

INTRODUCTION

- MNIST dataset served as a benchmark for machine learning.
- Fashion-MNIST dataset introduced to address limitations of MNIST.
- Sign Language MNIST dataset aims to provide a more challenging task for computer vision.
- Inspired by Fashion-MNIST, Sign Language MNIST follows a similar CSV format.
- Represents a multi-class problem with 24 classes of letters in American Sign Language (ASL).

OBJECTIVES

- Train a deep learning model to recognize hand gestures representing letters in ASL.
- Evaluate the model's performance using metrics like precision, recall, and F1 score.
- Develop a real-world application for sign language recognition using computer vision techniques.

DATASET AND ATTRIBUTES

Sign Language MNIST:

- Format closely mimics classic MNIST dataset.
- Consists of 27,455 training cases and 7,172 test cases.
- Each case represents a label (0-25) corresponding to an alphabetic letter A-Z.
- No cases for 9=J or 25=Z due to gesture motions.
- Each image is 28x28 pixels with grayscale values between 0-255.
- Data augmentation techniques used to expand the dataset, including cropping, resizing, rotation, and pixelation.



label,pixel1,pixel2,pixel3,pixel4,pixel5,pixel6,pixel7,pixel8,pixel9,pixel10,pixel11,pixel12,pixel13,pixel14,pixel15,pixel16,pixel17,pixel18,pixel19,pixel 5,126,128,131,132,133,134,135,135,136,138,137,137,138,138,138,139,137,142,140,138,139,137,137,136,135,134,132,129,132,129,132,134,135,135,135,135,137,139,139,139,140,10,85,88,92,96,105,123,135,143,147,152,157,163,168,171,182,172,175,185,183,184,185,185,185,183,182,181,178,86,88,93,96,108,125,137,145,149,154,160,166 21,72,79,87,101,115,124,131,135,139,142,144,147,150,153,156,159,160,162,164,165,166,166,167,167,168,168,167,73,80,89,104,117,126,132,136,140,143,146,1 10,93,100,112,118,123,127,131,133,136,139,140,143,144,145,146,149,151,153,154,155,156,159,159,160,161,163,164,93,102,113,119,123,128,131,134,138,140,18,212,213,214,213,214,213,213,214,215,214,213,212,213,212,212,211,211,212,211,210,210,207,207,207,210,191,83,213,214,215,216,216,214,215,216,216,216,214,2 21,128,131,133,135,137,139,140,142,145,146,146,145,144,149,147,147,148,148,146,147,147,147,147,149,148,145,145,145,145,145,142,129,132,134,137,139,140,143,145,146,147 7,95,105,119,144,155,163,169,172,173,177,179,181,182,183,184,185,186,185,184,182,181,181,180,178,176,175,172,170,95,106,121,145,157,164,170,173,175,179,18

PROPOSED METHODOLOGY

Proposed Methodology:

Custom CNN Architecture:

- Designing a tailored CNN architecture for sign language gestures.
- 2. Experimenting with layers to optimize feature extraction and model complexity.

Data Augmentation:

- 1. Applying preprocessing (cropping, resizing, grayscale) for standardization.
- 2. Employing augmentation (rotation, zoom, shifts) to increase dataset diversity.

Optimization Algorithms:

- 1. Using RMSprop, Adam, etc., for efficient loss minimization.
- 2. Employing early stopping, learning rate adjustments for dynamic training.

Model Evaluation:

- 1. Assessing performance with accuracy, precision, recall, F1 score.
- 2. Validating on training/test datasets for generalization.

Interpretability:

- 1. Visualizing CNN activations, feature maps for insights.
- 2. Analyzing misclassifications for model refinement.

Interactive User Interface:

- 1. Creating an interactive application for real-time gesture recognition.
- 2. Enabling users to communicate through sign language gestures in an intuitive manner.

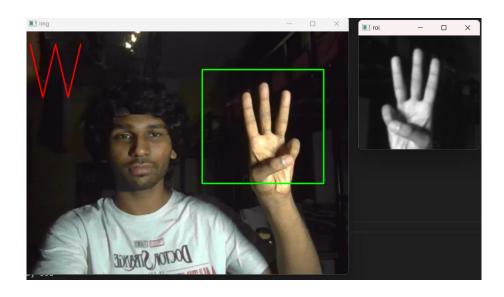
Evaluation and User Feedback:

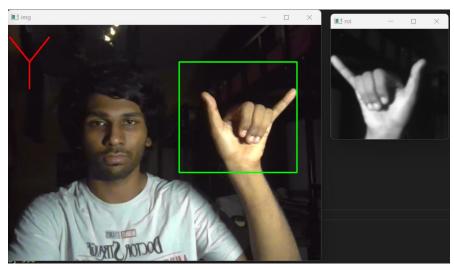
- Collecting user feedback to assess the effectiveness and usability of the application.
- 2. Evaluating model performance and user experience for further refinement.

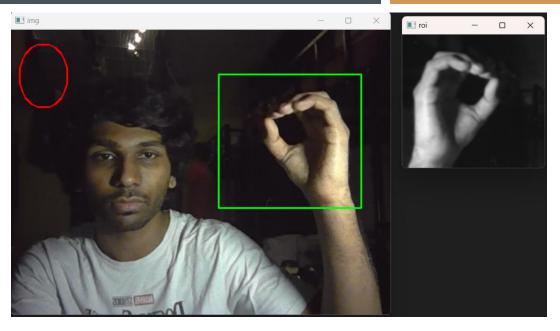
Model: "sequential"		
Layer (type)	Output Shape	Param #
conv2d (Conv2D)		
conv2d_1 (Conv2D)	(None, 28, 28, 64)	102464
<pre>max_pooling2d (MaxPooling2 D)</pre>	(None, 14, 14, 64)	0
dropout (Dropout)	(None, 14, 14, 64)	0
conv2d_2 (Conv2D)	(None, 14, 14, 32)	18464
conv2d_3 (Conv2D)	(None, 14, 14, 32)	9248
<pre>max_pooling2d_1 (MaxPoolin g2D)</pre>	(None, 7, 7, 32)	0
dropout_1 (Dropout)	(None, 7, 7, 32)	0
flatten (Flatten)	(None, 1568)	0
dense (Dense)	(None, 256)	401664
Total params: 539929 (2.06 MB) Trainable params: 539929 (2.06 MB) Non-trainable params: 0 (0.00 Byte)		

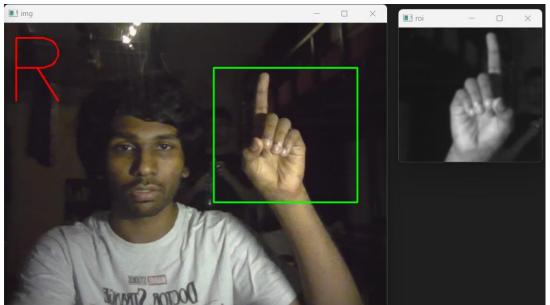
EXPERIMENTAL RESULTS

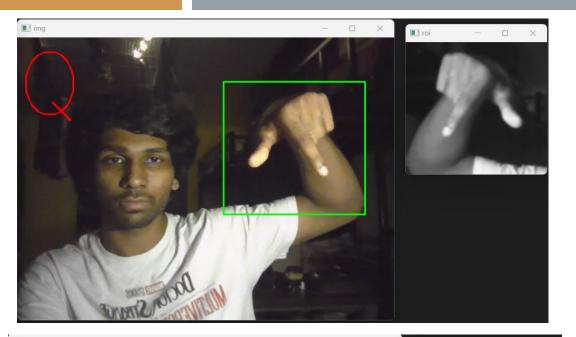
- Camera Calibration: Prior to gesture capture, camera calibration is performed to ensure accurate depth perception and spatial mapping of hand gestures.
- Real-time Processing: The system employs efficient algorithms for real-time processing of captured frames, minimizing latency and ensuring smooth interaction.
- Cross-Platform Compatibility: The software is designed to be compatible with multiple platforms, including Windows, macOS, and Linux, enhancing its accessibility and versatility.
- User Interface Design: A user-friendly interface is developed to provide intuitive controls and visual feedback, enhancing the user experience during gesture recognition.

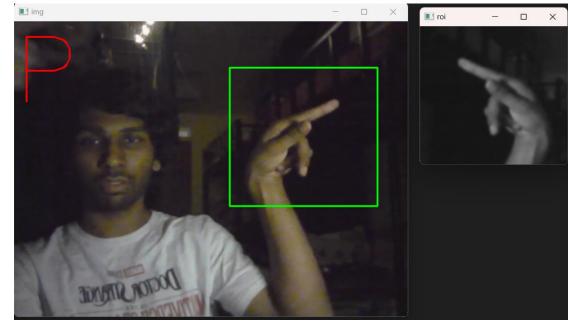












PERFORMANCE EVALUATION

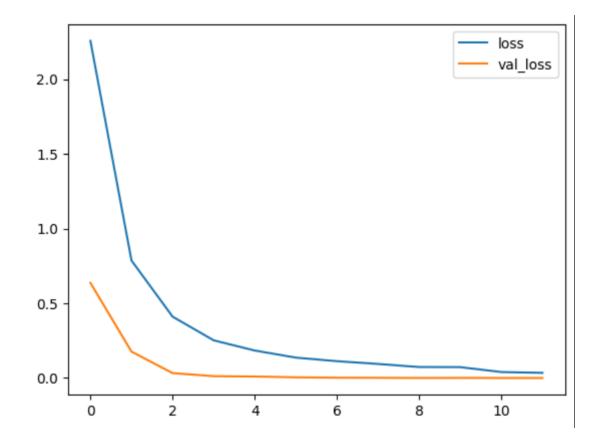
- Model Tuning: The project explores various hyperparameters and optimization techniques to fine-tune the CNN architecture for optimal performance.
- Validation Strategies: Cross-validation techniques such as k-fold validation are utilized to ensure robustness and reliability of the model's performance evaluation.
- Scalability Assessment: The scalability of the system is evaluated to determine its capability to handle increased workload and user interactions without compromising performance.
- Error Analysis: Detailed error analysis is conducted to identify common misclassifications and areas for model improvement, guiding future iterations and refinements.

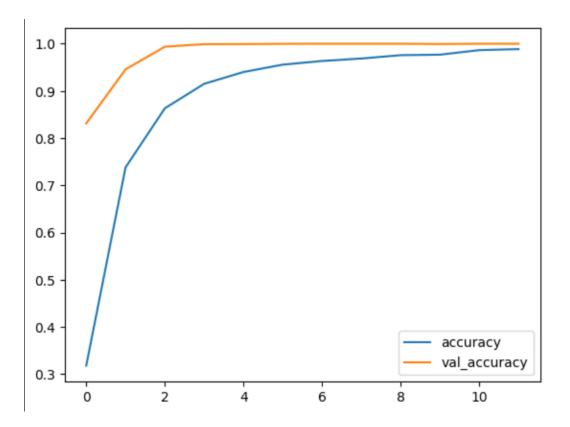
57/57 [========================] - 1s 8ms/step - loss: 0.0211 - accuracy: 0.9916 Testing accuracy of model : 99.16%

225/225 [==============] - 0s 2ms/step F1 Score: 0.9537261059762697

```
Label: 0
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
Label: 1
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
Label: 2
Precision: 0.9841269841269841
Recall: 1.0
F1 Score: 0.992
Label: 3
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
Label: 4
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
Label: 5
Precision: 1.0
Recall: 1.0
F1 Score: 1.0
```

Precision: 0.9935691318327974 Recall: 0.8879310344827587 F1 Score: 0.9377845220030349 Label: 7 Precision: 0.956140350877193 Recall: 1.0 F1 Score: 0.9775784753363229 Label: 8 Precision: 0.9442622950819672 Recall: 1.0 F1 Score: 0.9713322091062394 Label: 9 Precision: 0.0 Recall: 0.0 F1 Score: 0.0 Label: 10 Precision: 1.0 Recall: 1.0 F1 Score: 1.0 Label: 11 Precision: 1.0 Recall: 1.0 F1 Score: 1.0





RELATED WORKS AND LIMITATIONS

- **Comparison:** Existing sign language recognition systems often require complex setups and specialized hardware, limiting their scalability and practicality. While some systems achieve high accuracy, they may lack real-time performance or require extensive training data.
- **Pros and Cons:** Prior approaches have demonstrated advancements in gesture recognition accuracy, but they often face challenges related to cost, hardware requirements, and real-world deployment.

Citations:

- Wadhawan, A., Kumar, P. Deep learning-based sign language recognition system for static signs. Neural Comput & Applic 32, 7957–7968 (2020). https://doi.org/10.1007/s00521-019-04691-y
- N. Adaloglou et al., "A Comprehensive Study on Deep Learning-Based Methods for Sign Language Recognition," in IEEE Transactions on Multimedia, vol. 24, pp. 1750-1762, 2022, doi: 10.1109/TMM.2021.3070438
- https://www.kaggle.com/datasets/datamunge/sign-language-mnist

CONCLUSION AND FUTURE WORK

- Conclusion: In conclusion, the project demonstrates significant progress in real-time sign language recognition, contributing to accessibility and inclusivity for the deaf and hard-of-hearing community.
- **Future Directions:** Future research directions include investigating multimodal approaches incorporating audio and text-based inputs, enhancing the system's robustness in challenging environments, and expanding its functionality to support additional sign languages and communication modalities.
- **Community Engagement:** Engaging with the deaf and hard-of-hearing community in co-designing and co-developing future iterations of the system is essential to ensure its relevance, effectiveness, and inclusivity.
- **Long-term Impact:** The long-term impact of the project on society, education, and healthcare is considered, emphasizing the importance of leveraging technology for positive social change and empowerment.

