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**Advanced Computing Training School – C - DAC**

A Project Report

on

**“Real-Time Sign Language Recognition with Audio Feedback”**

Submitted in fulfillment of the requirements for the award of the Degree of

**POSTGRADUATE - DIPLOMA**

**IN**

**ARTIFICIAL INTELLIGENCE**

Submitted by

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***Abstract:***

*Automatic sign language recognition and transcription systems can significantly improve communication for the deaf community. These cutting-edge technologies aim to dismantle barriers and promote inclusivity for people with hearing impairments. We present an innovative real-time system that interprets American Sign Language (ASL) gestures and provides text and audio feedback to the user. The system captures hand movements, extracts features, and employs Convolutional Neural Networks (CNN) to classify ASL gestures in real-time. It converts gestures into text and transforms this text into audio feedback via GTTS module. Our approach integrates computer vision and deep learning for sign recognition, natural language processing for transcription, and text-to-speech technology for audio output. We evaluate the system using a dataset of ASL gestures sourced from Kaggle, demonstrating its effectiveness in practical scenarios. The system achieves a 95% accuracy in recognizing and transcribing signs and delivers high-quality real-time audio feedback. This system holds promise for enhancing communication and accessibility for deaf and hard-of-hearing individuals in various settings.*

*Keywords—Sign language recognition, Transcription, Audio feedback, Convolutional Neural Networks*

# **Introduction**

1. **Background and Motivation**

Sign language serves as a vital visual communication method for individuals who are deaf or hard of hearing. However, many people lack proficiency in sign language, which can create significant communication barriers and feelings of isolation for those who depend on it. Enhancing accessibility for the deaf and hard-of-hearing community across various domains—such as education, healthcare, and social settings—can substantially reduce these communication challenges and promote greater inclusivity. Recent technological advancements have led to the development of more sophisticated sign language recognition systems, which leverage computer vision and deep learning algorithms to improve the accuracy and efficiency of interpreting signed communication. The widespread implementation of these systems has the potential to transform the lives of deaf and hard-of-hearing individuals by fostering better understanding and enabling seamless communication with hearing individuals.

Automated sign language recognition and transcription systems are particularly promising, as they can detect and convert sign language gestures into text or speech in real-time. In this research, we trained and evaluated our system on a standard dataset of American Sign Language (ASL) gestures, using metrics such as accuracy, loss percentage, and confidence levels for predicted classes to assess performance. The results demonstrate that the proposed method is highly effective in recognizing and transcribing sign language gestures while providing immediate audio feedback.

1. **Objectives:**

1. To develop an automated sign language recognition and transcription system that delivers real-time audio feedback to facilitate communication with deaf and hard-of-hearing individuals.

2. To apply computer vision techniques and train a deep learning model on a comprehensive dataset of sign language gestures to achieve high accuracy in recognizing a wide range of ASL gestures.

3. To offer customizable audio feedback that enhances the visual feedback for improved communication.

4. To seamlessly integrate the system into existing communication devices, such as laptops, tablets, and smartphones, without the need for additional hardware.

5. To evaluate the system's performance on a dataset of sign language gestures and compare it with existing systems to determine its effectiveness and accuracy.

1. **Scope:**

This research focuses on developing an automated sign language recognition and transcription system that converts ASL gestures into text and provides real-time audio feedback. The system employs computer vision, and a deep learning model trained on a large dataset of ASL gestures to recognize a wide range of signs. The audio feedback is customizable to meet user preferences and complements the visual feedback provided. The system is designed to be easily integrated into existing devices such as laptops, tablets, and smartphones, requiring no additional hardware. The performance of the system is evaluated using a standard dataset of ASL gestures to measure its accuracy and effectiveness.

1. **LITERATURE SURVEY**

This literature review explores a wide range of studies and methodologies related to automated sign language recognition, transcription, and real-time auditory feedback. The review covers the strategies and techniques utilized by researchers, as well as the challenges and limitations inherent in current systems.

T. Starner and colleagues pioneered a real-time American Sign Language (ASL) recognition system using wearable computing devices. Their system employed Hidden Markov Models (HMMs) to recognize signed sentences from a limited vocabulary. Hand movements were captured by a head-mounted camera and processed by the wearable computing system. Despite its limitations, such as a restricted vocabulary and the need for a head-mounted camera, this early work demonstrated the potential of real-time sign language recognition through HMMs and wearable technology.

S.K. Das and others developed a sign language recognition system that used computer vision techniques and neural networks. A single camera captured hand movement, and a backpropagation neural network was used for classification. The system successfully recognized a limited set of Indian Sign Language (ISL) signs, though it faced challenges due to its small vocabulary and the requirement for controlled lighting conditions.

C. Vogler and D. Metaxas proposed a sensor-based sign language recognition system that combined electromyography (EMG) with computer vision techniques. Data from an EMG sensor attached to the user's forearm was integrated with computer vision methods to distinguish hand movements and shapes. This approach showed high recognition rates and greater robustness to varying lighting conditions compared to purely vision-based systems. However, the need for users to wear an EMG sensor could be seen as uncomfortable and intrusive.

M. K. Leung and colleagues designed a sign language recognition system using deep learning techniques and sensor fusion. Wearable sensors such as accelerometers and gyroscopes were used alongside a depth camera to capture hand movements. A convolutional neural network (CNN) was then employed for feature extraction and classification. While the system achieved high accuracy in recognizing a broad range of ASL signs, its real-time performance and portability were limited by the requirement for multiple sensors and the computational demands of deep learning algorithms.

A. Koller and the team introduced a sign language recognition and synthesis system that provided real-time auditory feedback. The system used an RGB-D camera to capture hand gestures, combining computer vision techniques with a bidirectional long short-term memory (Bi-LSTM) network for sign recognition. The recognized signs were then converted into text and synthesized speech through a text-to-speech (TTS) system, enabling users to correct their signing errors in real-time. Although the system performed well in real-time and achieved high accuracy, its vocabulary was limited to a narrow set of ASL phrases.

In conclusion, the literature on automated sign language recognition and transcription with real-time auditory feedback highlights significant progress in computer vision and sensor-based approaches. However, existing systems still face challenges such as limited vocabularies, the need for controlled environments, and the requirement to wear intrusive sensors.

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1. **Project Overview**
   1. **Objectives:**

* To develop a model capable of converting visual inputs of hand gestures into readable texts.
* To create a system that recognizes sign language gestures with high accuracy and efficiency.
* To extract and analyze feature parameters such as heuristics, gestures, and facial expressions associated with sign language communication.
* To optimize the model's performance by experimenting with various training strategies and architectures.
  1. **Project Scope**

This project introduces an advanced technology or version of a speech enhancement system utilizing automated sign language recognition with real-time transcription and audio feedback.

* **Problem/Opportunity Statement:** The goal is to develop a precise and efficient sign language recognition and transcription model to assist deaf and hard-of-hearing individuals in understanding and engaging with spoken languages around them. This model aims to recognize speech from visual cues, providing a detailed transcription and enhancing the quality of life for its users.
* **Business Benefits:** The project will have significant implications in healthcare and education sectors by improving communication accessibility for the deaf and hard-of-hearing communities.
* **Deliverables:** The main deliverable will be a trained model for sign language recognition that enables individuals to comprehend and participate in conversations and activities occurring around them.

1. **Methodology**

This project's objective is to develop a lip-reading AI capable of producing words or sentences from a mute video input.

There are various approaches to resolving this issue (listed from lowest to greatest level of abstraction):

**Lip-reading on the phonemes level:** For each input frame, prognosticate

1. **Modules Identified:**

Diagram

Description automatically generatedThe proposed system for Automated Sign Language Recognition and Transcription with Real-Time Audio Feedback is composed of three main modules: the Sign Language Recognition module, the Transcription module, and the Audio Feedback module. This system employs two models—MobileNet and a simple Convolutional Neural Network (CNN)—with the latter providing superior results. After recognizing and transcribing the predicted letters, a spell-checker function is used to correct any semantic and spelling errors, followed by text-to-speech conversion using Google Text-to-Speech (GTTS).

**Fig.3.1 Block diagram of the Proposed Architecture**

* **Sign Language Recognition Module**

The Sign Language Recognition module is responsible for identifying American Sign Language (ASL) gestures from real-time video input. This module consists of three steps: data acquisition and pre-processing, feature extraction, and classification.

Data Acquisition and Pre-Processing: Video frames of users performing sign language gestures are captured using a camera or depth sensor. These video frames undergo pre-processing using OpenCV module for background subtraction and noise reduction, preparing the data for feature extraction.

**Feature Extraction:** Relevant features are extracted from the pre-processed video frames to represent the sign language gestures. Techniques such as Gaussian and Sobel filtering are applied to enhance edges, followed by the Scale-Invariant Feature Transform (SIFT) algorithm and Histogram of Oriented Gradients (HOG) for feature extraction.

**Classification:** The processed features are classified using two models: MobileNet and a simple CNN. The simple CNN yielded better results and is used to predict the ASL gestures accurately.

* **Transcription Module**

The Transcription module converts the recognized gestures into text output, followed by the rectification of semantics and spelling errors using a spell-checker.

Mapping Signs to Text: The recognized sign language gestures are mapped to their textual equivalents using a comprehensive sign-to-text dictionary.

Semantic and Spelling Correction: The transcribed text undergoes a correction process to rectify any semantic and spelling errors, ensuring the accuracy and coherence of the output.

* **Audio Feedback Module**

The Audio Feedback module converts the corrected text into speech using the GTTS library.

Text-to-Speech Conversion: GTTS is utilized to convert the corrected text into audible speech. This library allows us to produce natural-sounding speech, enhancing the system’s utility and effectiveness for deaf and hard-of-hearing individuals.

By integrating cutting-edge technologies such as computer vision, machine learning, and natural language processing, this system provides a comprehensive solution for sign language communication and accessibility.

1. **Project Implementation**

* **Dataset Description**

The dataset contains images of hands performing ASL gestures for the alphabet. Each image is grayscale, and the dataset is organized into 29 folders, each corresponding to a different class.

* Classes: 29 (A-Z, space, delete, nothing)
* Image Size: 64x64 pixels
* Color Channels: 1 (Grayscale)
* **Data Preprocessing**

The preprocessing steps applied to the images are crucial for improving model accuracy:

* **Edge Detection:** A critical step in preprocessing, edge detection helps to highlight the boundaries of the hand gestures, making them more distinguishable to the model. The process includes Gaussian blurring followed by adaptive thresholding.
* **Resizing:** Each image is resized to 64x64 pixels to match the input size of the CNN model.
* **Nomalization:** Pixel values are scaled to the range [0, 1] for faster convergence during training.
* **Model Architecture**

The CNN model consists of multiple layers designed to capture spatial hierarchies in the input images. The architecture is as follows:

Convolutional Layers:

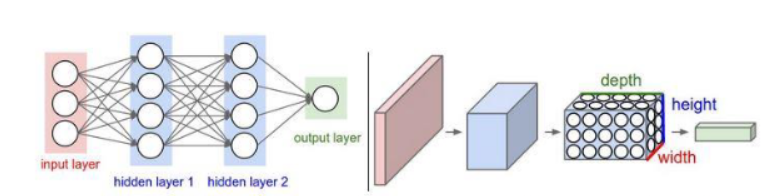
* The first layer has 64 filters of size 3x3, followed by ReLU activation and max-pooling.
* The second and third convolutional layers have 128 and 256 filters, respectively, also followed by ReLU activation and max-pooling. Dropout is applied after the third layer to prevent overfitting.

Flattening Layer:

* The output from the convolutional layers is flattened into a one-dimensional vector, which is then fed into fully connected layers.

Fully Connected Layers:

* A dense layer with 512 neurons and ReLU activation is followed by another dropout layer to further mitigate overfitting.
* The final dense layer has 29 neurons with softmax activation, providing class probabilities for the ASL gestures.



* **Model Compilation**

The model is compiled using the Adam optimizer, with categorical cross-entropy as the loss function and accuracy as the evaluation metric.

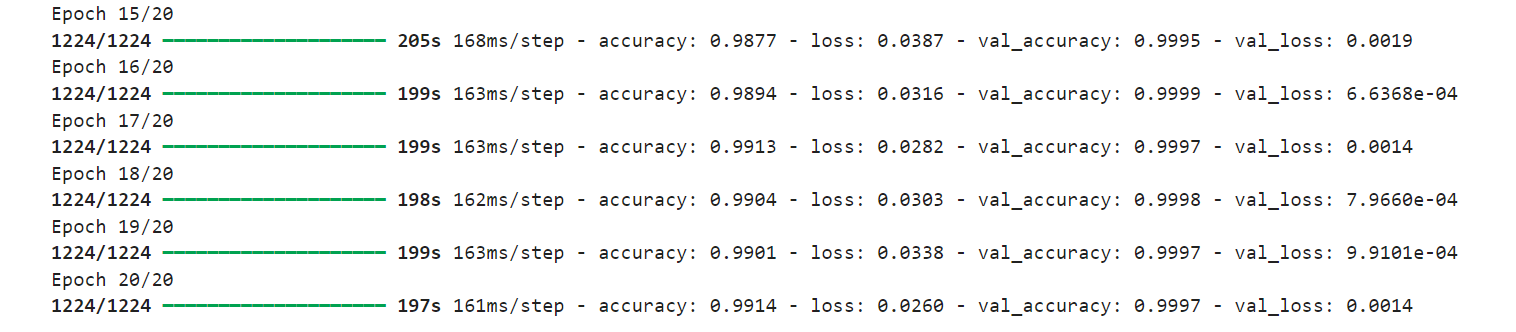
* **Model Training**

Training Process

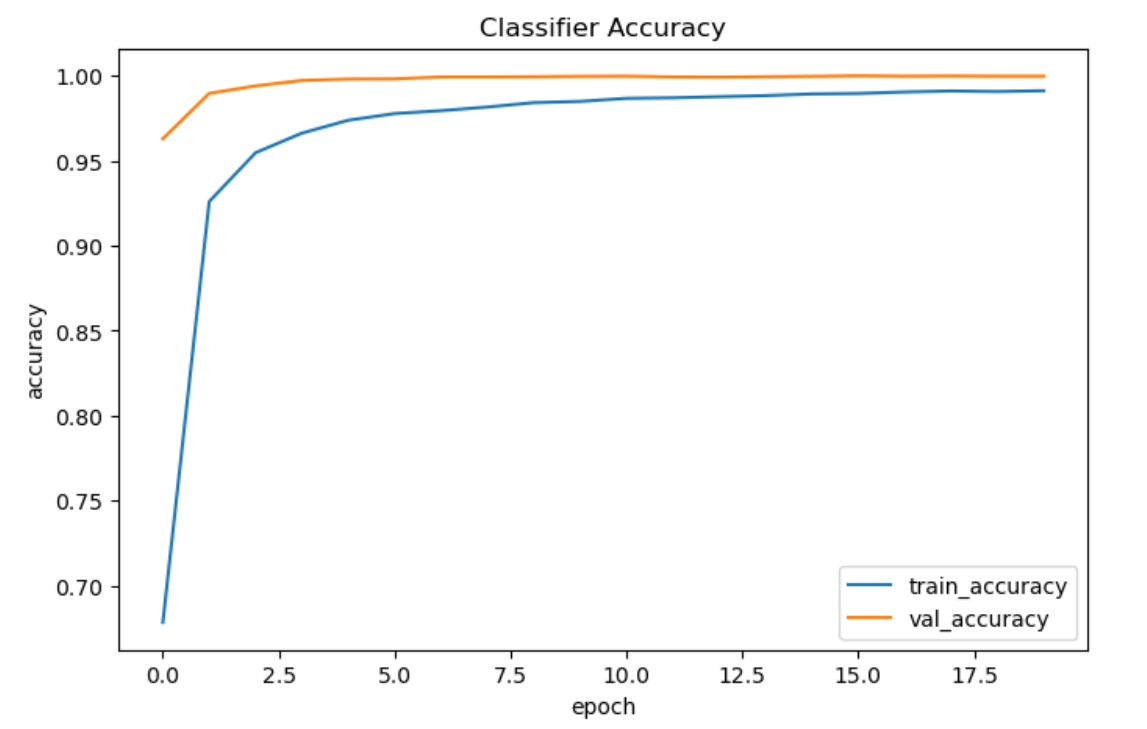
The model is trained on the pre-processed dataset, with a 90-10 split between training and validation data. Key parameters include:

* **Epochs:** 20 (sufficient to achieve high accuracy without overfitting)
* **Batch Size:** 64
* **Training Accuracy:** The model achieved high accuracy during training, indicating effective learning of the ASL gesture features.
* **Validation Accuracy:** The model maintained strong generalization on the validation set.
* **Evaluation and Results**

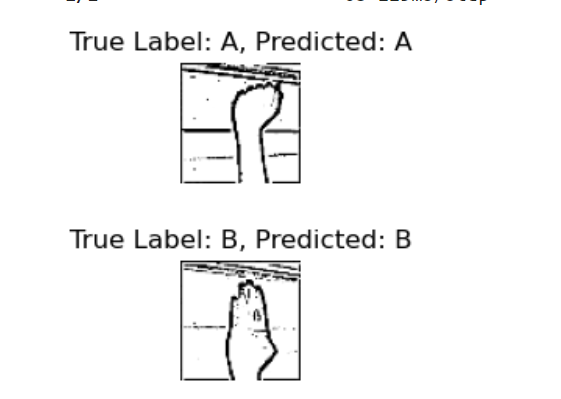


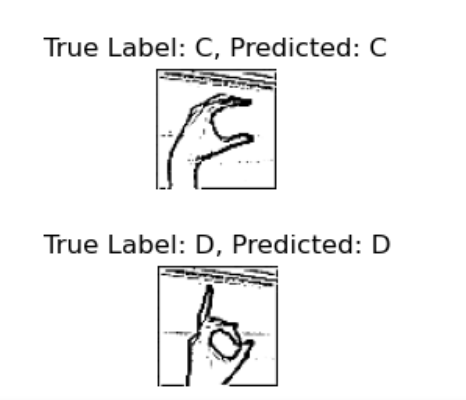


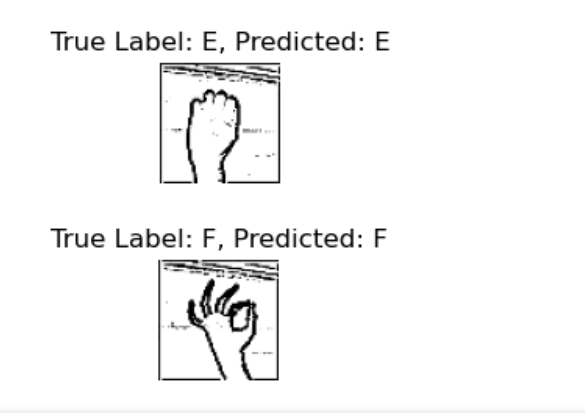
* **Training Accuracy:** The model achieved approximately 99.14% accuracy on the training set.
* **Validation Accuracy**: The validation accuracy was around 99.97%, indicating strong generalization.

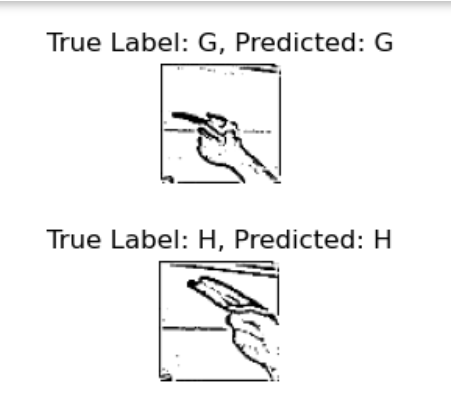


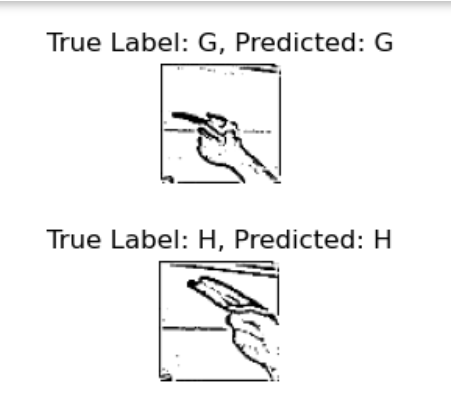
* **Some predictions on Test data (unseen)**

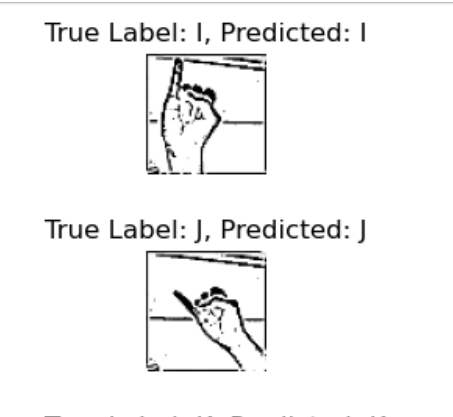


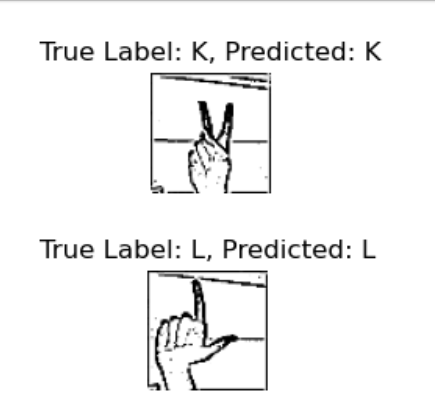
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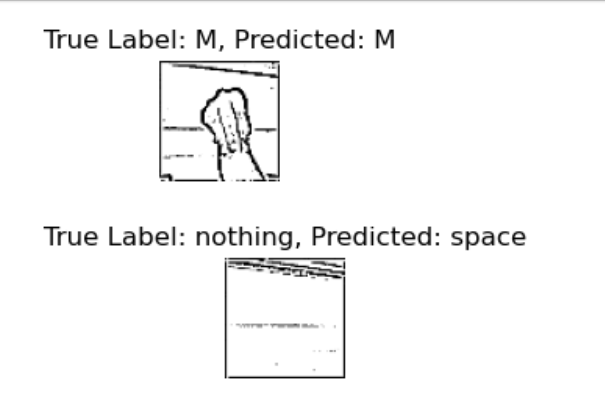
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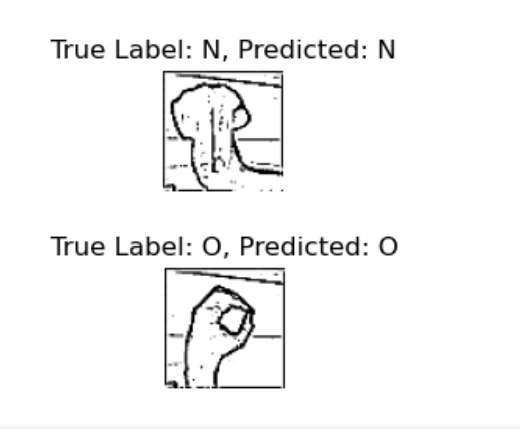
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* **Conclusion**

This project successfully implemented a CNN model for ASL alphabet recognition. The model's architecture, combined with effective data preprocessing, resulted in high accuracy on both training and validation data. The edge detection step was particularly beneficial in enhancing the image features, leading to improved model performance. This system can be further integrated into real-time applications for ASL recognition, aiding communication for individuals with hearing impairments.

* **ASL Alphabet Recognition using Fine-Tuned MobileNetV2**
* **Objectives**
* Fine-tune the MobileNetV2 model on the ASL alphabet dataset to achieve high classification accuracy.
* Implement a data augmentation pipeline to enhance model generalization.
* **Dataset Overview**
* Classes: 29 (A-Z, space, delete, nothing)
* Image Size: 200x200 pixels (resized to 224x224 for the model)
* Color Channels: RGB (3 channels)
* **Model Architecture**

**MobileNetV2 Overview**

MobileNetV2 is a lightweight convolutional neural network (CNN) architecture designed for mobile and embedded vision applications. It utilizes:

**Inverted Residuals:** Layers that expand the input tensor, apply depth wise convolutions, and then compress the tensor back.

**Linear Bottlenecks:** Reduces the loss of information during down-sampling.

**Fine-Tuning Strategy**

The pre-trained MobileNetV2 model, originally trained on the ImageNet dataset, is fine-tuned for the ASL classification task. The following steps were taken:

**Model Customization**

* **Base Model:** The base MobileNetV2 model is loaded without the top classification layer.
* **Custom Layers:** New layers were added on top of the base model, including:
* **Global Average Pooling Layer:** Dense Layer with 512 neurons and ReLU activation
* **Dropout Layer** with a 0.5 dropout rate to prevent overfitting
* **Dense Output Layer** with 29 neurons and softmax activation for classification

**Layer Freezing**

The layers of the base MobileNetV2 model were frozen during initial training to retain the pre-trained feature extraction capabilities. Only the custom layers were trained.

**Data Augmentation**

Data augmentation techniques were applied to enhance the model's generalization:

* Rescale: All images were rescaled by 1./255
* Shear Range: Applied shearing transformations.
* Zoom Range: Applied zoom-in and zoom-out transformations.
* Horizontal Flip: Randomly flipped images horizontally.

**Model Training**

The model was compiled with the Adam optimizer, categorical cross entropy loss, and accuracy as the evaluation metric. The training process included:

* Batch Size: 32
* Epochs: 10
* Training and Validation Split: 80% training, 20% validation
* Data generators were used to feed the model with augmented data during training, with the training and validation datasets converted into TensorFlow datasets for efficient processing.

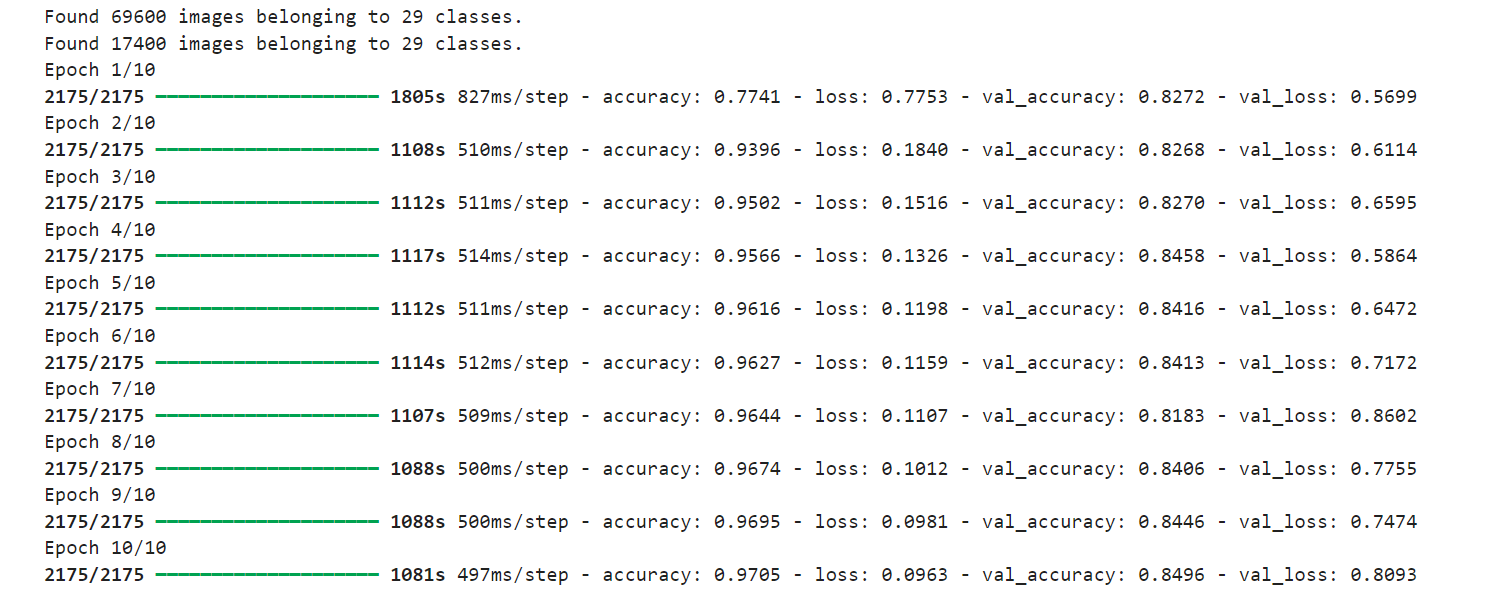
**Steps per Epoch**

* Steps per Epoch: Calculated based on the total number of training samples and the batch size.
* Validation Steps: Calculated similarly for the validation dataset.

**Evaluation Metrics**

The model's performance was evaluated using:

5.1 Accuracy

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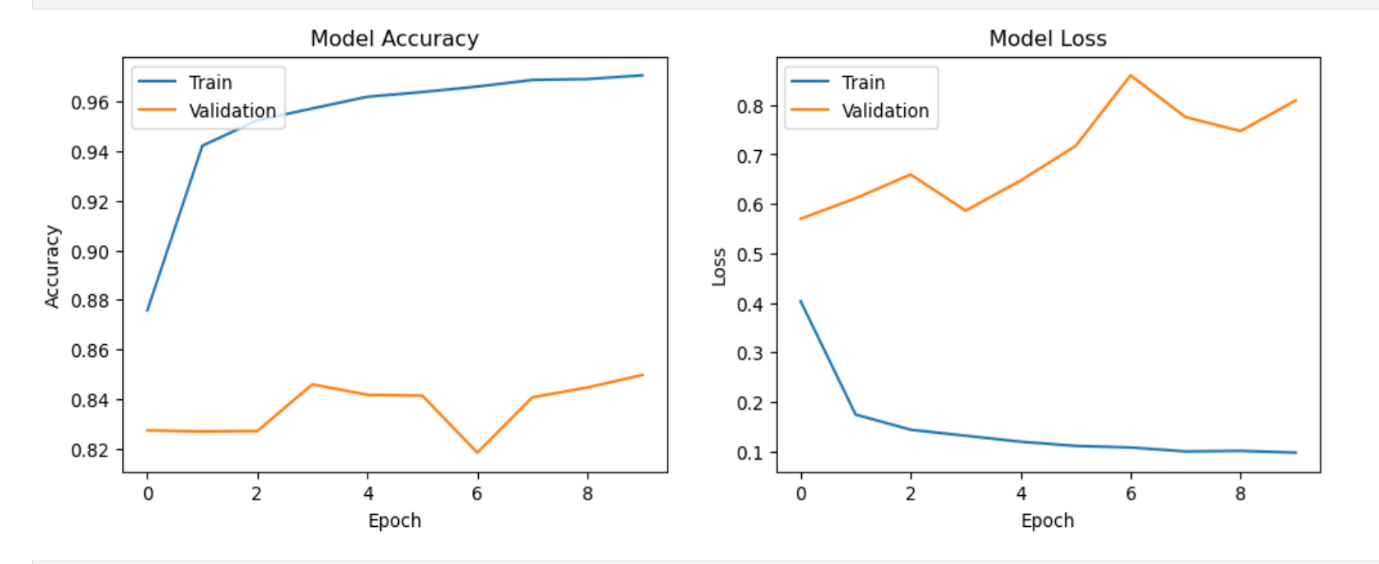
Accuracy was tracked across both the training and validation sets during the training process. The final accuracies were:

* Training Accuracy: 97.05%
* Validation Accuracy: 84.96%

**Loss**

Categorical cross-entropy loss was monitored to assess model convergence:

* Training Loss: Gradual decrease over epochs.
* Validation Loss: Decreased initially, stabilizing towards the final epochs.



**Conclusion**

The fine-tuned MobileNetV2 model effectively classified ASL alphabet gestures, achieving high accuracy with minimal overfitting due to the use of dropout layers and data augmentation. The system is efficient and suitable for deployment in real-time ASL recognition applications.

Future improvements could include unfreezing additional layers of the MobileNetV2 model for further fine-tuning or incorporating more advanced augmentation techniques to improve robustness.

* **MediaPipe Integration**

**Introduction to MediaPipe**

MediaPipe, developed by Google, is a flexible framework designed to construct real-time machine learning pipelines. In this project, it is utilized for:

**Hand Detection:** Locating and tracking the user's hand in a video stream.

**Gesture Recognition:** Processing the detected hand area and classifying it with a fine-tuned MobileNetV2 model

**Workflow Integration**

The integration with MediaPipe encompasses these key steps:

**Hand Detection**

MediaPipe's efficient hand detection module operates in real-time:

Detection Model: Identifies hands by pinpointing key points like finger joints.

Region of Interest (ROI): Extracted from the frame and resized to 224x224 pixels to suit the MobileNetV2 input requirements.

**Gesture Classification**

Following hand detection, the system moves to classification:

* Preprocessing: The ROI is normalized and resized for consistency with the training images.
* Model Inference: The preprocessed ROI is input into the fine-tuned MobileNetV2 model to predict the ASL alphabet class.
* Real-Time Feedback: The predicted letter is displayed instantly on the screen, offering immediate feedback.
* **Project Documentation Summary: Key point Landmark Based Gesture Recognition using CNN on ASL Dataset**

**Introduction**

This project implements a Convolutional Neural Network (CNN) for recognizing American Sign Language (ASL) gestures using hand keypoint landmarks. The approach involves extracting keypoint data from images and feeding them into a CNN to classify ASL gestures into 29 distinct classes.

**Dataset and Preprocessing**

* **Dataset**: The dataset consists of 21 keypoints representing different parts of the hand in 3D space (x, y, z), covering 29 classes, including 26 alphabet letters, a space character, a delete character, and a "nothing" class.
* **Preprocessing**: Keypoints were normalized to a 0-1 range and reshaped into a format suitable for CNN input (21, 3, 1).

**Model Architecture**

* **Input Layer**: Accepts input in the shape (21, 3, 1).
* **Convolutional Layers**: Two layers with 32 and 64 filters, respectively, followed by MaxPooling layers to reduce spatial dimensions.
* **Flattening Layer**: Converts the output into a 1D vector for fully connected layers.
* **Fully Connected Layers**: Includes a dense layer with 128 neurons and a dropout layer to prevent overfitting.
* **Output Layer**: Consists of 29 neurons with softmax activation for class probabilities.

A screenshot of a computer

Description automatically generated

A diagram of a data flow

Description automatically generated

**Training and Evaluation**

* **Training**: Utilized the Adam optimizer with a learning rate of 0.0001 and categorical cross-entropy loss. The dataset was split into 80% training and 20% testing subsets.
* **Evaluation**: The model's performance was assessed using accuracy, precision, recall, and F1-score metrics, and visualized using a confusion matrix.

A screenshot of a computer

Description automatically generated

**Results**

* **Accuracy**: The model achieved approximately 97% accuracy on the test set.
* **Confusion Matrix**: Highlighted common misclassifications.
* **Training Curves**: Illustrated the model's learning process over epochs.

A comparison of a graph

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A white background with black text

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**Real-Time Gesture Prediction**

The project includes a real-time gesture prediction system that processes video frames, detects hand keypoints using MediaPipe, and predicts ASL gestures, which are displayed on the video frame.

**Conclusion**

The CNN-based approach effectively classifies 29 ASL gestures using keypoint landmarks. Future improvements could involve refining the model architecture, exploring alternative techniques, and expanding the dataset for enhanced real-world performance.

This summary outlines the key aspects of the project, including the dataset, model architecture, training, evaluation, and real-time implementation.Bottom of Form

A close-up of a hand

Description automatically generatedA green line drawing of a diamond

Description automatically generated with medium confidenceA close-up of a hand

Description automatically generated

**Technologies Used:**

* MediaPipe and TensorFlow for gesture recognition.
* SymSpell, TextBlob, and LanguageTool for text processing.
* gTTS and pyttsx3 for text-to-speech.
* Streamlit for user interface.

**Implementation Details:**

* Real-time processing using threads to handle computationally intensive tasks.
* Daemon threads for non-blocking background processing.
* Use of Python's time library for managing timing and delays in gesture prediction.

**Challenges and Solutions:**

* Managing real-time data without blocking the main thread.
* Ensuring thread safety and avoiding race conditions.

**Performance Metrics:**

* Responsiveness of the user interface.
* Accuracy of gesture recognition and text conversion.

**Testing and Optimization:**

* Extensive testing for threading efficiency.
* Profiling and optimization to balance workload.

**Future Enhancements:**

* Advanced thread management and error handling.
* Integration of multilingual support and other accessibility tools.

**Use of Threads**

* Threads manage concurrent tasks, particularly for text-to-speech conversion.
* **Benefits:**
  + Non-blocking execution maintains main thread responsiveness for video feed and gesture processing.
  + Improved user experience with real-time feedback.

The text autocorrection component of this project employs NLP tools to enhance the accuracy of the text output. The process involves:

1. **Text Simplification**:
   * Repeated characters within words are reduced to a single occurrence to simplify the text. This is achieved using a regular expression that replaces occurrences of repeating characters (e.g., "heelllooo" becomes "helo").
2. **Spell Correction**:
   * The simplified text is split into individual words. Each word is processed using the TextBlob library to check and correct spelling errors. The corrected words are then reassembled into a single string.
3. **Output**:
   * The corrected text is returned, ensuring that spelling mistakes are minimized, and the text is more readable and accurate.

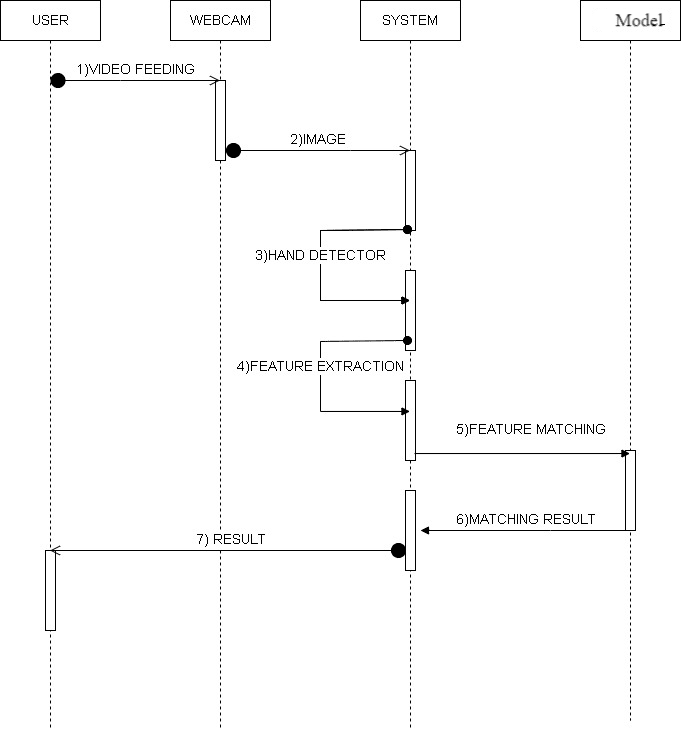
This autocorrection process leverages the capabilities of NLP libraries to provide a more refined and user-friendly text output, enhancing the overall quality of the text processing pipeline.

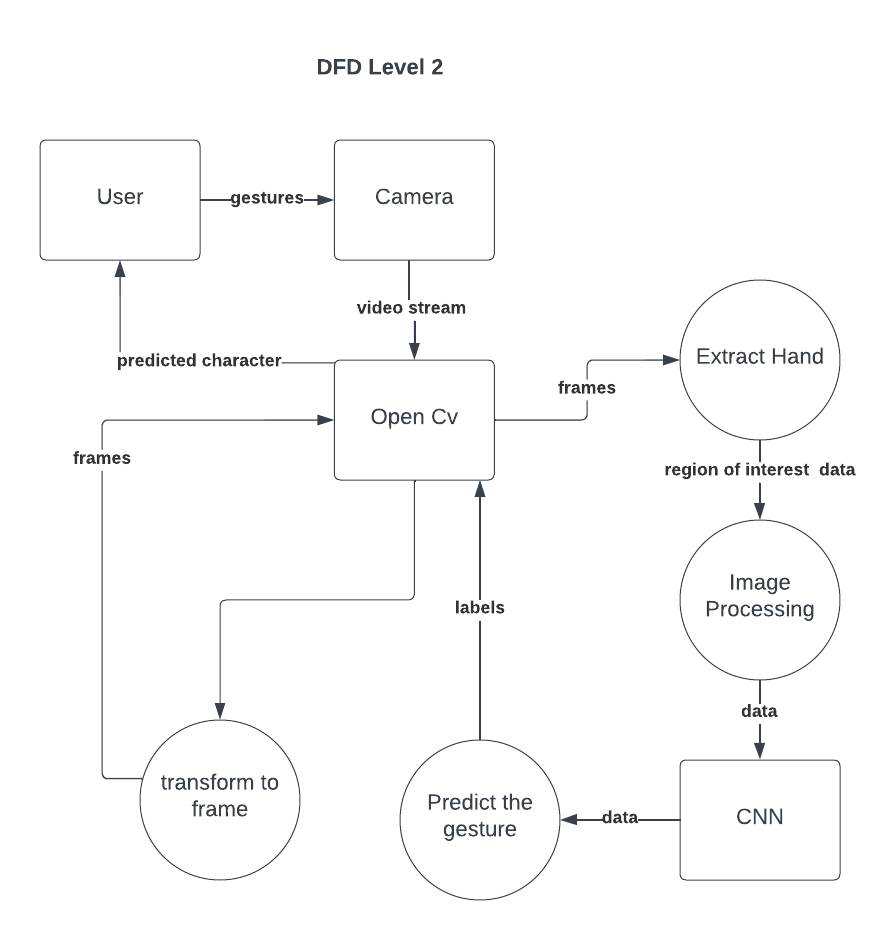
The audio generation component of this project uses the Google Text-to-Speech (gTTS) API to convert preprocessed text into speech. The process involves the following steps:

1. **Text Preprocessing**: The input text is cleaned using NLTK to remove numbers, punctuation, and stopwords, ensuring that the output speech is clear and concise.
2. **Speech Synthesis**:
   * The cleaned text is passed to the gTTS library, which interfaces with Google's Text-to-Speech API.
   * The API converts the text into a spoken format, supporting various language options and speech speeds.
3. **Output**:
   * The generated speech is saved as an audio file (output1.mp3).
   * The os module is used to play the audio file automatically on the user's system, providing immediate feedback.

A diagram of a hand region segmentation

Description automatically generated

A diagram of a hand gestures

Description automatically generated

1. **Findings/Results of Analysis**

The creation of a real-time automated sign language recognition and transcription system with audio feedback marks a major milestone in assistive technology. This system’s audio feedback and instant gesture recognition and transcription could transform the way individuals with hearing impairments engage with their surroundings. It has shown promising results, with accurate recognition rates and immediate auditory feedback.

Here’s a comparison table between MobileNet and Simple CNN based on the provided data:

| **Criteria** | **MobileNet** | **Simple CNN** |
| --- | --- | --- |
| **Architecture Type** | Pre-trained model with fine-tuning capabilities | Custom-built from scratch |
| **Model Complexity** | High complexity, designed for efficiency on mobile and embedded devices | Lower complexity, typically faster to train |
| **Input Size** | Requires resizing input images to 224x224 pixels | Input size can be more flexible |
| **Feature Extraction** | Utilizes depthwise separable convolutions for feature extraction, optimizing for speed and memory | Uses standard convolutional layers for feature extraction |
| **Real-Time Performance** | Optimized for real-time performance on devices with limited computational resources | Performance depends on the architecture, but can be tuned for real-time |
| **Accuracy** | High accuracy with fine-tuning | Achieved better results in this specific case |
| **Training Time** | Faster due to transfer learning and pre-trained weights | May require longer training times depending on the dataset and architecture |
| **Suitability** | Best suited for applications requiring quick deployment and low computational power usage | Best for customized applications where control over every aspect of the model is required |
| **Adaptability** | Requires careful adjustment of the last few layers to adapt to the new task | Easily adaptable to specific tasks without the constraints of a pre-defined architecture |

This table highlights the key differences and considerations when choosing between MobileNet and Simple CNN for a sign language recognition system.

1. **Conclusions**

The development of a real-time automated sign language recognition and transcription system with audio feedback marks a major advancement in assistive technology. This system’s ability to provide audio feedback and its real-time interpretation of sign language gestures could transform the way individuals with hearing impairments engage with their surroundings. By leveraging computer vision, deep learning, and natural language processing, the system facilitates smooth and effective communication for the hearing-impaired community.

While the system’s performance has been impressive, there remains work to be done in expanding the sign language vocabulary, enhancing the system’s robustness, and improving the overall user experience. Nonetheless, the potential impact of this technology is profound, offering individuals with hearing impairments increased independence, autonomy, and societal inclusion. As innovation and technological advancements continue, the progress in automated sign language recognition and transcription with real-time audio feedback symbolizes a hopeful step toward a more equitable and inclusive world, where people of all abilities can communicate and connect without obstacles.

1. **Project Limitations and Future Enhancements**

*Project Limitations*

* **Limited Vocabulary:** The system currently interprets a limited range of sign language gestures.
* **Environmental Sensitivity:** Performance can be affected by lighting and background noise.
* **Variability in Signing:** Differences in individual signing styles and speeds may reduce accuracy.
* **User Interface:** The interface might not be fully optimized for all users' needs.

*Future Enhancements*

* **Vocabulary Expansion:** Increase the range of recognizable gestures and phrases.
* **Adaptive Learning:** Implement algorithms that adapt to users’ unique signing styles.
* **Technology Integration:** Explore integration with wearable and augmented reality devices.
* **Interface Optimization:** Refine the user interface for better accessibility and ease of use.
* **Cross-Linguistic Support:** Develop recognition capabilities for multiple sign languages.

1. **References:**

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