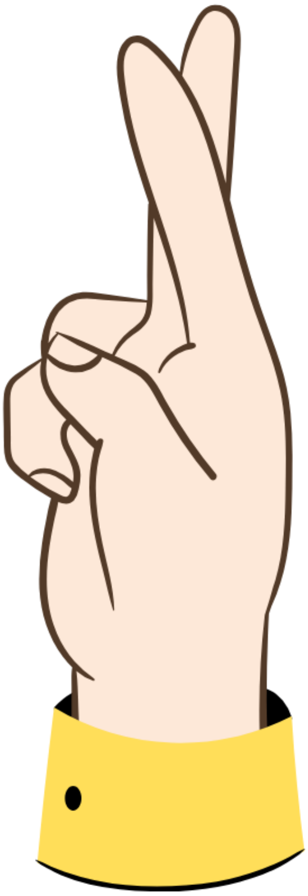
Sign Language Recognition

Obstacles, Challenges and Future Work



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Obstacles & Challenges in Our Project

1. Scarcity of Data

- **Challenge**: We could not find enough publicly available datasets that cover every possible Arabic sign word. Most existing datasets focus only on letters, not full words or sentences.
- **Solution**: We worked with the available ArSL alphabet dataset (letters only) as a starting point. This allowed us to build a baseline model, while keeping the system open for future expansion into words and phrases

2. Only Using Letters

- **Challenge**: Our model currently handles only individual letters, which limits real-life applications (since full communication requires words and sentences).
- **Solution**: We treated this as a startup prototype. By focusing on letters, we established a strong foundation. Future work can extend the dataset and model to cover combinations of letters → words → full sentences.

3. Limitation to the Arabic Alphabet

- **Challenge**: The dataset includes only the Arabic alphabet signs, meaning the model cannot handle other sign languages (like ASL or BSL).
- **Solution**: We narrowed our project scope to Arabic users, ensuring good accuracy in this specific domain. In the future, transfer learning or multi-language datasets can expand its capabilities.

4. Choosing the Most Suitable Layers to Recognize Patterns

- **Challenge**: Selecting the right neural network architecture was difficult. Dense layers alone did not capture spatial details of images well.
- **Solution**: We experimented with different models and found that Convolutional Neural Networks (CNNs) work best for recognizing patterns in hand signs. CNN layers automatically extract important features such as shapes, curves, and orientations, leading to much higher accuracy.

5. Detecting Essential Edges and Corners

- **Challenge**: Correctly recognizing hand gestures depends on detecting edges, corners, and contours of the hand. A simple model could not capture these subtle differences.
- **Solution**: We applied convolutional filters (Conv2D layers) in our CNN model. These filters detect edges, corners, and textures automatically during training, which improved recognition of similar-looking letters.

Future Work and Improvements

While our current CNN-based model achieved a strong accuracy of 94.4%, there are several opportunities to enhance and extend this work:

1. **Dataset Expansion**
   - Collect more diverse Arabic sign language data, including different backgrounds, lighting conditions, and hand variations.
   - Incorporate **dynamic signs** (video sequences) rather than static images.
2. **Transfer Learning**
   - Utilize pre-trained CNN architectures (e.g., ResNet, Inception, MobileNet) to improve generalization and reduce training time.
3. **Data Augmentation**
   - Apply transformations (rotation, flip, shift, zoom, noise addition) to improve robustness against variations.
4. **Real-Time Deployment**
   - Implement real-time sign detection using **OpenCV + TensorFlow Lite** for mobile/embedded devices.
   - Integrate into a **mobile app or web app** for accessibility.
5. **Advanced Models**
   - Explore **Recurrent Neural Networks (RNNs), LSTMs, or Transformers** to handle sequential video data for dynamic gestures.
   - Investigate **Vision Transformers (ViT)** for higher accuracy.
6. **User-Centered Applications**
   - Develop bilingual systems (ArSL ↔ text/speech).
   - Include personalization features to adapt to individual signing styles.