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Original Article

A Comprehensive Deep Learning Based System for Real Time Sign Language Recognition and Translation Using Raspberry Pi

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Abstract *- Sign language is an important aspect of human communication for a variety of reasons, particularly when deaf and dumb individuals are communicating. This study describes a novel method for translating sign language into spoken language that employs a Raspberry Pi 3 and the MobileNet-V2 deep learning model. Technology has advanced significantly, and many studies have been conducted to assist the deaf and dumb. Deep learning and computer vision can also be utilized to support the cause and have an impact on it. The system includes a camera that collects images of the signer's hand gestures and processes them for classification using the MobileNet V2 model. The translated text is entered into text-to-speech software. The system was trained on a huge dataset of sign language movements using transfer learning techniques, and it attained an accuracy of 99.52% on the validation set. The Raspberry Pi 3 was chosen as the hardware platform for its low cost, portability, and suitability for various applications and environments.*

Keywords *- MobileNet-V2, Deep learning, Sign language translator, Raspberry Pi 3.*

1. Introduction

A sign is a natural language that uses hand and body movements and facial expressions to convey a specific message. People having trouble hearing or speaking naturally communicate through sign language. Thanks to sign language, these people can communicate by gesturing with their hands, body, eyes, eyebrows, and postures. Sign language uses visual-manual modality to convey specific messages instead of spoken words [1].

A popular technology for assisting people with auditory-vocal disabilities is the Hand Gesture Recognition system. When other modes, like speech, are uncommunicative, the human hand has remained a common choice for communicating ideas and messages. With their possibilities, computers decipher human gestures as orders thanks to a perceptual computing user interface called gesture recognition. The ability of a computer to comprehend gestures and carry out orders based on those movements is the general definition of gesture recognition. The overall goal of the Hand Gesture Recognition System is to create a system with a Raspberry Pi and a camera module capable of recognising and monitoring some attributes for items that are specified according to image processing methods. Even though people who are deaf, hard of hearing, or mute can communicate with one another without much difficulty, integrating into society and at the workplace can be challenging for them. A person who is non-disabled and unfamiliar with the system of sign language faces barriers in communicating with a person who is impaired. [2, 3]. There were always discussions in finding solutions to overcome these issues that affect the integration of both categories.

With the advancement in technology, i.e., with the help of assistive technology, several solutions have been created in real time to overcome communication barriers. Assistive technology, which is the key core, has developed systems that include communication boards, speech output software, symbol-making software, and speech generating devices. The ability of computer systems to understand and display sign language has advanced significantly over the years. Technological innovations radically transform societal operations, enabling persons with disabilities to communicate freely, promoting critical thinking, enabling collaboration, and reducing the digital divide through literacy and technological tools.

This paper will examine the various components required to build a sign language translator on a Raspberry Pi. It includes accessories like a camera module, speaker unit, display unit, gesture recognition software, and text-to-speech or speech-to-text engines. This makes it easier for auditoryimpaired people to inter-communicate with others. This human body and sign language enabled communication system revolves around detecting a word by a distinct movement. It aims to convert human sign language and gestures into vocal expressions. This is accomplished via the Raspberry Pi's webcam and speaker [4, 6].

The implementation of this project is described in detail in this article. A summary of related research on sign language translation is provided in Section 2. The methodology is proposed in Section 3. The components of the system are also explained in Section 3. The results of the system are presented in Section 4. The conclusions and future scope can be found in Sections 5 and 6.

2. Related Works

Dipali Dhake et al. [5] proposed sign language communication with mute and deaf people. The suggested system creates text, words, and speech by analyzing hand gestures and images using a Raspberry Pi. Sign Language System (SLS) and IoT suggested by Samar Mouti et al. [6] This paper explains the Sign Language System (SLS) for the United Arab Emirates, which converts spoken language into sign language using a Raspberry Pi. The Google Speech engine, which translates Arabic speech into Arabic text, has a 92% accuracy rate with an average display delay of 2.66 seconds.

A portable sign language translator for emergency response teams was proposed by Mannava Vivek et al. [7]. The technique helps rescuers interpret the speech-impaired person's sign language using deep learning in a wearable gadget. This setup uses the TensorFlow Lite model to translate between sign languages while on the go. Saleh Ahmad Khan et al. [24] proposed an effective sign language translator that uses a CNN network and customized ROI segmentation. At a frame rate of 30 fps, the accuracy of identifying signs in movies is approximately 94%, despite the fact that image accuracy fluctuates with distance. N.M. Ramalingeswara Rao [8] proposed methods for converting speech to text and characters using a Raspberry Pi.

An intelligent Arabic sign language recognition system using two LMCs and GMM-based categorization was proposed by Mohamed Deriche et al. [10]. The proposed method beats glove-based and single-sensor solutions. The proposed design gets creative when one or both controllers' data are absent. About 92% of recognitions were accurate. Salma A. et al. [11] suggested the Sign Language Interpreter System for machine learning. The suggested glove has five flex sensors that connect to an arm control unit to convert Arabic Sign Language (ArSL) and American Sign Language (ASL) into voice and text for a simple Graphical User Interface. Understanding Sign Language and Converting Speech Use the Raspberry Pi, per Ramasuri Appalanaidu CH et al. [12] This paper proposes a CNN-based sign language recognition system for blind, deaf, and visually impaired people. The proposed system processes data rapidly and accurately. Daniel S. Breland et al. suggested the Edge Computing System for Deep Learning-Based Thermal Image Sign Language Digit Recognition [13]. A complete embedded system that can accurately detect hand motions in 32x32 pixel thermal pictures was developed in this research. The lightweight CNN model has 99.52% precision on the test dataset. Yande Li et al. propose real time game control and hand gesture detection utilizing a 6-axis wearable band. [14] Glove-based hand gesture recognition was over 99% accurate. Vaibhav Mehra et al. recommend Flex sensors, MPU6050, and Python for gesture-to-speech conversion. [15] Flex sensors, Arduino Unos, and MPU6050s were utilized to build the prototype. No other glove has all the necessary gear. The result is texted to the recipient. Lean suggested deep learning for static sign language recognition. Karlo S. Tolentino, others. [16] A CNN strategy was recommended. In a short time, our gesture recognition system obtained 99% training accuracy and 93.667% average, with letter recognition accuracy of 90.04%, number recognition accuracy of 93.44%, and static word identification accuracy of 97.52%.

Table 1. Summary of related works

Study	Neural Network Architecture	Dataset	Accuracy
Samar Mouti et al. (2020)	ANN	UAE Sign Language	92%
Saleh A. Khan et al. (2019)	CNN	Bangla sign language	94%
Lean Karlo et al. (2019)	CNN	American Sign language	93.667%
Yande li et al. (2018)	Glove-based	American Sign language	> 99%
Daniel S. et al. (2021)	CNN	Thermal images-hand gestures	99.52%
Salma et al.(2020)	Glove-based	American and Arabic Sign Languages	static -95% and dynamic -88% for gestures
Kim et al. (2018)	CNN	Korean Sign Language	95.3%
Liu et al. (2019)	Deep Learning	Chinese Sign Language	89.7%
Zhang et al. (2020)	CNN	American Sign Language	97.2%

3. Methodology

3.1. Dataset

The dataset contains 26 classes, each representing English alphabets. Each class contains 300 images of size 300×300 pixels. The sample dataset is given in Figure 1.

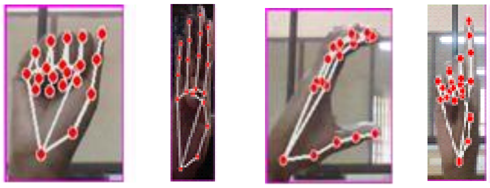

Fig. 1 Dataset for training the MobileNet V2

3.2. Data Pre-processing

Images are retrieved and then changed into a matrix shape so that each 224×224 pixel may be examined. Images are then flattened to identify things in the image. The training pipeline is developed by building a workspace where all the photos are tagged. The interface graph is exported when the training model has been created.

3.3. MobileNetV2

MobileNetV2 is a convolutional neural network architecture designed for embedded and mobile vision applications. It was released in 2018 by Google researchers [25]. The original MobileNet architecture, intended to be portable and practical, has been updated with MobileNetV2 by integrating several fresh features and optimisations. MobileNetV2 expands on the advantages of the first design by enhancing performance while preserving its compact size. Utilising an innovative block design known as the inverted residual block is one of MobileNetV2's distinguishing characteristics. This block consists of 1x1 and 3x3 convolutional layers, followed by a channel-conserving linear bottleneck layer. The precision of the network is maintained while the computational cost is decreased because of this architecture. Using a new activation function called Swish is one of MobileNetV2's most significant improvements. In numerous deep learning tasks, the soft and non-linear function swish outperforms more conventional activation functions like reLU. The usage of depth wise separable convolutions, linear bottlenecks, and skip connections are just a few of the additional enhancements that MobileNetV2 makes over the original MobileNet architecture.

3.4 Block Diagram

The Block Diagram of the Sign Language Translator is shown in Figure 3. The camera detects the sign language, and snapshots are taken each second. These images act as input to CNN. The CNN model is programmed inside the Raspberry Pi board. The board will process the image and compare it with the trained dataset. The dataset is trained by using a teachable machine website. Then, the corresponding messages are displayed on the LCD display and will be converted to audio.

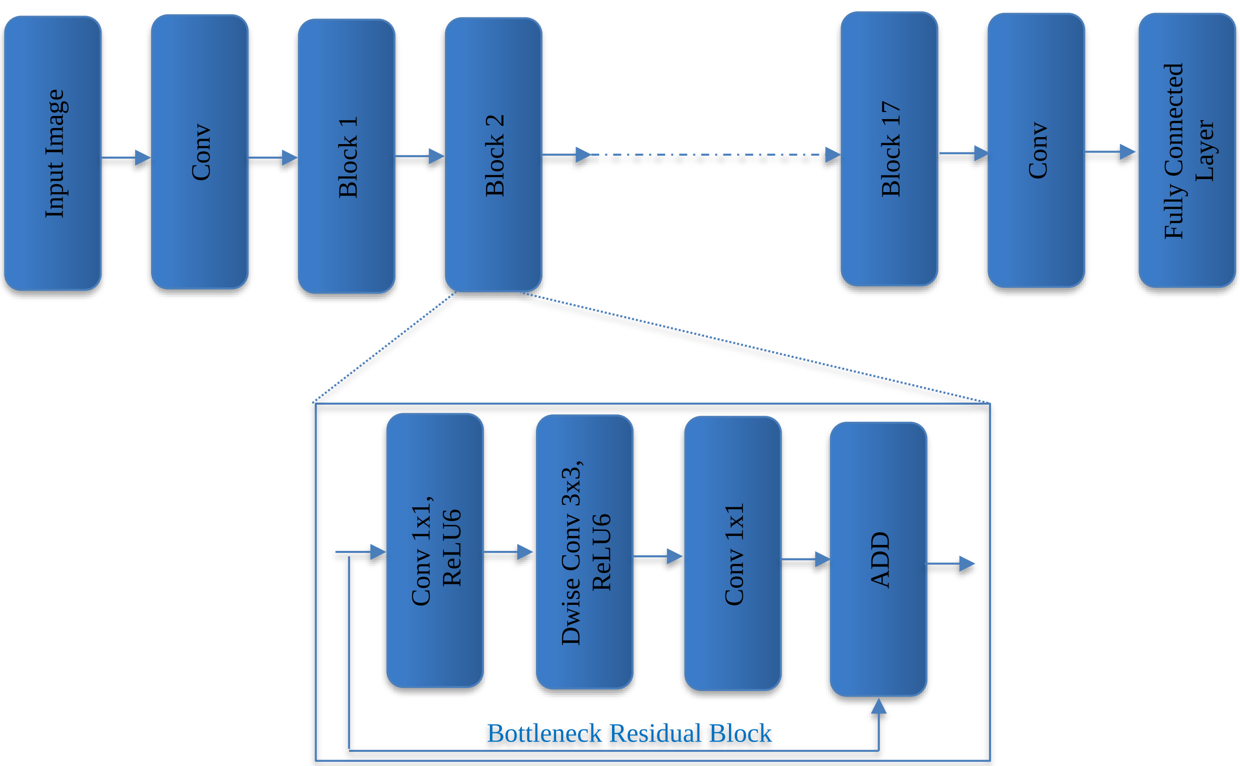

Fig. 2 Architecture of the MobileNetV2 network

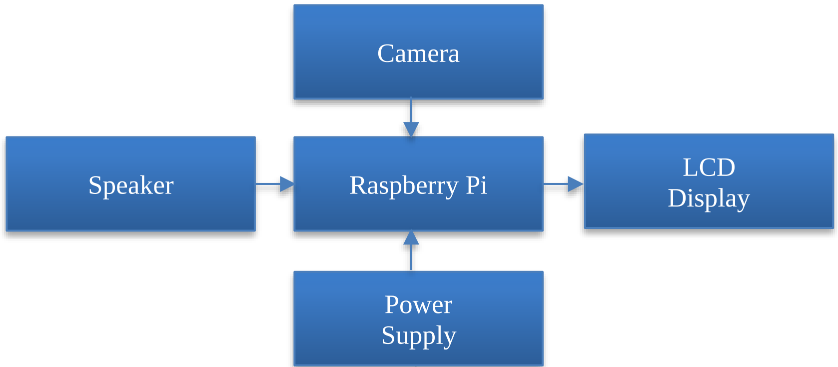

Fig. 3 Block diagram of sign language translator

The web camera is used to capture the user using sign language. Typically, a camera interface links this part to the Raspberry Pi board. The Raspberry Pi board is a tiny computer that processes the image data obtained by the camera module and runs the software. Input/output connections, a processor, and memory are commonly found on the board.

The images taken by the camera are categorized using the MobileNet V2 model, a pre-trained convolutional neural network. The model can correctly classify various signs because it was trained on a big dataset of images in sign language. The output was displayed on LCD, and the audio was on the speaker.

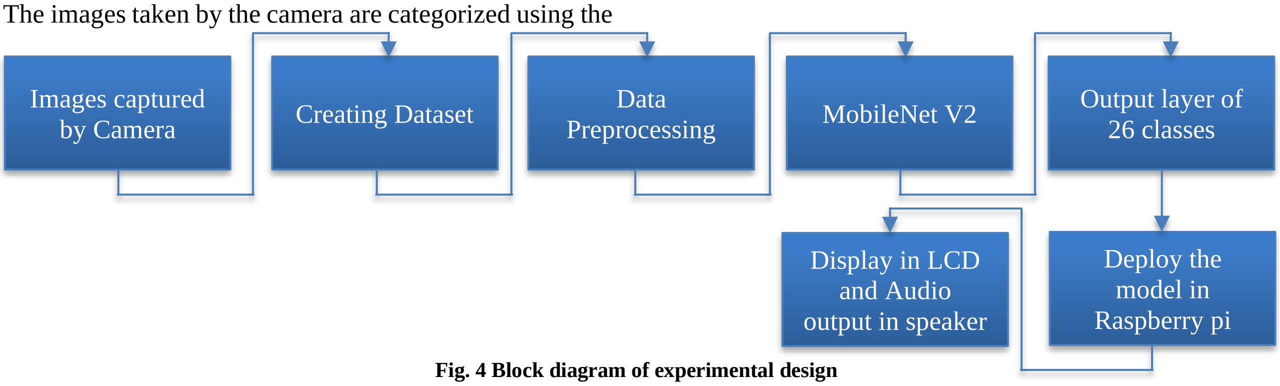

Fig. 4 Block diagram of experimental design

3.5. Flow Chart

A flowchart for a sign language translator system using a Raspberry Pi board and MobileNet V2 model is shown in Figure 5.

- Set up the Raspberry Pi board and connect the camera module, ensuring all necessary hardware configurations are complete.
- Start the image capture process using the camera to record signs made by the user continuously.
- Resize and normalize the captured images to match the input requirements of the MobileNet V2 model for efficient processing.
- Feed the preprocessed image data into the MobileNet V2 model to classify the captured signs into corresponding sign language categories.
- Retrieve the classification results from the MobileNet V2 model, which represents the identified signs.
- Convert the classification results into both text and audio formats. Display the translated text on an LCD screen and play the corresponding audio through a speaker.
- Present the recognized sign language translation visually on the LCD and audibly via the speaker for user interpretation.
- Check if the user has stopped signing. If the user has finished, stop the image capture process and terminate the program. Otherwise, return to step 2 to process the next sign.

3.6. Hardware Description

3.6.1. Raspberry Pi Model 3

Raspberry Pi 3 is a DIY and educational single-board computer. It uses a Broadcom BCM2837B0 1.4GHz Cortex-A53 64-bit SoC. The board's 1GB LPDDR2 SDRAM is enough for most applications. Networking is a key function of the Raspberry Pi 3. The board supports Bluetooth 4.2, IEEE 802.11b/g/n/ac wireless LAN at 2.4GHz and 5GHz, and Gigabit Ethernet over USB 2.0. It also has four USB 2.0 ports for external hard drives, keyboards, and mice. The Raspberry Pi 3 has HDMI, MIPI DSI display, MIPI CSI camera, 4-pole stereo output, and composite video. Micro SD slots are mostly utilized for OS installation and data storage. UART, I2C, SPI, and PWM interfaces are available on the Raspberry Pi 3's 40-

pin GPIO header. This simplifies connecting the board to sensors, actuators, and other electrical components. The board supports Raspbian, Ubuntu, Windows 10 IoT Core, Python, C/C++, and Java programming. This versatile solution suits simple electronics projects and advanced robotics and AI software. Professionals, students, and fans love its price, size, and accessibility.

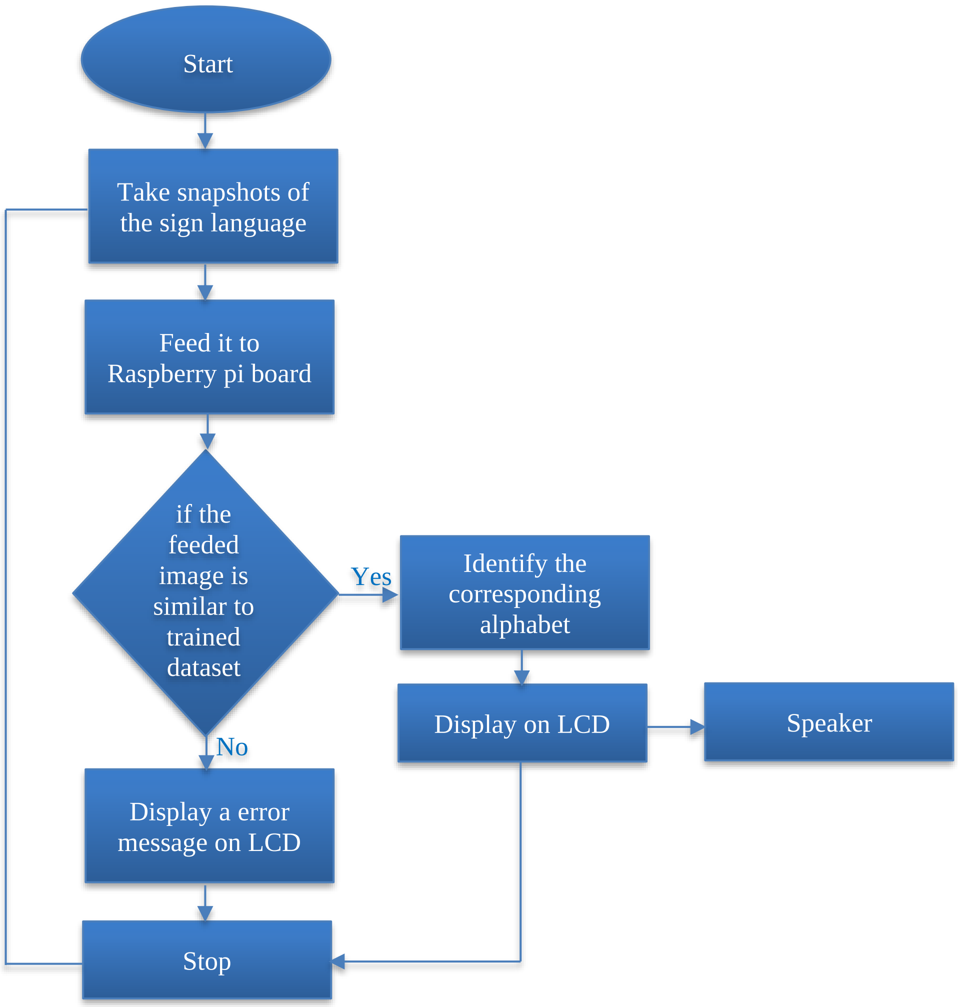

Fig. 5 Flowchart of sign language translator

Fig. 6 Raspberry Pi model 3

3.6.2. Web Camera

A webcam is a video camera engineered for recording or streaming to a computer or computer network. Its uses include video telephony, live streaming, social media, and security. Webcams are integrated into computer hardware or peripheral devices via USB or wireless protocols.

Fig. 7 Webcam

3.6.3. Speaker

Wireless speakers use RF waves to transmit audio signals instead of audio cables. The best-known ways audio transmits to wireless loudspeakers are WiFi- IEEE 802.11 and Bluetooth. The signal frequency range wireless speakers use is generally 900 MHz, ranging from 150 to 300 feet. Bluetooth has around 10 m range.

Fig. 8 Speaker

3.6.4. LCD Display

Liquid crystals are used in liquid crystal displays (LCDs). Because LEDs are used in computers, TVs, instrument panels, and cell phones, they have a wide range of consumer and commercial applications. LCDs are significantly advanced compared to earlier technologies like LEDs and gas-plasma panels. Compared to CRT screens, LCD screens were substantially slimmer. LCDs use less power because they block light than gas-display and LED displays. LCD liquid crystals use an LED light and a backlight to create an image. OLEDs and other emerging display technologies are replacing LCDs.

Fig. 7 Liquid crystal display

4. Result and Discussion

The result of our efforts is a Sign Language Translator that can interpret 26 standard alphabets with an accuracy of up to 98%. The scriptural image depicts the correctly translated sign language gestures identified by the model.

Fig. 6 Hardware of sign language translator

We tracked accuracy and loss during each training phase to ensure that our MobileNetV2-based Sign Language Detection Model was effective. Figure 7 shows how training and validation accuracy develop over time. The training accuracy curve demonstrates the model's capacity to reliably categorize gesture images in the training dataset, as it rises from epoch to epoch until it reaches a maximum accuracy of 0.97 after a few iterations. This demonstrates that the model can distinguish and record properties and patterns unique to sign language gestures.

However, the validation accuracy curve depicts the model's performance on unseen data from the validation dataset. To ensure the model does not overfit the training data and can effectively generalize to new cases, it is imperative to keep an eye on the accuracy of the validation. In our instance, the validation accuracy curve shows a steady rise over epochs, culminating in a 0.95 peak accuracy. This shows the model can correctly classify sign language motions on unseen data and generalize. It is crucial to remember that the abrupt decline in accuracy at epoch 8 is an aberration brought on by a technical problem that occurred during training and led to erroneous estimates. Nevertheless, this problem was quickly fixed, and the following accuracy values are trustworthy.

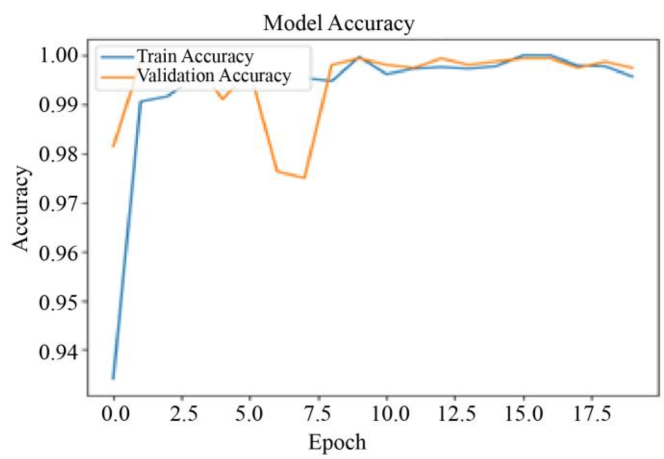

Fig. 7 Accuracy curve of sign language translator

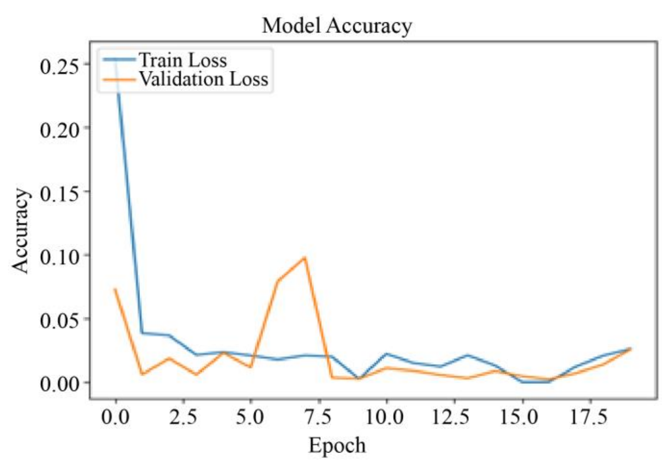

Fig. 8 Validation curve of sign language translator

The accuracy curves show the overall efficiency of our MobileNetV2-based Sign Language Detection Model. The consistently high training and validation accuracy values show that the model has effectively picked up the intricate patterns and characteristics required for precise gesture classification in sign language. The robustness and dependability of our model in actual sign language detecting situations are amply demonstrated by these outcomes.

Table 2. Proposed methodology comparison with previous methodologies

Reference	Methodology	Dataset	Accuracy
Samar Mouti et al.(2020)	ANN	UAE Sign Language	92%
Saleh Ahmad Khan et al.(2019)	Ensemble	Bangla Sign Language	94%
Lean karlo et al.(2019)	CNN	American Sign Language	93.667%
Yande li et al.(2018)	Glove-based	American Sign Language	Above 99%
Daniel S et al(2021)	CNN	Thermal images of hand gestures	99%
Salma et al.(2020)	Glove based	American and Arabic Sign Languages	95% for static and 88% for dynamic gestures
Proposed Methodology	MobileNet-V2	American Sign Language	99.52%

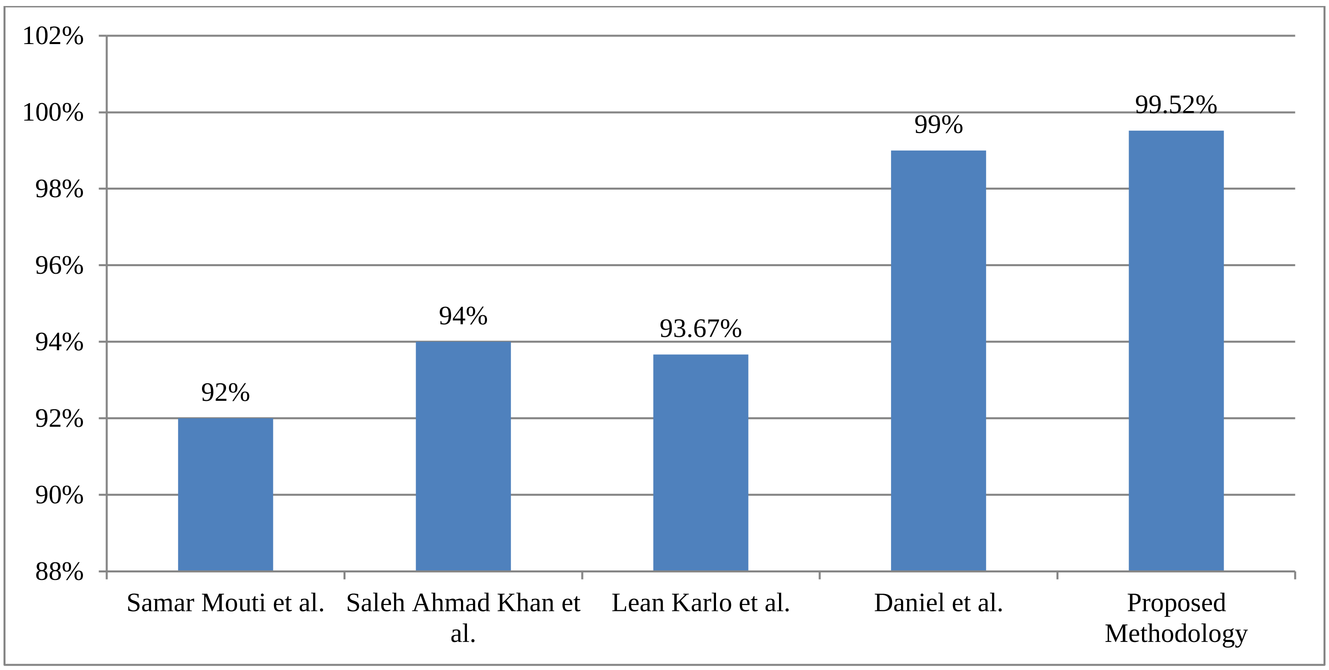

Fig. 9 Performance comparison of our proposed method with existing works

5. Conclusion

In conclusion, our deep learning-powered sign language translator could understand the 26 alphabets with an astounding 99.52% accuracy. The model was meticulously trained, showcasing its proficiency in understanding and translating sign language gestures. Integrating with Raspberry Pi adds a practical dimension, making it portable and accessible for real-world applications. This innovation holds great promise for bridging communication gaps between individuals with hearing impairments and the wider community. Its success, highlighted in this paper, emphasizes the potential impact of technology in fostering inclusivity. This accomplishment contributes to assistive technology and underscores the transformative power of deep learning in enhancing accessibility and communication.

6. Future Scope

The future scope of this paper lies in advancing the sign language translator to incorporate dynamic signs, enabling a more comprehensive communication experience. By extending the deep learning model to recognize and interpret dynamic gestures and facial expressions, the system can better capture the nuanced nature of sign language conversations.

Further research could also focus on expanding the language support and refining the user interface for improved user experience. These enhancements will propel the technology towards a more inclusive, versatile, and interactive tool for individuals with hearing impairments.

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