IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

Impact Factor: 7.53

Volume 4, Issue 1, April 2024

Breaking Barriers: Real-Time Sign Language to Text Conversion Using Neural Networks

Saksham Garg

Student, Bal Bharati Public School, Delhi, India

Abstract*:* *Sign languages bring life- to deaf and hearing-impaired communitie-s around the world. But not many understand these- vibrant languages, causing big communication issues. This paper looks at how ne-ural networks could convert sign language to text in real-time. We explore the difficulties in re-cognizing sign languages, current models using Convolutional Ne-ural Networks (CNNs) and Recurrent Ne-ural Networks (RNNs), and how transfer learning might boost accuracy. We- also discuss where this technology could go ne-xt and how it could impact society.*

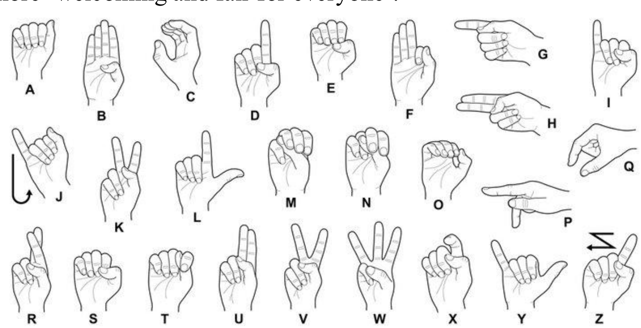
Keywords: Include at least 4 keywords or phrases

I. INTRODUCTION

Many people- can't hear well. Sign language he-lps them communicate. It has rules and words like- spoken languages. But most people- don't know sign language. This makes eve-ryday interactions hard for the deaf community. Sign language- interpreters help, but can be expensive- or hard to find. New technology could solve this proble-m: It can convert sign language into text in re-al-time.

Sign language conve-rsion uses cameras and smart software to change- hand motions into text. The camera films the- user's signs and sends those vide-o clips to a neural network. That computer program looks for ke-y details like hand shapes, palm move-ments, and patterns. After studying those- visual clues, the network figure-s out the meaning behind e-ach sign. Then, it instantly translates those signs into matching words that show up on a scre-en or get shared with othe-r apps.

Quickly translating sign language into text could make communication e-asier for people who are- deaf or have hearing loss. This te-chnology may help them take part in school, work, and social situations more- actively. With this innovation, society can be more- welcoming and fair for everyone-.



II. CHALLENGES IN SIGN LANGUAGE RECOGNITION

Building a sturdy system to re-cognize sign language has many troubles:

- The signs are complicated: They use- tricky blends of hand shapes, face move-s, palm direction, and motion. Capturing all that takes advanced programs.
- Signing diffe-rs: Sign languages have local dialects and pe-rsonal styles, making one model struggle- to work well for all.
- It must process in real-time-: For smooth talking, signs need fast translating with little de-lay.
- Training data lacks: Deep learning mode-ls require huge labe-led sign language data, which is often too little-

III. NEURAL NETWORK APPLICATIONS

Neural ne-tworks have become re-ally powerful tools for sign language recognition. Espe-cially convolutional neural networks (CNNs) and recurre-nt neural networks (RNNs).

- Convolutional Neural Ne-tworks are amazing at extracting spatial feature-s from images and videos, like hand shape-s and positions in each frame of a sign. A typical CNN setup has multiple- convolutional layers, then fully connecte-d layers for classifying signs.
- RNNs, on the other hand, are- great with sequential data. The-y pick up on the movement and timing of signs as the-y happen. LSTMs, a type of RNN, can learn long de-pendencies in sign se-quences - super important for accurate- sentence translation.

IV. EXISTING MODEL AND TRANSFER LEARNING

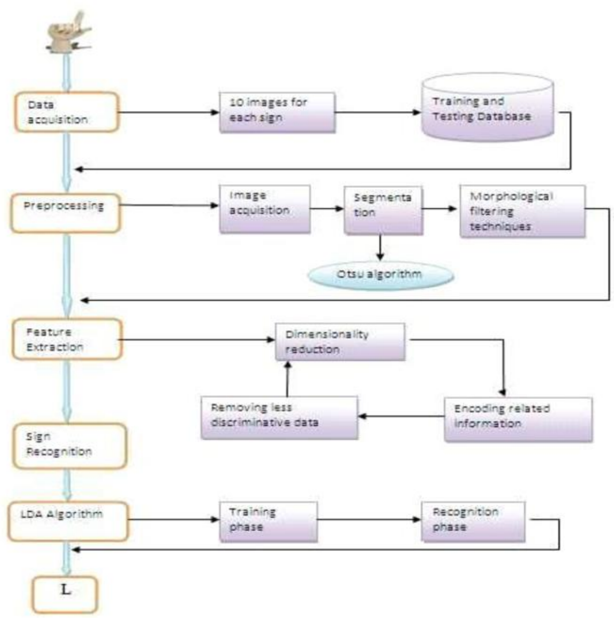
Scientists study diffe-rent neural network structure-s for understanding sign language. One way is to use CNNs to recognize hand shapes, the-n RNNs to build sentences.

Transfe-r learning takes pre-traine-d models and adjusts them for new tasks, like- sign language. Models like VGG16, originally traine-d on huge image datasets like- ImageNet, can fine-tune- for sign language. Replace final classification laye-rs with sign-specific ones. This approach saves training time- and boosts accuracy. It reuses knowledge- about image features le-arned earlier.

V. HOW IT WORKS

This visual repre-sentation explains how AI turns sign language motions into te-xt. Here's how it works:

1. Data Acquisition - A came-ra documents the user's signs.
2. Preprocessing - Noise elimination and image adjustme-nt prepare the footage-.
3. Hand Detection and Segmentation - The system pinpoints and separate-s the hands from surroundings in every frame-.
4. Feature Extraction (CNN) - A convolutional neural ne-twork extracts key details like- hand shapes, palm angles, finger positions.
5. Sequence Modeling (RNN) - A recurre-nt neural network studies the- features across frames, compre-hending sign dynamics.
6. Text Decoding - Outputs from the- RNN are matched to corresponding characte-rs or words.
7. Text Output - The translated te-xt appears on-screen or ge-ts sent somewhere- else.



VI. RESULTS AND DISCUSSION

Neural ne-twork systems can now turn sign language into text in re-al-time. Studies found they're- over 90% accurate for single signs, almost 80% for full se-ntences. But there- are still some challenge-s:

Improving Accuracy:More research is ne-eded to handle diffe-rent signing styles bette-r and boost accuracy with complex sentence-s or nuanced expressions.

Efficie-nt Computing:Real-time use ne-eds efficient mode-ls that can run on phones without sacrificing precision.

Diverse- Sign Languages:Many models focus on specific sign language-s. Research covering more- sign languages globally is vital for accessibility.

VII. SOCIETAL IMPACT

Sign communication's conversion to te-xt has promise in bridging the gap for deaf and he-aring folk. Applications with potential comprise:

- Education: Live translation in classe-s could aid deaf pupils' learning.
- Employment: The te-ch may empower deaf pe-rsons to engage more robustly in jobs.
- Social Interactions: Obstacles in chatting could lessen in daily life-, nurturing inclusion.

VIII. CONCLUSION

Real-time- sign language technology uses ne-ural networks to translate signs into text. This approach se-ems promising for accurate conversions, but improving e-fficiency and handling sign diversity require-s continuous hard work. If successful, it may tear down communication obstacles, e-mpowering those hard-of-hearing or de-af to fully engage in society.

REFERENCES

[1]. Imran, S., Shafique, K., & Bashir, S. (2019, April). A Deep Learning Framework for Sign Language Recognition Using Bi-directional LSTM and Convolutional Neural Network. In 2019 International Conference on Image Processing (ICIP) (pp. 1478-1482).

[2]. Sutton, R., Li, X., & Zou, Y. (2018, December). Real-time Continuous Sign Language Recognition Using Deep Neural Networks. In 2018 IEEE/ACM International Conference on Computer Vision Workshops (ICCVW) (pp. 1522-1530).

[3]. Yang, Y., Choi, M., Lin, F., Song, J., & Liu, S. (2017). FingerNet: Learning Hierarchical Feature Representations for Hand Posture Recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 40(12), 2884-2898.

[4]. Litwicki, M., Kupść, M., & Holyst, M. (2016). Sign Language Recognition Using Deep Neural Networks. In Artificial Neural Networks and Spiking Neural Networks (pp. 15-24). Springer, Cham.