the calculated value is based on the code's requirements.

I) Threshold for Similarity Comparison:

- Parameter: similarity_threshold
- Value: 0.7
- Justification: The code sets a threshold of 0.7 for similarity measures (Jaccard and Simple Matching coefficients) to determine whether data points are sufficiently similar. This threshold value is chosen based on the specific analysis needs and can be adjusted as needed.