



KSL FINGERSPELLING RECOGNITION



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INTRODUCTION

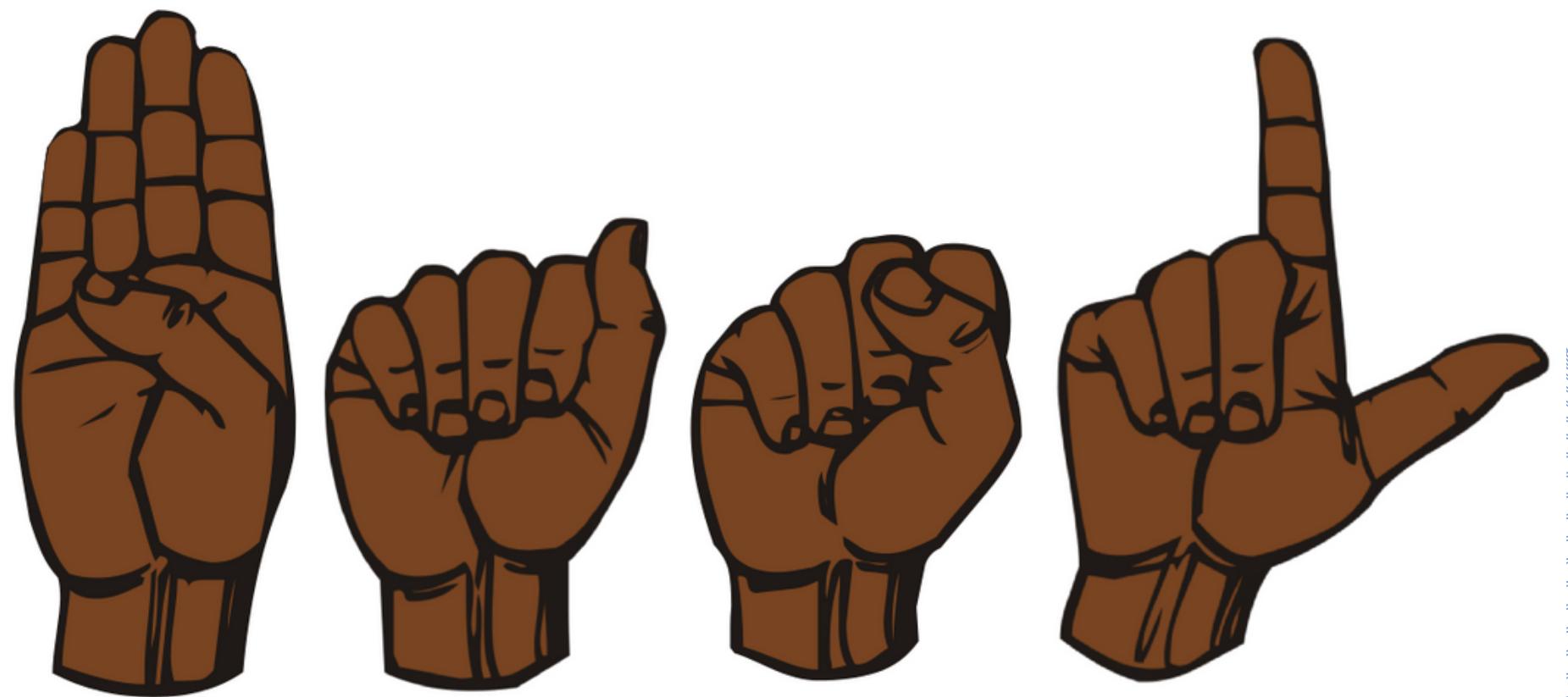
Fingerspelling is vital for communication among the deaf and hard of hearing community.

Bridging the gap between the deaf and the rest of the community is crucial for improving communication accessibility.



PROJECT OVERVIEW

Our mission is to bridge the communication gap through machine learning to empower the deaf and hard of hearing community.



PROBLEM STATEMENT

The deaf and hearing impaired community encounters significant communication barriers due to the limited understanding of sign language among the general population.

This results in difficulties and breakdowns in communication, hampering inclusivity and effective interaction with the broader society.



OBJECTIVES

To develop a machine learning model that translates fingerspelling into text.

1

Train a specialized CNN model for fingerspelling recognition.

2

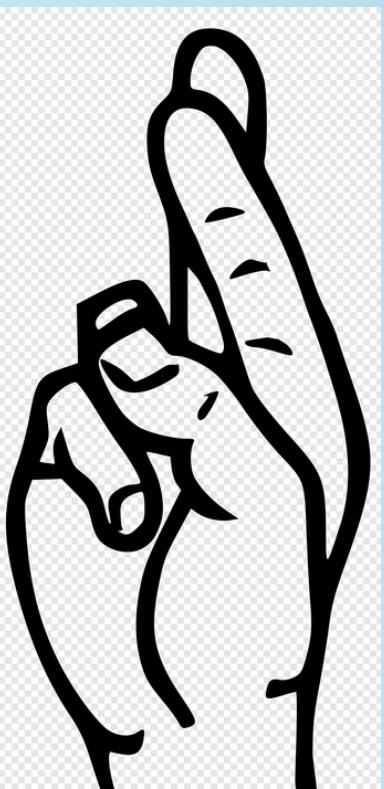
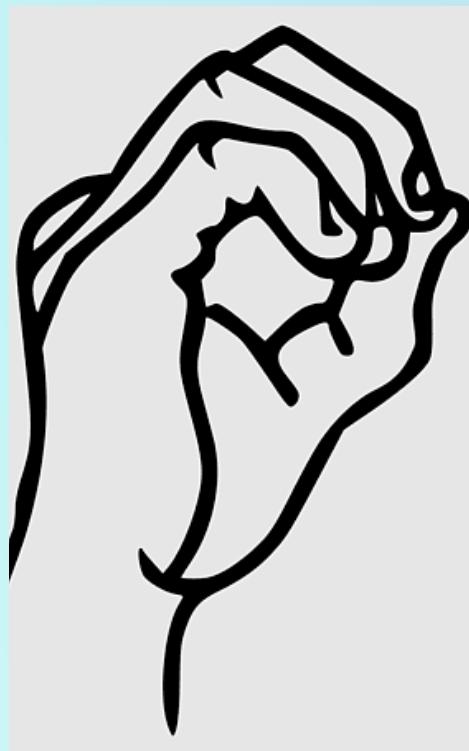
Evaluate the model's performance.

3

Deploying the model.

DATA UNDERSTANDING

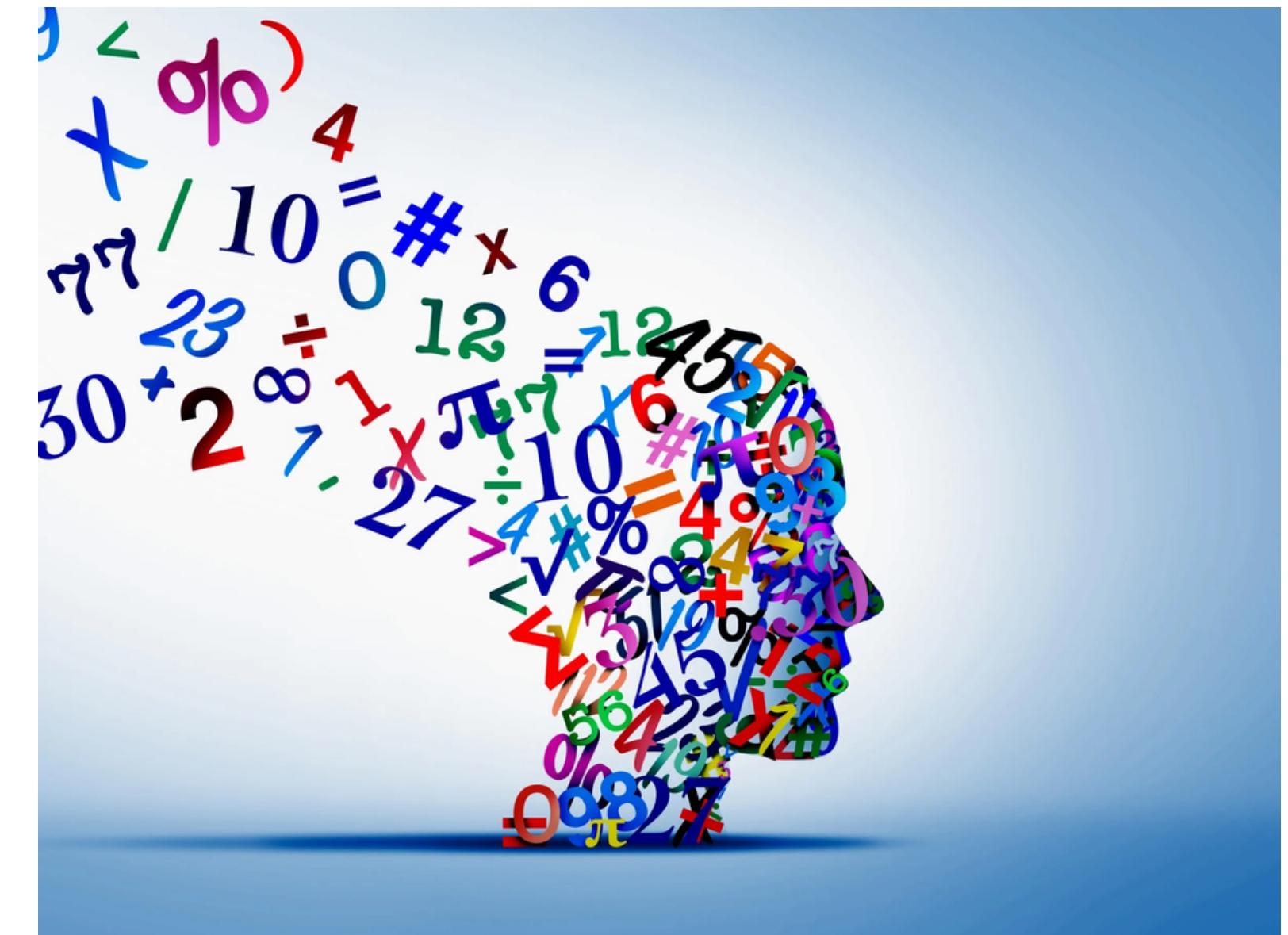
- The dataset was from Kaggle and supplemented with over 3,000 images collected by the team.
- The dataset includes 24 letter classes, excluding 'J' and 'Z' due to motion requirements.
- Kaggle training and test sets had 27,455 and 7,172 images



MODELING

Employed the following models:

- Densely connected model(baseline)
 - kaggle test set acc- 70%
 - CNN (Convolutional Neural Networks)
 - the raw test set acc- 96%
 - Google Teachable Machine



DEPLOYMENT

- Deployed model on Streamlit as a web app for real-time fingerspelling interpretation.
- Created a user-friendly interface for easy input and interpretation of fingerspellings.



CHALLENGES

- A small dataset and varying image quality had an impact on the accuracy.
- The model's inability to recognize fingerspelling beyond Kenyan Sign Language limits versatility.



CONCLUSION

- Despite the challenges, the model achieved an accuracy of over 90% on the test dataset.
- The model improves communication for deaf and hard-of-hearing individuals by enabling easier communication with non-sign language users.



RECOMMENDATIONS

- Dataset Expansion: More images
- Image Quality Improvement: Higher-quality images can lead to better pattern recognition
- Integration with Speech Recognition, NLP to do sentence prediction, and autocorrection.



NEXT STEPS

- Incorporate the use of IoT devices to enable our model to do real time translation.
- Train our model on a large dataset to allow more variations for the letters.
- Incorporate sensor motion to capture letters J and Z.

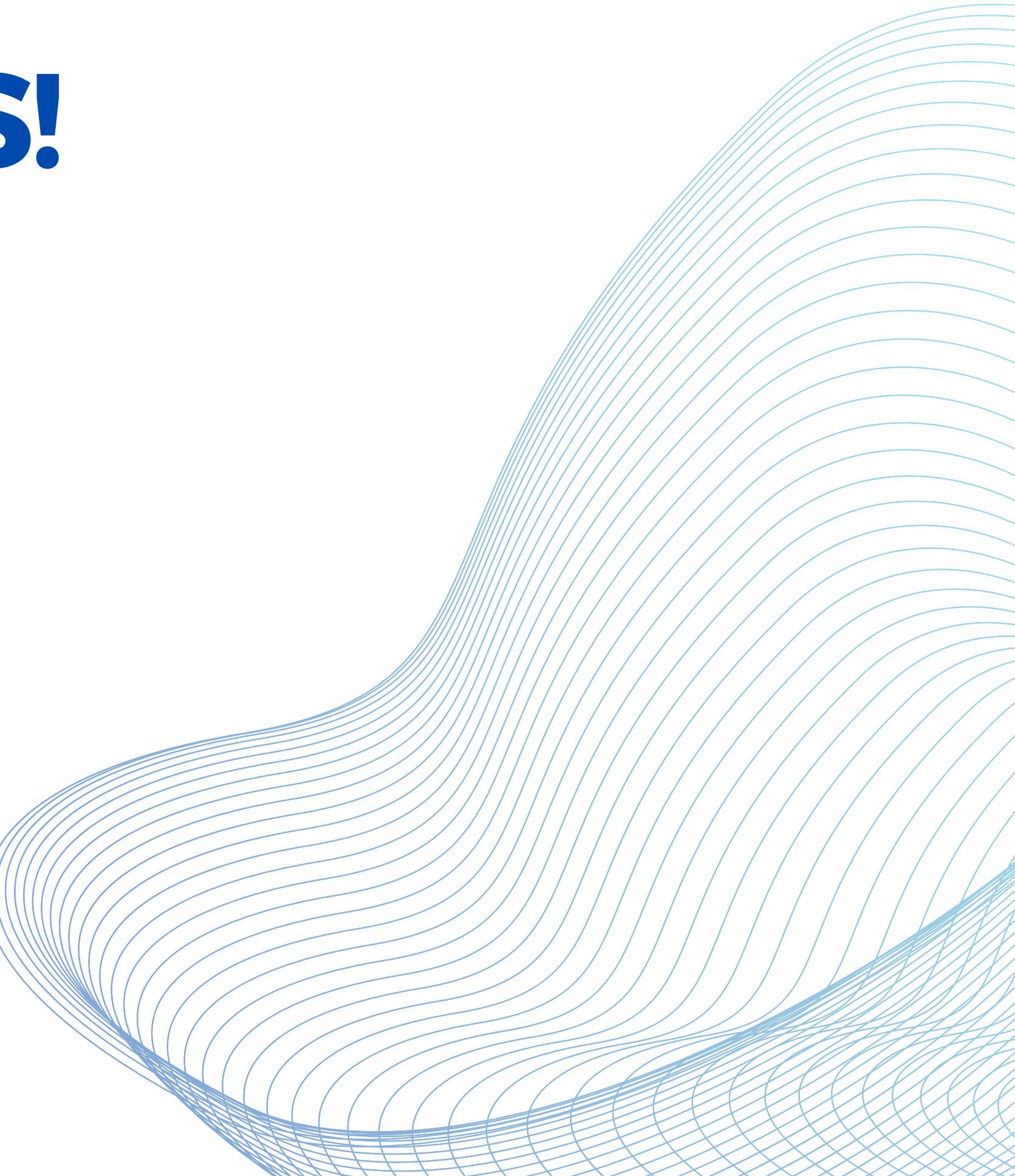


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THANK



YOU

