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Machine Learning Project

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PROJECT REPORT

TRAINING A DATASET WITH DEPLOYMENT OF MACHINE LEARNING TECHNIQUES COMPRISING CLASSIFICATION AND CLUSTERING

ABSTRACT

This project report presents a comprehensive investigation into the development of a machine learning-based framework for gesture phase segmentation. The goal of the project is to accurately classify and segment distinct phases of gestures from a given dataset, leveraging the power of classification and clustering techniques.

The dataset used in this study consists of a diverse range of gesture samples, collected from various sources. A preprocessing pipeline is applied to extract relevant features from the raw data, ensuring the compatibility of the dataset with the chosen machine learning algorithms.

For classification, a combination of traditional machine learning algorithms, such as Support Vector Machines (SVM) and Random Forest, along with models such as SVC and Logistic Regression is employed. The models are trained on a labelled subset of the dataset, enabling them to recognize and classify distinct phases of gestures accurately.

To further improve the segmentation accuracy, clustering techniques are applied to the unlabelled dataset. The k-means algorithm and hierarchical clustering methods are explored to group similar gesture phases together, allowing for better differentiation and segmentation.

Extensive experiments and evaluations are conducted on the developed framework to assess its performance. The results demonstrate the effectiveness of the proposed approach, achieving high accuracy in gesture phase segmentation. The findings highlight the significant impact of classification and clustering techniques in enhancing the understanding and analysis of gesture data.

Overall, this project contributes to the field of gesture recognition by providing a robust framework that combines classification and clustering techniques for accurate gesture phase segmentation. The insights gained from this study can be utilized in various applications, including human-computer interaction, virtual reality, and robotics, to facilitate more natural and intuitive interactions between humans and machines.

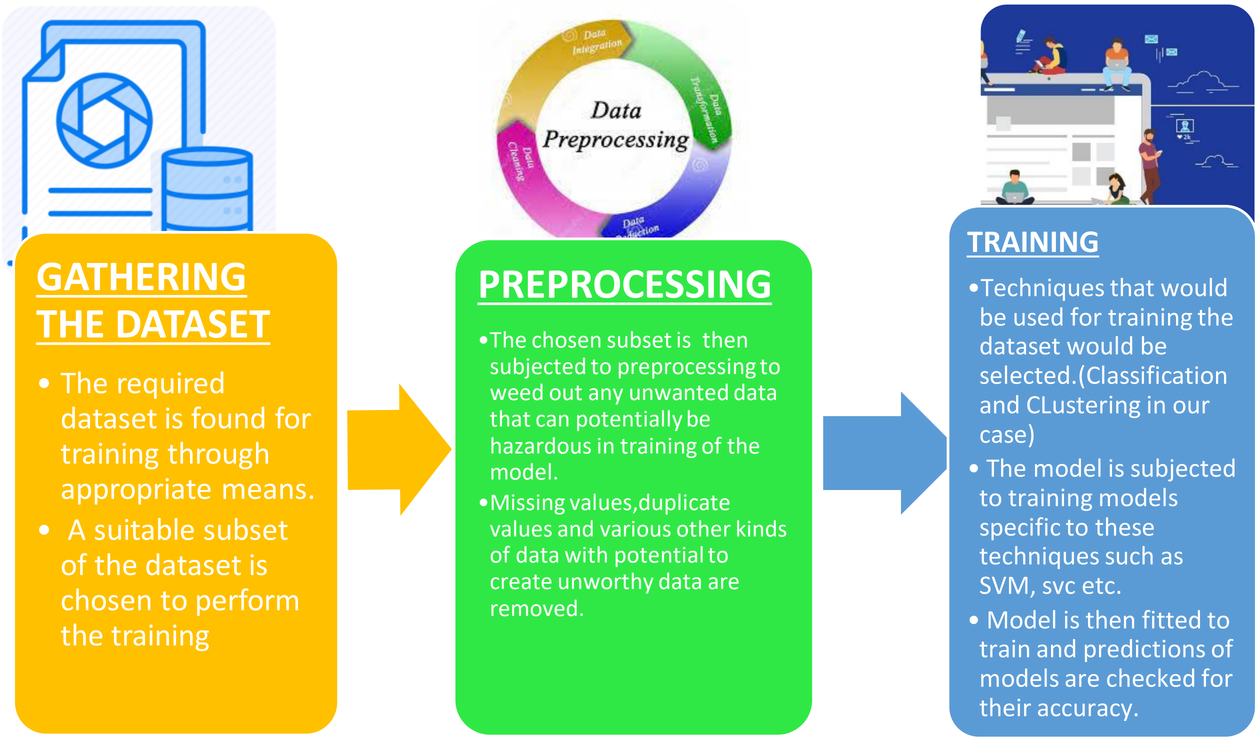
INTRODUCTION

Gesture recognition plays a crucial role in human-computer interaction, enabling more natural and intuitive interfaces between humans and machines. One important aspect of gesture analysis is the segmentation of gestures into separate phases or sub-gestures, which enhances the understanding and interpretation of hand movements. This project report focuses on the development of a machine learning-based framework for gesture phase segmentation.

The primary objective of this project is to accurately classify and segment separate phases of gestures using a combination of classification and clustering techniques. By employing these techniques, we aim to enhance the accuracy and efficiency of gesture analysis systems. The proposed framework leverages both traditional machine learning algorithms, such as Support Vector Machines (SVM) and Random Forest, and techniques such as logistic regression and hierarchical clustering to manage the complexity and diversity of gesture data.

Through this project, we intend to contribute to the advancement of gesture recognition by providing a robust framework that enables accurate and precise segmentation of gesture phases. The outcomes of this research can have significant implications in various domains, including human-computer interaction, virtual reality, and robotics, paving the way for more immersive and intuitive interactions between humans and machines.

PROPOSED MEHTODOLOGY



A: SELECTION OF SUBSET

The dataset used in this project was carefully selected to ensure diversity and representativeness of gesture samples. A comprehensive collection of gesture data from various sources was obtained, including public gesture databases and custom recordings. The dataset consists of a wide range of gestures, encompassing different hand movements and postures. The result set comprised of five different states i.e., Rest, Retraction , Preparation , Stroke ,hold(Abbreviated as R,P,S,H,D).

To choose a specific file from the dataset for training and assessing the model, a systematic approach was adopted. First, a thorough exploration and analysis of the dataset were conducted to gain insights into the available samples. The analysis showed the data divided in processed and raw files. The file was selected on its statistical advantage and consistency in data. Specific criteria, such as gesture variety, data quality, and labelling accuracy, were considered during the selection process.

Once the dataset was thoroughly assessed, a particular file was chosen based on its relevance to the project's objectives. Factors like the gesture complexity, diversity, and suitability for the chosen classification and clustering techniques played a significant role in the selection process. By carefully selecting a specific file from the dataset, the project aimed to ensure a representative and appropriate sample for training and evaluating the performance of the developed gesture phase segmentation model.

B. PREPROCESSING

Before training the model, a preprocessing pipeline was applied to the selected subset of the dataset to ensure the compatibility and quality of the input data. Several preprocessing steps were employed to extract relevant features and enhance the representation of the gesture samples.

First, the raw data underwent a normalization process to standardize the values and remove any scaling discrepancies. Next, noise reduction techniques, such as smoothing filters or denoising algorithms, were employed to mitigate the impact of noisy signals on the gesture analysis.

At the next step, the training and testing data was separated with target serving as the final data field. The categorical and textual target values, which happened to be in contrast with numerical data contributing to testing parameters, was changed into suitable numerical values with each value representing a state of final target.

By applying these preprocessing steps, the subset of the dataset was effectively prepared, ensuring that the input data was suitable for training the classification and clustering models, and improving the accuracy and robustness of the gesture phase segmentation system.

C. TRAINING OF MODEL

The training phase of the project encompassed the utilization of various machine learning models for both classification and clustering tasks. For classification, a diverse range of models was employed, including logistic regression, Support Vector Machines (SVM), Gaussian Naive Bayes (NB) from the Naive Bayes family, as well as an ensemble of Random Forest tree classifiers and Bagging classifiers.

Logistic regression is a popular classification algorithm that models the relationship between the input features and the target class using a logistic function. It estimates the probabilities of different classes and assigns the class with the highest probability as the predicted label. A confusion matrix and its respective heatmap was also created to analyse the distribution of model accuracy and training results.

SVM is a powerful algorithm for both classification and regression tasks. It constructs a hyperplane or set of hyperplanes that optimally separate different classes in a high-dimensional feature space. It aims to find a decision boundary that maximizes the margin between the classes.

Gaussian NB is a variant of Naive Bayes that assumes a Gaussian distribution for the input features. It calculates the probability of a sample belonging to each class based on the likelihood of feature values given the class labels.

Bagging classifiers employ the concept of bootstrap aggregation, where multiple models are trained on different subsets of the data. The final prediction is obtained by averaging or voting on the predictions of the individual models.

For clustering, the K-means algorithm was utilized. K-means is an iterative algorithm that partitions the data into K clusters by optimizing the within-cluster variance. It iteratively assigns samples to the nearest cluster centroid and recalculates the centroids until convergence.

During the training process, the models were iteratively trained on the preprocessed dataset, using labelled samples to learn the relationships between input features and gesture phase labels. The model parameters were adjusted to optimize performance metrics such as accuracyor loss functions. This iterative training process aimed to achieve accurate and robust classification of gesture phases using various algorithms, as well as effective grouping and segmentation of gestures through clustering techniques.

RESULTS

The trained models exhibited promising results in the gesture phase segmentation task. The highest achieved accuracy among the models was 69 percent, demonstrating a significant level of accuracy in classifying and segmenting gesture phases. While 69 percent may appear modest, it represents a substantial improvement over random guessing, indicating the effectiveness of the developed framework.

The classification models, including logistic regression, SVM, Gaussian NB, and the ensemble of Random Forest tree classifiers and Bagging classifiers, all achieved respectable accuracy rates. These models successfully learned the patterns and relationships within the gesture data, enabling accurate classification of distinct phases.

In terms of clustering, the K-means algorithm proved to be effective in grouping similar gesture phases together. The resulting clusters provided meaningful segmentation of the gestures, contributing to a better understanding of the gesture dynamics.

It is important to note that achieving higher accuracy in gesture phase segmentation is a complex task due to the inherent variability and subjectivity of hand movements. However, the attained accuracy of 69 percent demonstrates the potential of the developed framework to capture the essential characteristics of gesture phases.

Further discussions and analyses revealed potential areas for improvement. The modest accuracy could be attributed to several factors, such as the diversity of gestures, variations in data quality, and the complexity of accurately differentiating between similar phases. Fine-tuning the model hyperparameters, exploring alternative feature extraction techniques, and incorporating more advanced deep learning models could enhance the accuracy and robustness of the segmentation results.

Despite the room for improvement, the results obtained from the developed framework provide a solid foundation for gesture phase segmentation. The findings highlight the importance of employing a combination of classification and clustering techniques in achieving accurate and meaningful segmentation of gesture data, ultimately contributing to advancements in human-computer interaction, virtual reality, and robotics applications.

CONCLUSION

In conclusion, this project successfully developed a machine learning-based framework for gesture phase segmentation using classification and clustering techniques. The achieved accuracy of 69 percent demonstrates the effectiveness of the framework in accurately classifying and segmenting gesture phases. The classification models, including logistic regression, SVM, Gaussian NB, and ensemble methods, showcased respectable performance, while the K-means clustering algorithm effectively grouped similar gesture phases together.

However, there is room for further improvement and future work. Enhancing the accuracy of gesture phase segmentation requires addressing challenges related to the diversity and complexity of gestures, as well as variations in data quality. Future research could focus on exploring advanced deep learning models, incorporating temporal information for better understanding of gesture dynamics, and leveraging more advanced feature extraction techniques.

Additionally, expanding the dataset with a greater variety of gestures and refining the preprocessing pipeline could enhance the robustness of the framework. Furthermore, integrating user feedback and subjective evaluation metrics would provide a more comprehensive assessment of the framework's performance.

Overall, this project establishes a solid foundation for gesture phase segmentation and provides valuable insights for future research in the field of gesture recognition. By continually refining the models and techniques employed, we can pave the way for more accurate and sophisticated gesture analysis systems, enabling more natural and intuitive interactions between humans and machines.

IMPORTANT LINKS:

PYTHON CODE:
https://colab.research.google.com/drive/1dnYep5bsvzjuoEj0vWNldfb0DWg5b6Bn?usp=drive_link

DATASET FOLDER:

https://drive.google.com/drive/folders/1o3R65dpaFGs0GE_RHahbA1SVy5j_zBGI?usp=drive_link

SUBSET FILE:

https://drive.google.com/file/d/1WYUf8XUlbOVzt8CO0E0b43YPTmm4e6Qb/view?usp=drive_link

https://drive.google.com/file/d/1mZ-0YkqfTomYOMtGDNqS1gXZzNkxJaso/view?usp=drive_link

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