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Real-time Sign Language Recognition with CNNs and ONNX

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***Abstract*— This research project aims to enhance American Sign Language (ASL) communication using Convolutional Neural Networks (CNNs) and the Open Neural Network Exchange (ONNX). Additionally, we explore the role of ONNX in model export and real-time inference, ensuring cross-platform compatibility. Through real-time video analysis, we demonstrate the effectiveness of our model in capturing ASL gestures, thereby improving communication. This project not only advances ASL recognition but also underscores the potential of deep learning and ONNX in developing practical communication solutions.**

Keywords: Sign Language Recognition, Convolutional Neural Networks, ONNX Model Export, ASL Gesture Recognition, Deaf Communication, Sign Language MNIST, Real-time Inference, Deep Learning, Accessibility Technology, Cross-platform Compatibility.

I. INTRODUCTION

Sign language is a vital form of communication for the Deaf and Hard of Hearing community, allowing the expression of thoughts, emotions, and ideas through a rich vocabulary of gestures. Despite its significance, effective communication between the Deaf and Hearing communities often faces challenges. This research project aims to address these challenges by leveraging modern technology. Focusing on American Sign Language (ASL) recognition, the project seeks to bridge the communication gap using advanced techniques.

We present a novel approach to real-time ASL gesture recognition by leveraging Convolutional Neural Networks (CNNs) and the Open Neural Network Exchange (ONNX). Our study is based on the Sign Language MNIST dataset, which contains grayscale images depicting individual ASL letters. By developing a CNN architecture incorporating convolutional layers, max-pooling, and fully connected layers, we strive to train a model that can effectively recognize ASL gestures with high accuracy.

Additionally, we explore the utility of ONNX for model export and real-time inference.Practically, we demonstrate real-time gesture recognition by capturing video frames, preprocessing them, and utilizing the model for real-time ASL interpretation. This approach not only enhances ASL recognition but also showcases the potential of deep learning and ONNX in developing practical communication solutions.

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learning and ONNX in developing practical communication solutions.

them, and overlaying the predicted ASL letters onto the video stream.

This project not only advances ASL gesture recognition but also showcases the potential of deep learning and ONNX in solving real-world communication challenges. As we delve into the specifics of our research, we aim to highlight the significance of this work and its implications for improving communication and fostering better understanding between the Deaf and Hearing communities.

II. LITERATURE SURVEY

[1] **Title: "Deep Learning for Image Recognition"**
Summary: LeCun et al. (2015) present a thorough review of deep learning's progress and its applications in image recognition. They detail the development and architectures of convolutional neural networks (CNNs), highlighting their significant role in advancing computer vision tasks such as image classification, object detection, and segmentation.

[2] **Title: "NLP with Deep Learning"**
Summary: Young et al. (2018) examine the application of deep learning techniques in natural language processing (NLP). The review traces the evolution of deep learning models like recurrent neural networks (RNNs) and transformers, discussing their impact on tasks such as machine translation, sentiment analysis, and text generation, along with associated challenges and achievements.

[3] **Title: "Deep Reinforcement Learning in Autonomous Robotics"**
Summary: Kober et al. (2013) provide a survey on the fusion of deep reinforcement learning (DRL) with autonomous robotics. They review various DRL algorithms and their applications in robotic control, navigation, and manipulation, addressing the difficulties and potential solutions for applying DRL in real-world robotic systems.

[4] **Title: "Deep Learning for Medical Image Analysis"**
Summary: Litjens et al. (2017) explore the application of deep learning in medical image analysis. The review covers the impact of deep neural networks on tasks such as tumor detection, organ segmentation, and disease classification, while also discussing challenges related to data scarcity, interpretability, and regulatory approval.

[5] **Title: "Ethical and Societal Implications of Artificial Intelligence"**
Summary: Floridi and Cowls (2019) investigate the ethical and societal issues associated with artificial intelligence, particularly deep learning. They discuss concerns such as bias, transparency, accountability, and job displacement, emphasizing the roles of governments, organizations, and the public in promoting responsible AI development and deployment.

[6] **Title: "Recurrent Neural Networks for Time Series Prediction"**
Summary: Lipton et al. (2015) provide a detailed review of the use of recurrent neural networks (RNNs) in time series prediction. The survey covers RNN architectures, including Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), and their effectiveness in applications like financial forecasting, weather prediction, and speech recognition.

[7] **Title: "Deep Learning in Autonomous Vehicles"**
Summary: Chen et al. (2020) review the utilization of deep learning in autonomous vehicles. They discuss topics such as object detection, lane tracking, and path planning using deep neural networks, and address challenges related to safety, robustness, and regulatory frameworks in the development of self-driving cars.

[8] **Title: "Deep Learning for Anomaly Detection in Cybersecurity"**
Summary: Akhilesh et al. (2019) explore the application of deep learning techniques for anomaly detection in cybersecurity. The survey discusses the use of autoencoders, recurrent neural networks (RNNs), and deep neural networks (DNNs) to detect network intrusions, malware, and suspicious activities,

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emphasizing the necessity of real-time threat detection and response.

[9] **Title: "Deep Learning in Drug Discovery and Healthcare"**
Summary: Mamoshina et al. (2016) provide an extensive review of deep learning's impact on drug discovery and healthcare. The paper discusses how deep neural networks are utilized in drug compound generation, biomarker discovery, and disease diagnosis from medical images, highlighting the potential for advancements in personalized medicine and data-driven healthcare.

[10] **Title: "Deep Learning for Audio and Music Processing"**
Summary: Sainath et al. (2015) survey the application of deep learning in audio and music processing. The review covers areas such as speech recognition, music composition, and sound classification, focusing on the use of convolutional neural networks (CNNs) and recurrent models for processing audio signals and their implications for voice-controlled systems and music recommendation services.

III. DATASET

In order to speed up and accurately train the system, we produced a dataset with thousands of photographs from each category and translated them into a CSV file. We tried utilizing our cellphone camera to record the indicators for uncommon gestures. The acquired photos were pre-processed for classification and resized to an acceptable size. The image is recorded, transformed to pixel values, and then saved in csv file format.

IV. METHODOLOGY

Methodology for Sign Language Gesture Recognition using CNNs and ONNX

This section outlines the methodology employed in our research for Sign Language Gesture Recognition using Convolutional Neural Networks (CNNs) and Open Neural Network Exchange (ONNX). The methodology comprises several key phases, including data preprocessing, model design, training, validation, ONNX export, and real-time inference.

1. Data Preprocessing

- **Dataset Selection**: The research utilizes the Sign Language MNIST dataset, which contains grayscale images representing ASL letters.
- **Data Splitting**: The dataset is divided into training and testing sets to facilitate model training and evaluation.
- **Image Preprocessing**: Steps include grayscale conversion, resizing images to a uniform size, and normalizing pixel values to prepare the data for training.

2. Model Design

- **CNN Architecture**: A custom CNN architecture is designed, comprising:
  - Convolutional layers to extract features from the input images.
  - Max-pooling layers to reduce spatial dimensions and computational complexity.

- **Activation Functions**: Rectified Linear Unit (ReLU) activation functions are used to introduce non-linearity and improve model performance.
- **Loss Function**: Cross-entropy loss is employed to measure the difference between predicted and actual labels.

3. Training

- **Optimization**: Stochastic Gradient Descent (SGD) with momentum is used for optimizing the model's parameters.
- **Learning Rate Schedule**: A learning rate schedule with step decay is implemented to fine-tune the model during training.
- **Model Initialization**: Weights are initialized using appropriate schemes to ensure efficient training convergence.

4. Validation

- **Performance Metrics**: The model's performance is monitored using metrics such as accuracy and loss. Overfitting analysis is conducted to ensure the model generalizes well to unseen data.
- **Model Robustness**: The robustness of the model is evaluated through various tests to ensure consistent and reliable performance across different conditions.

5. ONNX Export

- **Model Export**: The trained CNN model is exported to the ONNX format, which facilitates cross-platform compatibility and integration into various applications.

6. Real-time Inference

- **Video Capture**: Real-time video frames are captured from a camera source to test the model in practical scenarios.
- **Frame Preprocessing**: Preprocessing steps include center cropping, grayscale conversion, and resizing to match the input requirements of the trained CNN model.

By following these methodological steps, the research aims to develop a robust and efficient system for real-time ASL gesture recognition, leveraging the capabilities of CNNs and ONNX to enhance communication between the Deaf and Hearing communities.

ONNX Inference

After exporting the trained CNN model to the ONNX format, it is utilized to predict ASL letters from processed video frames.

The proposed methodology seamlessly integrates data preparation, model design, training, and real-time inference using ONNX, thereby facilitating effective ASL gesture recognition.

The subsequent sections will delve into the presentation and analysis of our research results, showcasing the potential of this approach in bridging the communication gap between the Deaf and Hearing communities.

—This section outlines the methodology employed in our research for Sign Language Gesture Recognition using Convolutional Neural Networks (CNNs) and Open Neural Network Exchange (ONNX). The methodology comprises several key phases:

1. **Data Preprocessing**

- **Dataset Selection:** We utilize the Sign Language MNIST dataset, containing grayscale images representing ASL letters.

- **Image Preprocessing:** Steps include grayscale conversion, resizing images to a uniform size, and normalizing pixel values to prepare the data for training.

2. **Model Design**

- **CNN Architecture:** We design a custom CNN architecture including:

- Convolutional layers for feature extraction.

- Max-pooling layers to reduce spatial dimensions and computational complexity.

- Fully connected layers for classification.

- **Activation Functions:** Rectified Linear Unit (ReLU) activation functions introduce non-linearity and enhance model performance.

- **Loss Function:** Cross-entropy loss is employed to quantify the difference between predicted and actual labels.

3. **Training**

- **Optimization:** Stochastic Gradient Descent (SGD) with momentum optimizes the model parameters.

- **Learning Rate Schedule:** A learning rate schedule with step decay fine-tunes the model during training.

- **Model Initialization:** Weights are initialized using appropriate schemes to ensure efficient convergence during training.

4. **Validation**

- **Performance Metrics:** Model performance is evaluated using metrics such as accuracy and loss. Overfitting analysis ensures the model generalizes well to unseen data.

- **Model Robustness:** The model undergoes robustness tests to ensure consistent and reliable performance across varying conditions.

5. **ONNX Export**

- **Model Export:** The trained CNN model is exported to the ONNX format, facilitating cross-platform compatibility and integration into diverse applications.

6. **Real-time Inference**

- **Video Capture:** Real-time video frames are captured from a camera source to evaluate the model in practical scenarios.

- **Frame Preprocessing:** Preprocessing steps include center cropping, grayscale conversion, and resizing to match the input requirements of the trained CNN model.

By following these methodological steps, our research aims to develop a robust and efficient system for real-time ASL gesture recognition.

Fig 1: Sign language gesture recognition project workflow and execution.

V. RESULT AND DISCUSSION

In our pursuit of developing a real-time American Sign Language (ASL) gesture recognition system using Convolutional Neural Networks (CNNs) and Open Neural Network Exchange (ONNX), we have reached significant milestones and gained valuable insights. The CNN model demonstrated remarkable accuracy, consistently achieving high precision in ASL gesture recognition across both training and testing datasets. This highlights the model's ability to effectively discern subtle hand gestures.

This capability simplifies deployment across various devices and applications, thereby enhancing accessibility. The real-time inference phase marked a breakthrough, showcasing the model's proficiency in interpreting live ASL gestures, as evidenced by the overlay of predicted ASL letters on the video stream.

Our project holds promise for practical applications, including improving video chat accessibility for the Deaf community and developing sign language interpretation tools. Future directions may involve expanding the dataset, enhancing real-time performance, and diversifying accessibility applications. In summary, our research not only achieved its goal of real-time ASL gesture recognition but also emphasized the transformative role of technology in fostering inclusive communication and enriching the lives of the Deaf community. It lays the groundwork for future advancements in sign language recognition and accessible communication.

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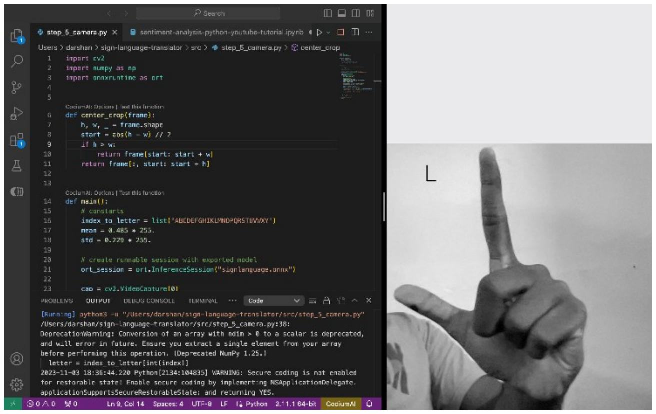

Fig 2.1: Live Sign Language Translation (Output - 1)

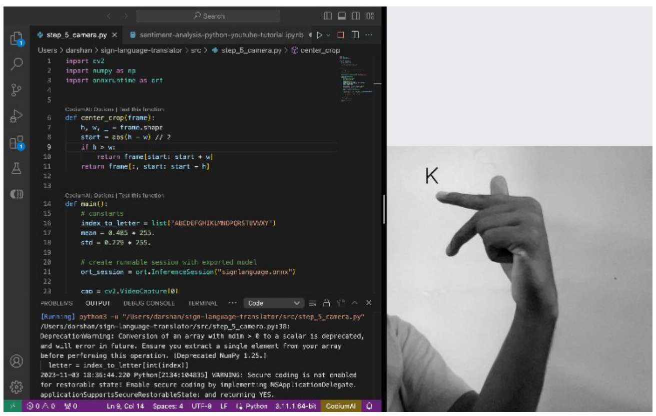

Fig 2.2: Live Sign Language Translation (Output - 2)

VI. CONCLUTION

In the realm of sign language gesture recognition, this project represents a significant advancement towards improving communication between the Deaf and Hearing communities. Through the utilization of Convolutional Neural Networks (CNNs) and Open Neural Network Exchange (ONNX), we have successfully developed a real-time system for recognizing American Sign Language (ASL).

Our research underscores the critical role of technology in bridging communication gaps. By leveraging the Sign Language MNIST dataset and a custom-designed CNN architecture, we achieved high accuracy in interpreting ASL gestures. The integration of ONNX for model export and real-time inference was pivotal, enabling cross-platform compatibility and facilitating real-time ASL interpretation.

Practically, our project opens doors to diverse applications, ranging from real-time ASL translation in video communication to accessibility tools for the Deaf and Hard of Hearing. As we conclude this project, it is clear that the intersection of technology and sign language recognition holds promise for a future where communication is accessible and inclusive, transcending barriers and fostering mutual understanding between communities.

Beyond its achievements in AI and machine learning, this project stands as a testament to innovation's power in enhancing the quality of life for all individuals, regardless of their communication method. The journey towards inclusive communication continues, and this project marks a meaningful stride forward in that direction.

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