KSL-FINGERSPELLING-RECOGNITION

1. Business Understanding:

Overview:

Fingerspelling, a technique that utilizes hand formations to represent words and letters, plays a vital role in communication for individuals who are deaf or hard of hearing. However, merging this manual communication method with modern technology, such as smartphones, poses challenges as fingerspelling is typically faster than device recognition. Bridging this gap between fingerspelling and smartphone typing is crucial to improve communication accessibility..

Problem Statement:

The deaf and hearing impaired community encounters significant communication barriers with the rest of society. The lack of widespread understanding of sign language among the general population results in difficulties and breakdowns in communication. To tackle this issue, this project aims to develop a Convolutional Neural Network (CNN) model specifically designed for fingerspelling recognition. The model will enable accurate identification of individual letters and complete words in different sign languages. By enhancing the recognition of fingerspelling gestures, the model aims to improve communication accessibility for individuals who are deaf or hard of hearing, promoting inclusivity and effective communication with the broader society.

Objectives:

Main Objective:

The main objective of this project is to create an innovative machine learning model that acts as a vital bridge, connecting the deaf and mute community with the wider society by translating fingerspelling images to text.

Specific Objectives:

1. Develop a Convolutional Neural Network (CNN) model specifically designed for fingerspelling recognition in different sign languages.
2. Train the model using a large dataset of fingerspelling gestures in various sign languages, ensuring accuracy and reliability in recognizing individual letters and complete words.
3. Conduct extensive testing and evaluation to assess the model's performance and accuracy in recognizing fingerspelling gestures across different sign languages.
4. Deploy the model to facilitate real-time fingerspelling recognition and translation, enabling improved communication accessibility for individuals who are deaf or hard of hearing.

By achieving these objectives, the project aims to contribute to breaking down communication barriers, promoting inclusivity, and fostering effective communication between the deaf community and the broader society.

2. Data Understanding:

The dataset used in this project consists of fingerspelling gesture images in Kenyan Sign Language (KSL). The dataset is a combination of a publicly available Kaggle dataset and a custom dataset collected specifically for this project.

- **Kaggle Dataset**: The project utilized a publicly available dataset sourced from Kaggle. The dataset is based on the Kenyan Sign Language letter database, comprising 24 classes of letters, excluding J and Z. This dataset provided a foundational resource for the project's fingerspelling recognition model.
- **Custom Dataset**: To augment the Kaggle dataset and address potential limitations, the project team conducted a separate data collection effort. The custom dataset was collected by the project team themselves, involving the capture of high-quality images of fingerspelling gestures in KSL. This custom dataset aimed to provide a more comprehensive and diverse set of fingerspelling gesture images for training and evaluation.

By combining the Kaggle dataset and the custom dataset, the project aimed to leverage both resources and enhance the model's ability to recognize fingerspelling gestures accurately in KSL.

3. Data Preparation:

During the data preparation phase, the following tasks were performed:

- **Data Cleaning**: The Kaggle dataset was checked for duplicates and inconsistencies to ensure data quality and reliability.
- **Image Processing**: The custom dataset images underwent preprocessing techniques to enhance their quality, remove noise, and standardize them for further analysis and model training.

4. Exploratory Data Analysis (EDA):

The analysis conducted on the data included the following:

- **Previewing Images:** The dataset was visually explored to gain insights into the fingerspelling gestures' characteristics, such as hand shapes, finger positions, and movements.
- **Univariate Analysis**: An analysis of the labels was performed to understand the distribution of individual letters in the dataset and identify any potential class imbalance issues.

5. Modeling:

The models developed for fingerspelling recognition in KSL include:

- **Dense Neural Network:** This model was trained using the preprocessed fingerspelling gesture images and their corresponding labels. The dense neural network architecture was chosen for its ability to capture complex patterns and relationships within the data.
- **Convolutional Neural Network (CNN)**: The CNN model, specifically designed for image recognition tasks, was trained using the raw fingerspelling gesture images. The CNN architecture leveraged convolutional layers to learn spatial features and improve the model's ability to recognize fingerspelling gestures.

6. Evaluation:

The success metric used to evaluate the models was accuracy. Both the dense neural network and the CNN model were evaluated on a validation set. The model with the highest accuracy was selected as the best performing model for fingerspelling recognition in KSL.

7. Challenges:

- The dataset was relatively small, which could have limited the accuracy of the model.
- The images in the dataset were not of uniform quality, which could have also affected the accuracy of the model.
- The hand gestures in the dataset were limited to the 24 letters of the Kenyan Sign Language, which means that the model would not be able to recognize fingerspelling for other letters or words.

8. Conclusions:

- Despite the challenges, the model was able to achieve a high accuracy of above 90% on the test dataset.
- The model could be used to improve communication for deaf and hard of hearing individuals, as it would allow them to communicate more easily with people who do not know sign language.

9. Recommendations:

- The dataset could be expanded to include more images of fingerspelling gestures, which would improve the accuracy of the model.
- The images in the dataset could be improved in terms of quality, which would also improve the accuracy of the model.
- The model could be extended to recognize fingerspelling for other letters and words, which would make it more versatile.
- The model could be integrated with other technologies, such as speech recognition, to provide a more comprehensive communication solution for deaf and hard of hearing individuals.