**MACHINE LEARNING PROJECT**

**ABSTRACT**

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**SIGN LANGUAGE RECOGNITION**

**Abstract:**

The Sign Language Recognition project aims to develop model that identify hand gestures in American Sign Language (ASL) using image inputs. The dataset consists of images of hands performing signs, annotated with labels for letters A-Z. The project utilizes computer vision and machine learning techniques, specifically neural networks, to enable real-time recognition of sign language gestures. The ultimate goal is to create an application that predict the sign language, thereby enhancing communication between the deaf and hard-of-hearing community and non-signers, promoting inclusivity and accessibility.

**Problem Statement:**

To develop a machine learning-based system for predicting and identifying sign language gestures in real-time. Using image data, the system will recognize hand gestures and translate them into letters, facilitating communication between signers and non-signers.

**Objective:**

The system aims to bridge the communication gap between signers and non-signers by providing a fast, accurate, and user-friendly tool for translating sign language into text in real time. Current solutions for real-time sign language translation are limited, leading to a need for an accessible, efficient system that can predict and translate signs into text.

**Dataset:**

* **Dataset Link:** [**hand\_sign\Data**](hand_sign/Data)
* **Dataset Description:**

The dataset used for this project is focused on American Sign Language (ASL) hand gestures, including representations for the 26 alphabetic letters (A-Z) .This type of dataset is often employed to train machine learning models for sign language recognition tasks.

**Key Features:**

* Images:

Format: The dataset consists of image files representing hand gestures. Images are typically in common formats like PNG or JPEG.

Resolution: Images might have varying dimensions, but for model training, they are resized to a fixed resolution (e.g., 64x64 pixels or 128x128 pixels).

Channels: The images are usually in RGB (3 color channels), but depending on the dataset, they may also be in grayscale.

* Classes (Labels):

Number of Classes: The dataset includes 36 distinct classes representing:

26 letters: A-Z, each represented by a unique hand gesture.

Class Distribution: Each class contains multiple images (hundreds), capturing the variability in hand positioning, background, and lighting conditions.

* Image Augmentation:

To improve model robustness, additional augmentations may be applied, such as:

Rotation: Small rotations to simulate real-world variation in hand orientation.

Zooming: Zoom-in and zoom-out operations to simulate different distances between the hand and the camera.

Flipping: Horizontal flipping to capture mirrored gestures.

Brightness Adjustment: Adjusting brightness to simulate different lighting conditions.

* Target Feature:

The target or label for each image is the corresponding letter (A-Z). This is a categorical feature, meaning the task is a multi-class classification problem.

**Approach (Methodology) :**

The methodology involves analyzing images of hands performing American Sign Language (ASL) gestures, labeled with corresponding letters (A-Z). The first steps include conducting exploratory data analysis (EDA) on the dataset to understand the distribution of sign categories and variations in hand positioning. Image preprocessing techniques such as resizing, normalization, and data augmentation (e.g., rotation, flipping) will be applied to prepare the data. Feature extraction will be performed using convolutional neural networks (CNNs) to automatically identify relevant patterns in the images. Different models, including CNNs, transfer learning models (such as ResNet), and traditional classifiers like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), will be explored for classifying the hand gestures.

### Key Results :

Initial models will use extracted features from the images to classify hand gestures into their respective letters and numbers. Feature importance and model performance will be analyzed to determine which aspects of the hand gestures (e.g., contours, positioning) contribute the most to accurate classification. The models will be evaluated based on their ability to correctly classify the signs, and tested for generalizability across different hand sizes, orientations, and lighting conditions to ensure robust performance in real-world settings.

**Machine Learning Techniques:**

* Data Pre-processing:

Handle missing values in the dataset.

Normalize image pixel values to the range [0, 1].

Apply data augmentation (e.g., rotation, flipping) to increase variability.

Split the dataset into training, validation, and testing sets.

* Exploratory Data Analysis (EDA):

Analyze the distribution of images per class (A-Z and 0-9).

Visualize sample images to assess variability.

Examine features that contribute to accurate predictions.

* Classification Models:

Convolutional Neural Networks (CNNs): The primary model for image classification.

Transfer Learning: Utilize pre-trained models (e.g., VGG16, ResNet) for improved performance.

Additional Techniques: Consider using K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) for additional comparisons.

* Model Evaluation:

Use metrics like Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.Implement k-fold cross-validation for robust performance assessment.

* Hyperparameter Tuning:

Perform grid search to optimize hyperparameters (e.g., learning rate, batch size).Optionally use random search for efficient tuning.

**Conclusion (Impact):**

The development of a real-time sign language recognition system could transform communication for the deaf and hard-of-hearing community by providing an accessible and scalable tool for interpreting hand gestures into text. This project could lead to improved social integration and foster inclusivity in environments such as education, healthcare, and public services. In the long term, automated sign language recognition systems have the potential to bridge communication gaps between signers and non-signers, promoting greater awareness and understanding of sign language, while enabling more seamless interactions in both personal and professional settings.