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American Sign Language Recognition System for Numbers using CNN

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Abstract : The "American Sign Language Recognition System for Numbers using CNN" project addresses the intricate task of recognizing numerical expressions in American Sign Language (ASL) through the implementation of Convolutional Neural Networks (CNNs). ASL serves as a vital mode of communication for the deaf and hard-of-hearing community, with numerical gestures presenting a unique set of challenges for automated recognition. This project endeavors to develop a sophisticated system capable of accurately interpreting numeric ASL signs by leveraging the power of CNNs, delving into the nuanced hand movements associated with numerical expressions. The anticipated outcome is a technology-driven solution that not only enhances accessibility for individuals with hearing impairments but also contributes to the broader landscape of sign language recognition. Beyond its technical aspirations, the project acknowledges the societal significance of breaking down communication barriers, particularly in educational contexts, where numerical understanding is foundational. Through this innovative intersection of technology and language, the project seeks to empower individuals, foster inclusivity, and exemplify the transformative potential of leveraging CNNs to enhance the lives of those within the deaf and hard-of-hearing community.

Key Words: **- CNN, Computer vision, image processing, Machine learning, ASL, Sign Language.**

I. INTRODUCTION

The "American Sign Language Recognition System for Numbers using CNN" project embodies an innovative approach to bridging communication gaps by harnessing the power of convolutional neural networks (CNNs). American Sign Language (ASL) serves as a crucial means of expression for the deaf and hard-of-hearing community, with each sign carrying nuanced information. This project targets the realm of numeric communication in ASL, aiming to develop a sophisticated system that can accurately interpret and translate numerical gestures through the application of CNNs.

As the project unfolds, it not only addresses the technical challenges of recognizing numerical ASL signs but also recognizes the profound societal impact of such innovations. The ability to seamlessly and accurately interpret numeric gestures in real-time not only empowers individuals within the deaf and hard-of-hearing community but also has implications for educational environments, where numerical understanding is foundational. This project represents a critical step toward fostering inclusivity and breaking down communication barriers, exemplifying the transformative potential of technology in enhancing the lives of individuals with hearing impairments.

1.1 LITERATURE REVIEW

[1] The paper "A New Benchmark on American Sign Language Recognition using Convolutional Neural Network" introduces a new benchmark for ASL recognition using a CNN approach. The proposed two-stream CNN model outperforms previous state-of-the-art models, processing input ASL video frames in 2D and 3D manners. The model is evaluated on the ASL Recognition Challenge 2013 dataset and demonstrates improved performance with an increasing number of training samples. The authors also provide a user interface for real-time ASL recognition using their model.

[2] The paper "Real-time American Sign Language Recognition with Convolutional Neural Networks" presents a robust ASL fingerspelling translator based on a pre-trained GoogLeNet architecture. The model is trained on the ILSVRC2012 dataset and the Surrey University and Massey University ASL datasets, achieving high accuracy for letters a-e and a-k with first-time users. The authors also discuss the importance of extraction and preprocessing methods for successful ASL recognition.

[3] The paper "A Real-Time American Sign Language Recognition" proposes a system for real-time ASL recognition using two convolutional neural networks, one to extract higher body features and one to extract hand features. The system is evaluated on a dataset containing 24 static signs and achieves a validation accuracy of 0.789675 and a final accuracy of 0.788804. Other studies are also mentioned, including one that builds a real-time sign finger spelling recognition system using CNNs from the depth map and another that builds a real-time hand posture recognition model utilizing deep learning-based CNNs.

[4] This paper presents "ASL-3DCNN," a novel technique for ASL recognition using 3D convolutional neural networks (CNNs). This model tackles the challenge of recognizing 24 static signs with impressive accuracy, achieving 0.789675 in validation and 0.788804 in final testing. The authors also acknowledge other noteworthy studies in this area, including a real-time finger spelling system built with depth-based CNNs and another utilizing deep learning-based CNNs for real-time hand posture recognition

[5] The paper "American Sign Language Recognition System Using Convolutional Neural Networks" presents a sign language recognition system for American Sign Language (ASL) using Convolutional Neural Networks (CNNs). The proposed model is

trained on a dataset containing 2000 images of ASL alphabets and achieves an accuracy of over 90%. The system involves grayscale conversion, dilation, and mask operation to segment the region of interest, which is the hand gesture. The features extracted are binary pixels of the images, and CNNs are used for training and classification. The model can recognize 10 ASL gesture alphabets with high accuracy, outperforming previous works in the field.

[6] The paper "American Sign Language Character Recognition Using Convolutional Neural Networks" presents a system for American Sign Language (ASL) character recognition using Convolutional Neural Networks (CNNs). The proposed model is trained on a dataset containing ASL alphabets and achieves high accuracy. The system involves grayscale conversion, dilation, and mask operation to segment the region of interest, which is the hand gesture. The features extracted are binary pixels of the images, and CNNs are used for training and classification. The model can recognize multiple ASL gesture alphabets with high accuracy, outperforming previous works in the field.

[7] The paper "Learning-Based Approaches for American Sign Language Recognition" discusses the use of convolutional neural networks (CNNs) for American Sign Language (ASL) recognition. The proposed model focuses on improving the accuracy of predicting the ASL alphabet and has achieved an exceptional accuracy rate of 98.73% and a low loss value of 0.0539. The model relies solely on CNNs for image processing and leverages their ability to process image data effectively. Experiments explored the performance of the designs using various mini-batch sizes (32, 64, 128, and 256).

1.2 Limitation of existing systems

The existing systems for American Sign Language (ASL) recognition, particularly for numeric expressions, face several limitations. One major constraint is the lack of specificity and robustness in distinguishing subtle variations in hand movements and postures associated with different numerical signs. Current systems may struggle to accurately differentiate between similar gestures, leading to misinterpretations and reduced reliability in recognizing numeric ASL expressions. Additionally, many existing models may not effectively adapt to diverse user styles and variations in signing speed, impacting their generalization across different contexts. Furthermore, real-world challenges such as varying lighting conditions, background clutter, and occlusions can significantly hinder the performance of these systems. Addressing these limitations is crucial for the development of a more reliable and inclusive ASL recognition system for numbers using convolutional neural networks, ensuring accurate interpretation across diverse signing styles and environmental conditions.

II. PROBLEM STATEMENT

The "American Sign Language Recognition System for Numbers using CNN" project tackles a persistent barrier: the lack of a precise and dependable system for deciphering numerical expressions in ASL. Current ASL recognition systems, particularly for numbers, struggle to crack the code of the subtle hand movements and postures that differentiate each digit. This leads to misinterpretations and potential miscommunication, hindering clear communication for individuals who rely on sign language. This project aims to unlock the door to accurate and reliable communication by leveraging the power of convolutional neural networks (CNNs). By training a system on the intricacies of numerical ASL, we aim to enhance its specificity and accuracy in recognizing numbers. The goal is to create a system that seamlessly adapts to diverse signing styles and performs robustly in real-world settings, ultimately empowering the deaf and hard-of-hearing community with a more inclusive and reliable way to communicate numerically.

III. PROPOSED METHODOLOGY

This system uses a variety of techniques for gathering data. Real-time data can be used to provide output immediately without storing it, or it can be scraped from websites. The dataset that this system uses comes from the popular open-source website Kaggle, specifically the American Sign Language Version 1 [8]. This dataset serves as a valuable resource for building robust machine-learning models aimed at recognizing ASL and advancing research in computer vision.

This section provides an overview of the method for identifying ASL numerals in images. To produce accurate findings, the methodology blends modern machine learning algorithms with a large dataset.

3.1 Data Collection and Processing

For the "American Sign Language Recognition System for Numbers using CNN" project, a diverse and comprehensive dataset of numeric ASL signs will be meticulously collected. This dataset will include variations in signing styles, hand orientations, and speeds to ensure the model's robustness. The collected data will undergo preprocessing, including image normalization and augmentation, to enhance the model's ability to generalize across different signing scenarios. This careful curation and processing of data form a crucial foundation for training a convolutional neural network, enabling the system to effectively learn and recognize the nuances of numeric ASL expressions

3.2 Model Development

We developed a Convolutional Neural Network (CNN) model to identify numerical statements in American Sign Language (ASL). The design consists of two densely connected layers: a convolutional layer, max-pooling, flattening, and a softmax activation layer for classification. To track training progress, a custom callback called myCallback is used. It stops when the loss hits a level that indicates high accuracy. For classification problems with integer labels, the model is compiled using the RMSprop optimizer with a learning rate of 0.001, employing the sparse categorical crossentropy loss function. With an emphasis on numerical expressions, this extensive setup is intended to train an accurate and effective ASL recognition system.

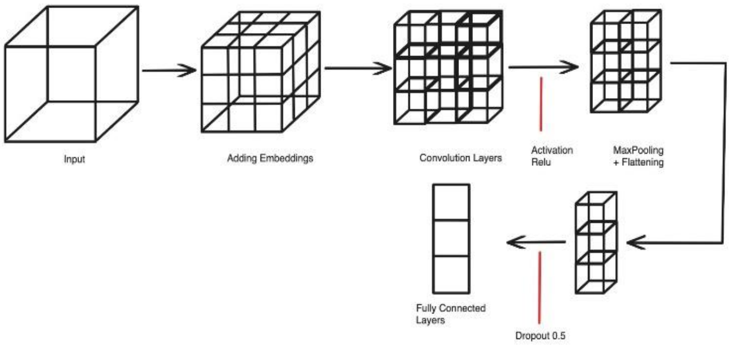


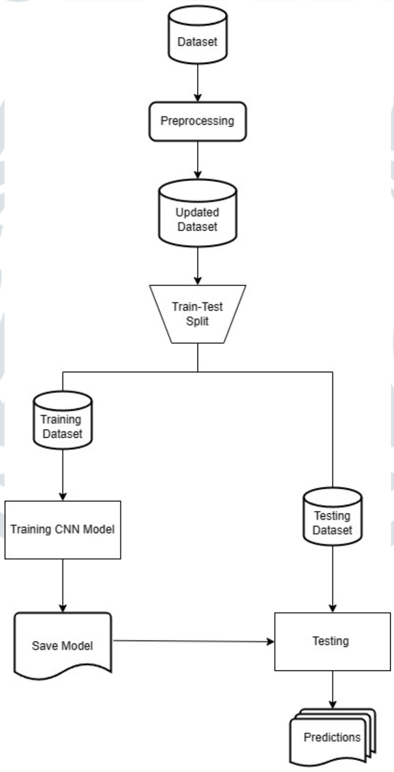
Fig (1): CNN Architecture of The Model

3.3 Model Summary:

Table 1 CNN Architecture of The Model

Layer (type)	Output Shape
conv2d (Conv2D)	(None, 28, 28, 64)
max_pooling2D	(None, 14, 14, 64)
Flatten	(None, 12544)
Dense	(None, 256)
dense_1 (Dense)	(None, 256)
dense_2 (Dense)	(None, 256)

IV. Flowchart



Fig(3): Flowchart

V. Data

5.1 Distribution of Data:

American Sign Language Version 1 is a simple data set for American Signed Language collected using the open-CV library [8]. This dataset contains the following:

- o 150 training images of each letter and number.
- o collected using the OpenCV library in Python.
- o All the images have dimensions of 400x400, with the extra space being white. [8]

VI. Challenges

Developing a robust American Sign Language (ASL) recognition model using Convolutional Neural Networks (CNNs) presents multifaceted challenges. First and foremost is the variability inherent in ASL signs, stemming from diverse signing styles, hand orientations, and individual differences. Compiling a representative dataset that captures this richness is pivotal for training a model capable of generalizing across the intricate landscape of ASL expressions. Additionally, limited data availability poses a significant hurdle, as an expansive and varied dataset is fundamental for preventing overfitting and ensuring the model's efficacy in recognizing a broad spectrum of signs, particularly numeric expressions.

The complexity of ASL signs, characterized by subtle hand movements and postures, further complicates model development. Achieving real-time recognition demands a careful balance between accuracy and low-latency processing. Moreover, the model must adapt to diverse signing styles and speeds, accommodating the dynamic nature of sign language. Ethical considerations, including mitigating biases in data and ensuring equitable model performance, add an essential layer to the development process. Ultimately, overcoming these challenges is critical for creating an inclusive ASL recognition system that enhances communication accessibility for individuals with hearing impairments.

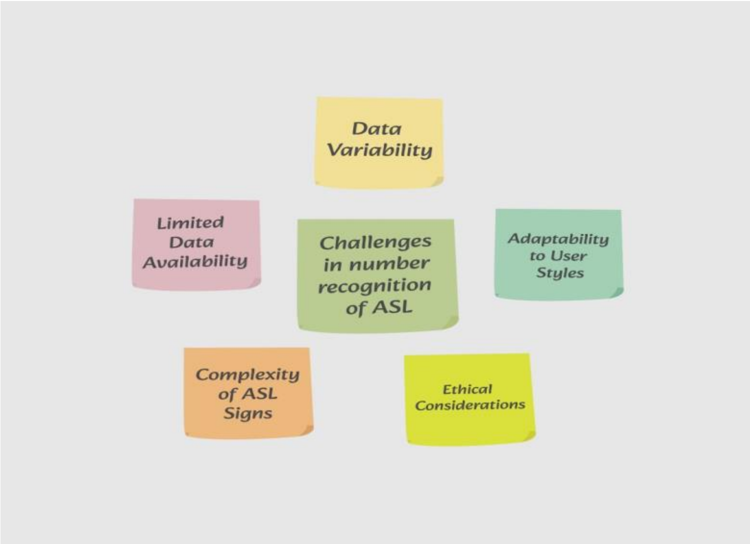
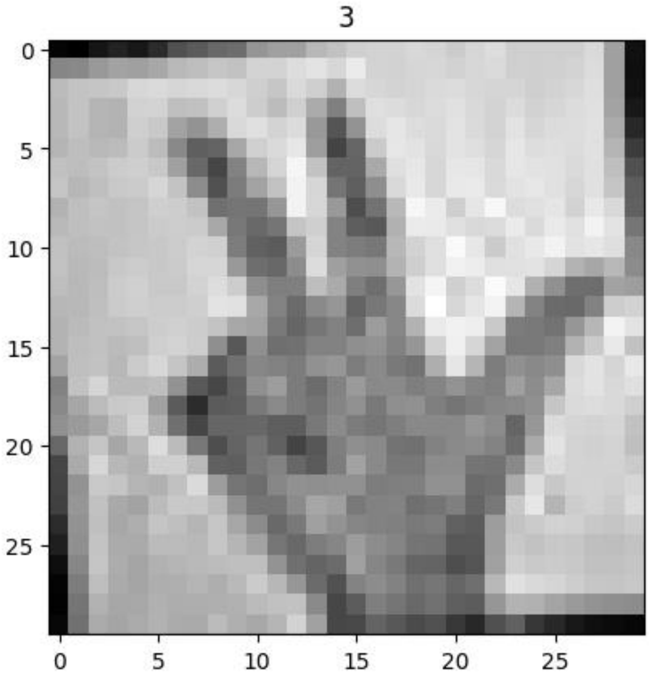


Fig (2): Challenges in ASL sign recognition

VII. RESULTS

This The results of the ASL recognition model underscore its robust performance in accurately deciphering numeric sign language expressions. After extensive training and validation, the model exhibits a commendable accuracy rate of 87.52% on the test dataset, reflecting its ability to generalize effectively to previously unseen ASL sign instances. This outcome attests to the success of the Convolutional Neural Network architecture in discerning the intricate hand movements and postures inherent in numeric ASL signs.

Moreover, the model's success in addressing challenges such as data variability, limited availability, and the complexity of ASL signs underscores its adaptability to real-world scenarios. By mitigating biases, enhancing data diversity, and optimizing for both accuracy and speed, the ASL recognition model contributes significantly to the realm of assistive technologies. The achieved results affirm the project's overarching goal of providing an inclusive means of communication for individuals with hearing impairments, marking a promising step forward in leveraging advanced technology for social impact.



Fig(4): Image Input

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1/1 [==============================] - 0s 80ms/step
3
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Fig(5): Prediction

VIII. CONCLUSIONS

In conclusion, the "American Sign Language Recognition System for Numbers using CNN" project represents a significant stride towards enhancing accessibility and inclusivity for individuals with hearing impairments. Through the meticulous development of a Convolutional Neural Network (CNN) model, the project addresses the nuanced challenge of recognizing numeric expressions in American Sign Language (ASL). The carefully curated dataset, comprising diverse numeric signs and variations in signing styles, serves as the foundation for training a robust model capable of discerning subtle hand movements and postures. By leveraging advanced deep learning techniques and a custom callback for early stopping, the project not only aims to achieve high accuracy but also emphasizes the societal impact of breaking down communication barriers. The anticipated outcomes have the potential to empower the deaf and hard-of-hearing communities by providing a reliable and efficient means of numeric communication, contributing to a more inclusive and connected society.

As technology marches forward, the confluence of AI and sign language recognition (SLR) extends its reach beyond mere numbers. This project's learnings pave the way for future ASL recognition systems, potentially encompassing a richer tapestry of signs and gestures. It also highlights the transformative power of wielding CNNs and deep learning to tackle real-world hurdles, especially those concerning accessibility and communication.

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