



KIET
GROUP OF INSTITUTIONS
Connecting Life with Learning



A
Project Report
on
SIGN LANGUAGE RECOGNITION
submitted as partial fulfillment for the award of
BACHELOR OF TECHNOLOGY
SESSION 2023-24
in
COMPUTER SCIENCE & ENGINEERING

By
Riya Gupta (2000290100119)
Priyanka Anand (2000290100107)
Khushboo Jha (2000290100083)

Under the supervision of

Mr. Gagan Thakral

KIET Group of Institutions, Ghaziabad

Affiliated to

Dr. A.P.J. Abdul Kalam Technical University, Lucknow

(Formerly UPTU)

May, 2024

DECLARATION

We hereby declare that this submission is our own work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Date:

Signature:

Name: Riya Gupta

Roll No.: 2000290100119

Date:

Signature:

Name: Priyanka Anand

Roll No.: 2000290100107

Date:

Signature:

Name: Khushboo Jha

Roll No.: 2000290100083

CERTIFICATE

This is to certify that Project Report entitled "**SIGN LANGUAGE RECOGNITION**" which is submitted by **Riya Gupta, Priyanka Anand, Khushboo Jha** in partial fulfillment of the requirement for the award of degree B. Tech. in Department of Computer Science & Engineering of Dr. A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidates own work carried out by them under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

.

Date:

Mr. Gagan Thakral

(Assistant Professor)

(Department of CSE)

Dr. Vineet Sharma

(Head of Department)

ACKNOWLEDGEMENT

It gives us a great sense of pleasure to present the report of the “**SIGN LANGUAGE RECOGNITION**” Project undertaken during B. Tech. Final Year. We owe special debt of gratitude to **Mr. Gagan Thakral, Department of Computer Science & Engineering, KIET, Ghaziabad**, for his constant support and guidance throughout the course of our work. His sincerity, thoroughness and perseverance have been a constant source of inspiration for us. It is only his cognizant efforts that our endeavors have seen light of the day.

We also take the opportunity to acknowledge the contribution of **Dr. Vineet Sharma, Head of the Department of Computer Science & Engineering, KIET, Ghaziabad**, for his full support and assistance during the development of the project. We also do not like to miss the opportunity to acknowledge the contribution of all the faculty members of the department for their kind assistance and cooperation during the development of our project.

We also do not like to miss the opportunity to acknowledge the contribution of all faculty members, especially faculty/industry person/any person, of the department for their kind assistance and cooperation during the development of our project. Last but not the least, we acknowledge our friends for their contribution in the completion of the project.

Date:

Date:

Date:

Signature:

Signature:

Signature:

Name: Riya Gupta

Name: Priyanka Anand

Name: Khushboo Jha

Roll No.: 2000290100119

Roll No.: 2000290100107

Roll No.: 2000290100083

ABSTRACT

“Language shapes the way we think, and determines what we can think about. Sign language, too, makes an enormous difference in the way we can think.” - Temple Grandin

Sign language is also known as a form of nonverbal communication that relies on the visual-manual modality. One popular way that people with hearing disabilities interact with each other is through gestures, and there are a variety of options possible for their interaction, including sign language. In this paper, by using video or hand gesture input, the device can recognize various alphabetical sequences with a color background provided using American Sign Language. Different parameters and feature extraction methods were used in the experiments to improve the model's detection accuracy. Overall, the findings highlight the promise of machine learning methodologies for sign language identification as well as the importance of developing precise and effective systems in narrowing the communication divide between the auditors and the deaf.

TABLE OF CONTENT	PAGE NO.
DECLARATION.....	ii
CERTIFICATE.....	iii
ACKNOWLEDGEMENT.....	iv
ABSTRACT.....	v
LIST OF FIGURES.....	viii
LIST OF ABBREVIATIONS.....	ix
CHAPTER 1 (INTRODUCTION).....	1
1.1 Introduction	1
1.2 Problem Statement	2
1.3 Problem Solution	2
1.4 Project Description	3
CHAPTER 2 (LITERATURE SURVEY).....	5
2.1 Human – Computer Interaction	5
2.2 Method	9
2.2 Results	11
CHAPTER 3 (PROPOSED METHODOLOGY).....	13
CHAPTER 4 (RESULTS AND DISCUSSION).....	15
CHAPTER 5 (CONCLUSIONS AND FUTURE SCOPE).....	17
REFERENCES	20
APPENDIX 1 (ACCEPTED RESEARCH PAPER)	24

APPENDEX 2 (RESEARCH PAPER)	25
APPENDEX 2 (PLAGIARISM REPORT)	37

LIST OF FIGURES

Figure No.	Description	Page No.
1	American Sign Language Dataset	7
2	CNN based system workflow	10
3	Real-Time Sign Language Recognition	12

LIST OF ABBREVIATIONS

S.No.	ABBREVIATION	DESCRIPTION
1	DHH	Deaf and hard of hearing
2	SLR	Sign Language recognition
3	CNN	Convolutional neural networks
4	RNN	Recurrent neural networks
5	HCL	Human-Computer Interaction
6	AI	Artificial Intelligence
7	ISL	Indian Sign Language
8	ASL	American Sign Language
9	ReLU	Rectified Linear Unit

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Effective communication is vital for human connection in today's interconnected society. However, conventional communication techniques may not fully meet the diverse needs of people with hearing impairments. Sign language, a visual language based on gestures, serves as the primary means of communication for many in the Deaf and Hard of Hearing community. Gesture recognition provides a natural and intuitive method for human computer interaction, particularly in converting sign language to text. Ensuring good communication and accessibility for this population is crucial.

The need for sign language recognition arises from the desire to make information and communication more accessible to the deaf and hard of hearing (DHH) community. While sign language is a primary mode of communication for many DHH individuals, there are barriers to its widespread understanding and use. By developing technologies that can recognize and translate sign language into spoken or written language, we can facilitate better communication and inclusion for the DHH population.

One of the key challenges in SLR is the diversity of sign languages and the variability of signing styles within each language. Sign languages differ across regions and cultures, with distinct vocabularies, grammar rules, and dialects. Additionally, individual signing styles can vary based on factors such as age, gender, and educational background. This variability makes it difficult to create a universal SLR system that can accurately interpret all sign languages and signing styles.

To address these challenges, researchers have explored various approaches to SLR, including

computer vision, machine learning, and deep learning. Computer vision techniques are used to extract features from sign language videos, such as hand movements, facial expressions, and body postures. Machine learning algorithms are then applied to classify these features and recognize the corresponding signs. Deep learning, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has shown promising results in improving the accuracy and robustness of SLR systems.

In recent years, there has been a growing interest in multimodal SLR, which combines information from multiple modalities, such as video, depth, and skeletal data, to improve recognition performance. By leveraging the complementary information provided by these modalities, multimodal SLR systems can achieve higher accuracy and better generalization to different signing styles and conditions.

In conclusion, sign language recognition is a challenging yet rewarding field with the potential to significantly improve the lives of DHH individuals. By advancing SLR technology, we can break down communication barriers and promote inclusivity and accessibility for all.

1.2 PROBLEM STATEMENT

People with speech impairments and deafness find it difficult to communicate smoothly due to the existing absence of efficient sign language recognition technologies. To facilitate effective communication between sign language users and non-signers, there is an urgent need for a reliable system that can recognize sign language motions and translate them into text.

1.3 PROBLEM SOLUTION

The recommended approach is to create a reliable system for recognizing sign language and use computer vision and machine learning to transform sign language motions into text. With the integration of text-to-speech and speech-to-text features, this system will provide two-way communication. Prioritizing user-centered design and accessibility, ongoing enhancements will be made in response to user input. In general, this approach seeks to transform

communication for those who are deaf or have speech problems, enabling them to successfully express themselves using sign language.

1.4 PROJECT DESCRIPTION

The project's implementation involves creating a model to detect sign language using an OpenCV webcam to capture hand gesture images. Convolutional Neural Networks (CNNs) are ideal for this task, as they excel in image and video analysis by extracting features through convolution and pooling layers. CNNs are particularly valuable for computer vision tasks like image recognition and object classification. However, challenges remain, such as classifying gestures accurately and distinguishing sign gestures from transitional movements.

Researchers are addressing the communication gap for the speech-impaired community by focusing on hand gesture recognition systems tailored to their needs.

These systems aim to interpret hand gestures into audible speech or text, facilitating communication with the wider community. Advances in deep learning and neural networks have significantly improved the accuracy and efficiency of these systems, offering promising avenues for inclusivity and enhancing communication for the speech-impaired.

The project's implementation involves developing a model to detect sign language using an OpenCV webcam for capturing hand gesture images. Convolutional Neural Networks (CNNs) are well-suited for this task, as they excel in analyzing images and videos by extracting features through convolution and pooling layers. CNNs are particularly valuable for computer vision tasks such as image recognition and object classification. However, challenges remain in gesture recognition, including issues with classification and distinguishing sign gestures from transitional movements.

Researchers are addressing the communication gap for the speech-impaired community by focusing on hand gesture recognition systems tailored to their needs. These systems aim to interpret hand gestures into audible speech or text, facilitating communication with the broader community. Advances in deep learning and neural networks have significantly improved the

accuracy and efficiency of these systems, offering promising avenues for inclusivity and enhancing communication for the speech-impaired.

CHAPTER 2

LITERATURE REVIEW

2.1 HUMAB-COMPUETER INTERACTION AND GESTURE RECOGNITION

The research, planning, and design of human-computer interaction, or HCI, focuses on the relationship between humans and computers. It focuses on the interfaces that humans (users) employ to communicate with computers and the ways in which these interfaces enable user-computer interaction. In order to facilitate connection with computers or other devices, gesture recognition is a subfield of human-computer interaction (HCI) that focuses on identifying and interpreting human gestures.

Sensors, cameras, and other equipment are used by gesture recognition technology to record and interpret human gestures. These gestures can be expressed with the hands, the body, the face, or even the eyes. The intention is to provide users with the ability to engage with computers and other gadgets in a more instinctive and natural manner, akin to how they would converse with one another.

Applications for gesture recognition can be found in many domains, such as virtual reality, gaming, healthcare, and smart device user interfaces. Gesture recognition, for instance, can be utilized in video games to control characters or actions without the need of a conventional controller. It might be utilized in the medical field for activities in rehabilitation or remote patient monitoring.

- **Common Devices in Human-Computer Interaction (HCI)**

Traditional HCI relies heavily on devices like mice, keyboards, touch screens, and remote controls. Different gadgets are used in human-computer interaction (HCI) to make it easier for people to engage with computers. These gadgets are essential for allowing consumers to communicate with computer systems in an efficient and natural way, input data, and get feedback.

In HCI, touchscreens are becoming more and more common because they let people interact with displays directly by touching them. This method is frequently used in tablets, smartphones, and kiosks.

Voice-activated gadgets have become more and more common in recent years, allowing users to communicate with computers and other devices using voice commands. To understand and carry out commands, these devices frequently use speech recognition technology.

HCI also uses gesture recognition technology, such as motion sensors or cameras, to identify and decipher hand motions. These components are frequently found in virtual reality and game consoles.

Additional hardware utilized in human-computer interaction (HCI) includes joysticks, trackpads, and a variety of sensors (such as proximity and motion sensors) that facilitate different kinds of interaction.

In general, the particular interaction needs and the intended user experience determine the device selection in HCI. In order to improve the user experience overall, the objective is to choose gadgets that offer users simple and effective means of interacting with digital systems.

- **Advancements in HCI**

Human-Computer Interaction (HCI) needs to advance quickly to keep up with the rapid advancements in software and technology, according to Zhi-Hua Chen and his colleagues. They contend that the needs of contemporary computing environments are being unmet by traditional types of HCI, which frequently mostly rely on keyboards and mouse. Consequently, they suggest creating new and advanced modalities of interaction, like speech and gesture recognition.

With the use of artificial intelligence (AI) and computer vision technologies, these sophisticated modalities are able to recognize and react to human speech and movements instantly.

These techniques should improve computing's intuitiveness, efficiency, and accessibility for a larger spectrum of users by allowing users to interface with computers using voice commands and natural gestures.

According to Chen and his associates, the incorporation of artificial intelligence and computer vision technologies into human-computer interaction (HCI) would eventually result in more efficient and adaptable interaction paradigms, improving the user experience in general and opening up new avenues for human-computer collaboration.

- **Gesture Recognition**

An essential part of Human-Computer Interaction (HCI), which focuses on comprehending and interpreting human movements, is gesture recognition. Real-time gesture analysis and interpretation in this discipline is frequently achieved through the use of computer vision or artificial intelligence (AI) technology.

Real-time motion-driven recognition is one of the hot topics of gesture recognition research. This method entails seeing and deciphering motions in real time so that the system can react instantly. This real-time feature is very helpful in applications where correct and timely gesture interpretation is crucial, such virtual reality, gaming, and healthcare.

For instance, using a face detector and an optical flow feature together, a noteworthy study from 2013 showed substantial results in gesture identification. This strategy demonstrated the possibility of combining several technologies and approaches to improve gesture recognition accuracy and efficacy, with a success rate for gesture recognition of 68%.

Ultimately, gesture recognition is essential to the advancement of human-computer interaction (HCI) because it provides new means of user interaction and facilitates a more intuitive and natural computing environment.

- **Speech Recognition**

A key component of Human-Computer Interaction (HCI), which focuses on comprehending and interpreting human speech, is voice recognition. The accuracy and dependability of speech recognition systems have been considerably improved by recent developments in artificial intelligence (AI) and machine learning, offering them a competitive advantage over more conventional input devices like keyboards and mouse.

Through the analysis of audio input, this technology transforms information into words or commands that a computer can comprehend and execute. Due to these developments, speech recognition is now widely used in a variety of applications, such as dictation software, which enables users to dictate text rather than write it, and virtual assistants like Siri, Alexa, and Google Assistant.

For those with impairments or those who prefer hands-free engagement, in particular, the use of speech recognition in HCI has greatly enhanced the accessibility and usability of computing equipment. Moreover, speech recognition has created new avenues for human-computer connection, allowing for more intuitive and natural ways to engage with technology.

- **Improving Gesture Recognition Accuracy**

One of the primary goals of HCI research is to improve the accuracy of gesture recognition, which encompasses hand, sign, and body movements. Recognition technology can identify various objects for different applications, including faces, patterns, hand or body motions, and movements. For example, a study in 2007 proposed a sign language recognition system using support vector machines trained on an Indian sign language (ISL) dataset.

- **Conclusion**

In conclusion, HCI is a multidisciplinary field that seeks to improve the interaction between humans and computers.

Advances in hardware and software have led to the development of new forms of HCI, including gesture and speech recognition. These technologies leverage AI and computer vision to interpret human gestures and speech, offering more effective and flexible interaction modalities. Improving the accuracy of gesture recognition is a key area of research in HCI, with applications in various fields. Overall, these advancements are enhancing the way we interact with computers, making HCI more intuitive and accessible.

2.2 METHOD

A. Input Method

- In our approach, to capture sign language performed by signers on a real-time basis and interpret the language to produce textual output for the illiterate.
- For this, a camera-based approach will be made use of, owing to the ease of portability and movement that the camera-based method offers over other techniques.

B. Dataset

For dataset, the skin portion of the image dataset was segmented. Their primary focus, the classification, involved extracting pertinent features from the skin-segmented images [10]. The model was trained using these extracted features and image recognition was performed using the trained model [10].

- Collecting colored images of ASL with OpenCV and webcam.
- **Dataset is trained using the CNN algorithm.**

Streamline model training and evaluation processes, optimizing the number of epochs and batch size for effective convergence.



Fig. 2: American Sign Language Dataset

- **Real time detection using OpenCV.**

The first stage in this research is to use a webcam to collect a dataset of colored images that represent numerals and alphabets in American Sign Language (ASL). The OpenCV library is then used to record hand movements in real time. Since color information can provide more features for gesture identification, using colored images is essential to improving the accuracy and resilience of the model.

Following dataset collection, preprocessing is applied to the data using methods such

as background subtraction and data augmentation. Although data augmentation broadens the dataset and enhances the model's capacity to generalize to new data, background removal aids in separating the hand motions from the background noise.

Next, using TensorFlow and Keras, a custom Convolutional Neural Network (CNN) model is created and trained. The model architecture is made up of several layers, including as pooling layers for dimensionality reduction, convolutional layers for feature extraction, and dense layers for classification. The aforementioned layers are designed to efficiently identify and assimilate patterns within the input images that match to distinct ASL movements.

In order to properly learn the representation of the motions, the model is trained to identify patterns in the input photos and link them to corresponding ASL labels. Real-time sign language recognition is possible because, once trained, the model may be used to anticipate ASL motions from fresh input photos. This method demonstrates how real-time processing, deep learning, and computer vision may be used to create an effective ASL gesture detection system.

C. Result

Finally, the trained model is used in conjunction with OpenCV for real-time hand gestures recognition, where the webcam captures hand gestures, and the model predicts the corresponding sign language interpretation, facilitating effective communication for the hearing-impaired. Continued advancements in gesture and speech recognition, supported by artificial intelligence and computer vision technologies, are paving the way for innovative human-computer interaction methods. Research efforts focusing on expanding the scope of sign language recognition to include more languages and integrating machine learning

techniques further improve the accuracy and efficiency of sign language interpretation systems.

Overall, these technologies have the potential to revolutionize communication accessibility, providing equitable opportunities for individuals with diverse communication needs.

CHAPTER 3

PROPOSED METHODOLOGY

- Collecting colored images of ASL with OpenCV and a webcam.
- Dataset is trained using the CNN algorithm.
- Streamline model training and evaluation processes, optimizing the number of epochs and batch size for effective convergence.
- Real-time detection using OpenCV.
 - **Data Collection:** Use OpenCV and a webcam to collect colored images of American Sign Language (ASL) gestures, including numbers and alphabets. Colored images can help improve the accuracy and robustness of the ML model.
 - **Data Preprocessing:** Preprocess the collected data using techniques like background subtraction and data augmentation to enhance the quality of the dataset.
 - **Model Training:** Train a custom Convolutional Neural Network (CNN) model using TensorFlow and Keras. The model should include various layers such as convolutional, pooling, and dense layers for effective feature extraction and classification.
 - **Model Optimization:** Streamline the model training and evaluation processes by optimizing the number of epochs and batch size to achieve effective convergence.

- **Real-Time Detection:** Use OpenCV for real-time hand gesture recognition. Integrate the trained CNN model with OpenCV to detect hand gestures using a live webcam.

Overall, the project demonstrates how computer vision and machine learning can be combined to create a system for real-time ASL gesture recognition, which can have applications in accessibility and communication for the deaf and hard of hearing community.

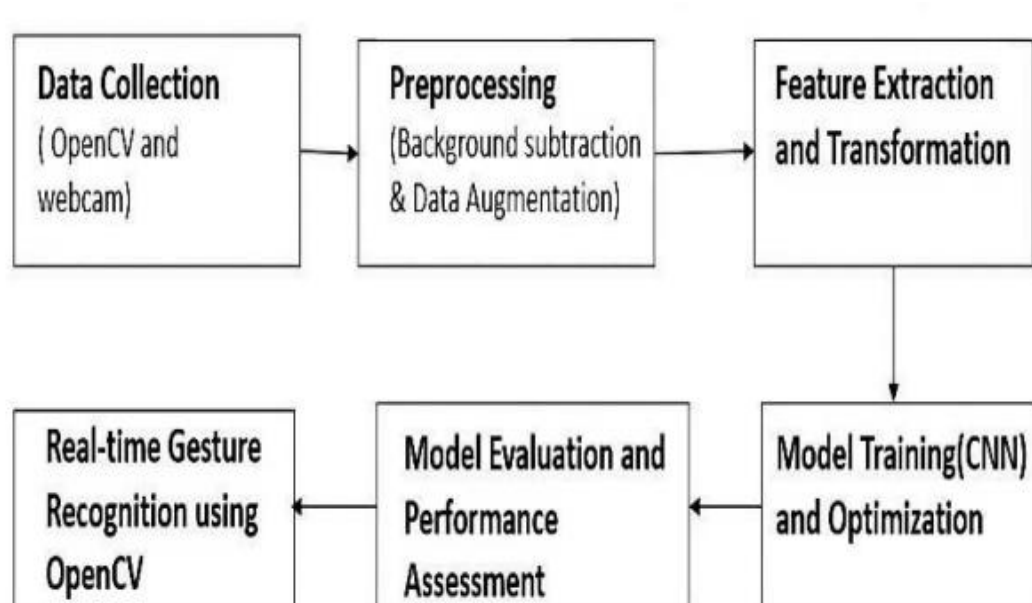


Fig. 1: CNN based system workflow

CHAPTER 4

RESULTS AND DISCUSSION

The CNN model was trained using data augmentation, a technique that enhances dataset diversity and reduces overfitting. Data augmentation involves creating new training samples by applying transformations like rotation, scaling, and flipping to existing images. The Image Data Generator was used to effectively process augmented data, ensuring seamless integration into the network.

The CNN architecture comprised multiple layers of convolution and max pooling, which adeptly captured complex features from the colored dataset. The inclusion of a dense layer with Rectified Linear Unit (ReLU) activation further enhanced the model's ability to differentiate between gestures and extract intricate patterns. A dropout layer was also integrated to mitigate overfitting, contributing to the model's robustness.

After 25 training epochs, the CNN achieved an impressive accuracy of 98.21% in recognizing hand gestures. This high accuracy demonstrates the model's proficiency in accurately classifying gestures, making it an invaluable tool for improving communication accessibility for individuals with hearing impairments.

During the real-time testing phase, implemented via a web-based interface, the system successfully preprocessed hand gestures using background subtraction. The CNN model accurately detected class labels corresponding to the gestures in the live stream, providing a user-friendly interface. This application significantly improves communication accessibility for individuals with hearing impairments, demonstrating the CNN's capability to recognize and interpret dynamic hand gestures.

The successful training of the CNN model underscores the importance of data augmentation in enhancing dataset diversity and reducing overfitting. The model's impressive accuracy in recognizing hand gestures, coupled with its robust architecture and real-time testing capabilities, highlights its effectiveness in improving communication accessibility for individuals with hearing impairments. As such, the CNN model represents a significant advancement in sign language recognition technology, offering a promising solution for enhancing communication and inclusivity for individuals with hearing impairments.

In conclusion, the CNN model for sign language recognition trained successfully using data augmentation, demonstrating its proficiency in accurately classifying gestures. The model's architecture, high accuracy, and real-time testing capabilities highlight its effectiveness in improving communication accessibility for individuals with hearing impairments.

Overall, the CNN model represents a significant advancement in sign language recognition technology, offering a promising solution for enhancing inclusivity and communication for individuals with hearing impairments.

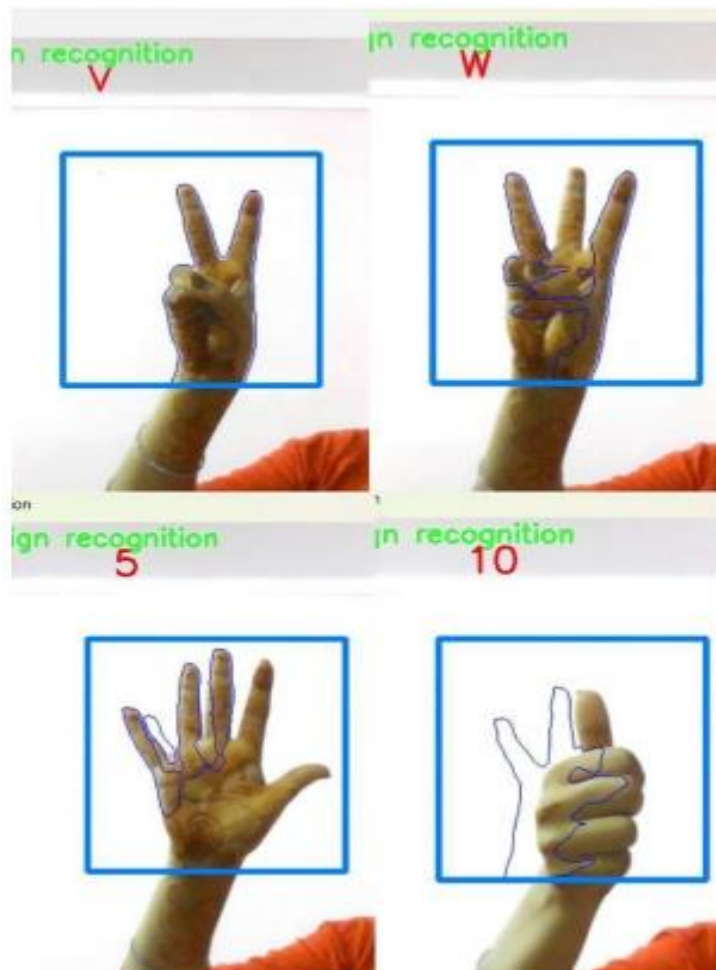


Fig. 3: Real-Time Sign Language Recognition

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1. Conclusion

This research presents the development of a real-time sign language recognition system using OpenCV techniques and a deep learning algorithm (CNN). The system's ability to accurately identify and interpret various sign language gestures highlights its potential as a transformative tool for enhancing communication accessibility for users with hearing and speech impairments. Not only does the system facilitate smooth communication, but it also promotes an inclusive learning and working environment through its user-friendly interface and adaptable design. This research sets a precedent for future advancements in supportive technology, emphasizing the importance of technological innovation in providing equitable opportunities for individuals with diverse communication needs.

Expanding the scope and impact of this technology can be achieved by incorporating more sign languages, such as regional or international sign languages like American Sign Language (ASL) and Indian Sign Language (ISL). Additionally, continually training and diversifying the neural network's dataset can enhance the accuracy and adaptability of the model, enabling it to comprehend a wider range of complex hand gestures and signs.

In this study, a real-time system for recognizing sign language gestures was developed using OpenCV and a deep learning algorithm (CNN). The system's ability to accurately identify and interpret these gestures positions it as a tool for improving communication accessibility for individuals with hearing and speech impairments. The system not only facilitates smooth communication but also promotes inclusivity in learning and working environments through its user-friendly interface and adaptable design. This research demonstrates the potential of technology to support equitable opportunities for individuals with diverse communication needs.

5.2. Future Scope

- **Improved Accuracy:** Machine learning algorithms can be further refined to achieve higher accuracy in sign language recognition, allowing for more precise interpretation of gestures.
- **Expansion of Language Support:** Currently, most systems focus on recognizing a few specific sign languages. Future advancements could include the ability to recognize a wider range of sign languages, including regional and international variations.
- **Real-Time Translation:** Machine learning models could be developed to translate sign language gestures into text or speech in real-time, enhancing communication between individuals who use sign language and those who do not.
- **Enhanced Gesture Recognition:** Future research could focus on developing algorithms that can accurately differentiate between similar gestures and recognize subtle variations in hand movements.
- **Incorporation of Facial Expressions:** Facial expressions play a crucial role in sign language communication. Machine learning algorithms could be trained to recognize and interpret facial expressions to improve the overall accuracy and context of sign language interpretation.
- **Accessibility Features:** Machine learning can be used to develop accessible technologies for individuals with hearing impairments, such as sign language recognition in smart devices and applications.
- **Gesture Prediction:** By analyzing patterns in sign language gestures, machine learning models could be developed to predict the intended message based on partial or incomplete gestures.
- **Integration with Augmented Reality:** Future applications could integrate sign language recognition with augmented reality (AR) to provide real-time translations or visualizations of sign language gestures in the user's environment.

- **Gesture Synthesis:** Machine learning algorithms could be used to synthesize realistic sign language gestures, which could be helpful for educational purposes or creating virtual sign language avatars.
- **Enhanced User Experience:** Continued advancements in machine learning could lead to more intuitive and responsive sign language recognition systems, improving the overall user experience for individuals who use sign language.

To broaden the impact of this technology, future efforts could focus on including more sign languages, such as ASL and ISL, and expanding the neural network's dataset to improve the model's accuracy and adaptability.

This study highlights the importance of technological innovation in advancing supportive technology for individuals with diverse communication requirements

REFERENCES

[1] Areeb, Qazi Mohammad, Mohammad Nadeem, Roobaea Alroobaea, and Faisal Anwer. "Helping hearing-impaired in emergency situations: A deep learning-based approach. "IEEE Access 10 (2022): 8502-8517.

<https://ieeexplore.ieee.org/abstract/document/9681062>

[2] Real Time Sign Language Detection

<https://www.irjet.net/archives/V9/i4/IRJETV9I4506.pdf>

[3] Munnaluri, Vishal, Vishal Pandey, and Parminder Singh. "Machine Learning based Approach for Indian Sign Language Recognition." In 2022 7th International Conference on Communication and Electronics Systems (ICCES), pp.1128-1132. IEEE, 2022.

<https://ieeexplore.ieee.org/document/9835908>

[4] Chabeb, Y., O. Elghoul, and M. Jemni. "WebSign: A Web-Based Interpreter of Sign Language." In International Conference on Informatics and its Applications, Oujda. 2006.

https://www.researchgate.net/publication/235760500WebSign_A_WebBased_Interpreter_of_Sign_Language

[5] Bhadra, Rajarshi, and Subhajit Kar. "Sign language detection from hand gesture images using deep multi-layered convolution neural network." In 2021 IEEE Second International Conference on Control, Measurement and Instrumentation (CMI), pp. 196-200. IEEE, 2021.

<https://ieeexplore.ieee.org/document/9362897>

[6] Patani, Ayushi N., Varun S. Gawande, Jash V. Gujarathi, Vedant K. Puranik, and Tushar A. Rane. "Methodologies for Sign Language Recognition: A Survey." (2021).

<https://ijisrt.com/assets/upload/files/IJISRT21APR505.p>

[7] Obi, Yulius, Kent Samuel Claudio, Vetri Marvel Budiman, Said Achmad, and Aditya Kurniawan. "Sign language recognition system for communicating to people with disabilities." *Procedia Computer Science* 216 (2023): 13-20.

<https://www.sciencedirect.com/science/article/pii/S1877>

[8] Rani, Reddygari Sandhya, R. Rumana, and R. Prema. "A Review Paper on Sign Language Recognition for The Deaf and Dumb." *International Journal of Engineering Research & Technology* 10, no. 10 (2021).

<https://www.ijert.org/a-review-paper-on-sign-language-recognition-for-the-deaf-and-dumb>

[9] Rokade, Rajeshree S., and Dharmpal D. Doye. "Spelled sign word recognition using key frame." *IET Image Processing* 9, no. 5 (2015): 381-388.

<https://doi.org/10.1049/iet-ipr.2012.0691>

[10] Shirbhate, Prof. Radha, Vedant D. Shinde, Sanam A. Metkari, Pooja U. Borkar, and Mayuri A. Khandge, "Sign Language Recognition Using Machine Learning Algorithm." In *2020 International Research Journal of Engineering and Technology (IRJET)*, Volume: 07 Issue: 03, 2020.

[11] Dabre, Kanchan, and Surekha Dholay. "Machine learning model for sign language interpretation using webcam images." In *2014 International Conference on Circuits, Systems, Communication and Information Technology Applications (CSCITA)*, pp. 317- 321. IEEE, 2014.

[12] Zhang Q, Xiao S, Yu Z, Zheng H, Wang P. Hand gesture recognition algorithm combining hand-type adaptive algorithm and effective-area ratio for efficient edge computing. *Journal of Electronic Imaging*. 2021;30(6):063026.

[13] Chen Zh, Kim JT, Liang J, Zhang J, Yuan YB. Real-time hand gesture recognition using finger segmentation. *The Scientific World Journal*. 2014;2014.

[14] Bayazit M, Couture-Beil A, Mori G. Real-time Motion-based Gesture Recognition Using the GPU. In: *MVA*. Citeseer; 2009. p. 9-12

[15] Rosero-Montalvo, P.D., Godoy-Trujillo, P., Flores-Bosmediano, E., Carrascal-Garcia, J., 12 Otero-Potosi, S., Benitez-Pereira, H., PeluffoOrdonez, D.H.: Sign Language Recognition Based on

Intelligent Glove Using Machine Learning Techniques. 2018 IEEE 3rd Ecuador Tech. Chapters Meet. ETCM 2018. (2018).

<https://doi.org/10.1109/ETCM.2018.8580268>

[16] Konstantinidis, D., Dimitropoulos, K., Daras, P.: Sign language recognition based on hand and body skeletal data. 3DTV-Conference. 2018-June, (2018).

<https://doi.org/10.1109/3DTV.2018.8478467>

[17] Zheng, L., Liang, B., Jiang, A.: Recent Advances of Deep Learning for Sign Language Recognition. DICTA 2017 - 2017 Int. Conf. Digit. Image Comput. Tech. Appl. 2017- Decem, 1–7 (2017). <https://doi.org/10.1109/DICTA.2017.8227483>

[18] . Suharjito, Anderson, R., Wiryana, F., Ariesta, M.C., Kusuma, G.P.: Sign Language Recognition Application Systems for Deaf-Mute People: A Review Based on InputProcess Output. Procedia Comput. Sci. 116, 441–448 (2017).

<https://doi.org/10.1016/J.PROCS.2017.10.028>

[19] Liang, Z., Liao, S., Hu, B.: 3D Convolutional Neural Networks for Dynamic Sign Language Recognition. Comput. J. 61, 1724–1736 (2018).

<https://doi.org/10.1093/COMJNL/BXY049>.

[20] Kumar, P., Roy, P.P., Dogra, D.P.: Independent Bayesian classifier combination-based sign language recognition using facial expression. Inf. Sci. (Ny). 428, 30–48 (2018).

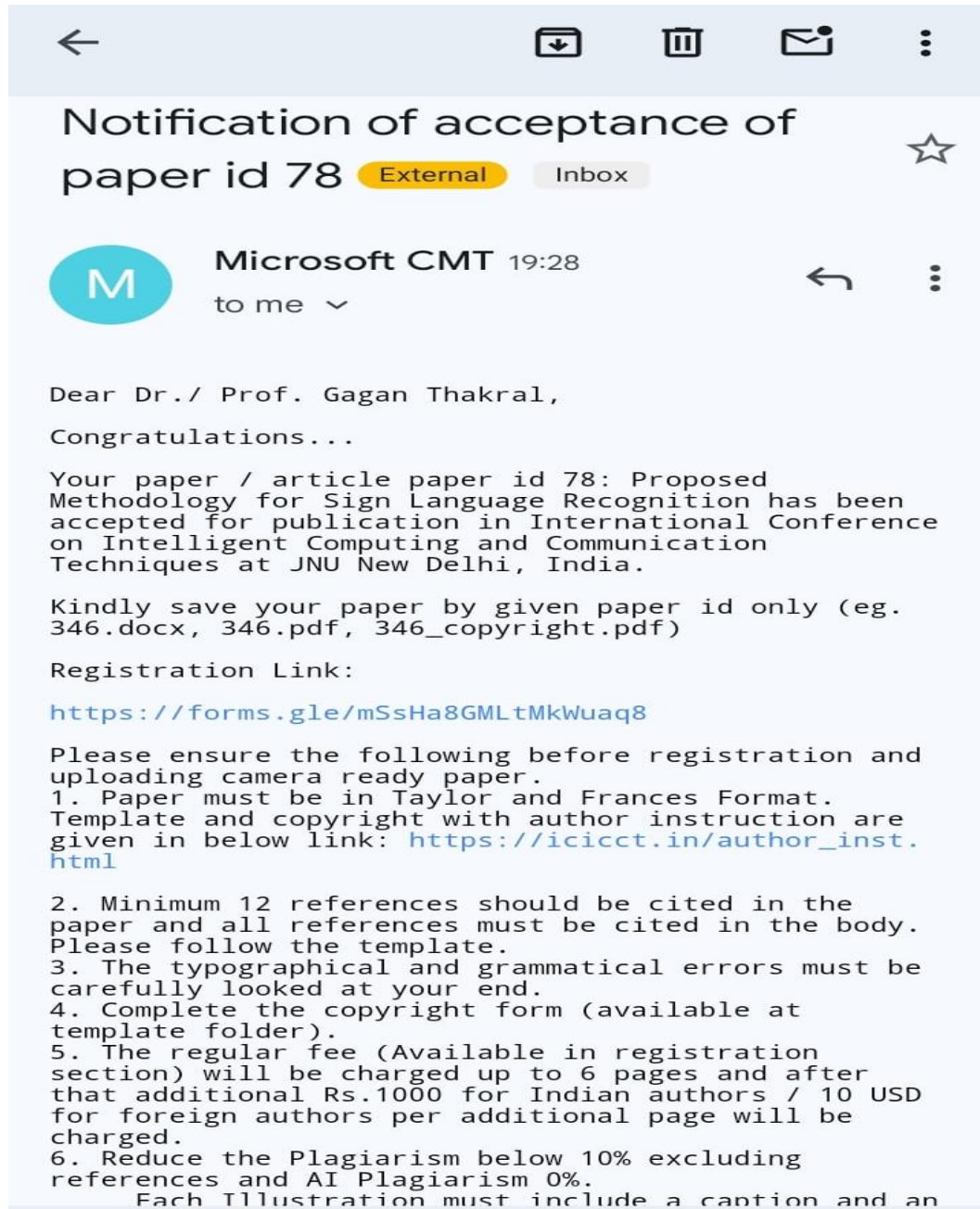
<https://doi.org/10.1016/J.INS.2017.10.046>

[21] Pigou, L., Van Herreweghe, M., Dambre, J.: Gesture and Sign Language Recognition with Temporal Residual Networks. Proc. - 2017 IEEE Int. Conf. Comput. Vis. Work. ICCVW 2017. 2018-Janua, 3086–3093 (2017).

<https://doi.org/10.1109/ICCVW.2017.365>

[22] Thakral, Gagan, Sapna Gambhir, and Nagender Aneja. "Proposed methodology for early detection of lung cancer with low-dose CT scan using machine learning." In 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), vol. 1, pp. 662-666. IEEE, 2022.

APPENDIX 1 (SCREENSHOT OF ACCEPTED RESEARCH PAPER)



APPENDIX 2 (RESEARCH PAPER)

Abstract- "Language shapes the way we think, and determines what we can think about. Signlanguage, too, makes an enormous difference in the waywe canthink." -Temple Grandin

Sign language is also known as a form of nonverbal communication that relies on the visual-manual modality. One popular way that people with hearing disabilities interact with each other is through gestures, and there are a variety of options possible for their interaction, including sign language. In this paper, by using video or hand gesture input, the device can recognize various alphabetical sequences with a color background provided using American Sign Language. Different parameters and feature extraction methods were used in the experiments to improve the model's detection accuracy. Overall, the findings highlight the promise of machine learning methodologies for sign language identification aswell as the importance of developing precise and effective systems in narrowing the communication divide between the auditors and the deaf.

Keywords- American Sign Language, Hand Gesture Recognition, Tensor flow, ConvolutionNeural Network (CNN), OpenCV

1. INTRODUCTION

Effective communication is vital for humanconnection in today's interconnected society. However, conventional communication techniques may not fully meet the diverse needs of people with hearing impairments. Sign language is used by manypeople who are deaf or hearing-impaired, a visual language based on gestures, is their primary form of communication. Gesture recognition provides a natural and intuitive method for human computer interaction, particularly in converting sign language to text. It is crucial to ensure good communication and accessibility for this population [1].

Nonverbal communication, encompassing body language, gestures and facial expressions plays an important role for individuals affected by conditions like mumps, Down syndrome, autism, ear infections, meningitis, measles, rubella, brain disorders, genetic factors, and speech impairments. This form of communication serves as the vital means for conveying emotions, intentions, and messages, especially for those facing challenges in verbal expressions [1][2].

Because of the rapid structural changes in signed motions and the variability in interpretations across nations, identifying sign language poses challenges. Creating an efficient system for recognizing signs can significantly improve international sign-based communication. While recent advances in machine learning and computer vision show promise, much more work in this area is required to achieve the desired results in sign language recognition [1].

The project's implementation entails developing a model to detect sign language using an OpenCV webcam to capture hand gesture images [2]. Convolutional Neural Networks (CNNs) are ideal for image and video analysis because they extract features from images and videos via convolution and pooling layers. CNNs are particularly useful in computer vision applications like object classification and image recognition. Despite progress, challenges in gesture recognition include issues with classification and distinguishing sign gestures from transitional movements [9].

Recognizing the communication gap for the speech-impaired community, researchers are focusing on hand gesture recognition systems that are tailored to their specific requirements. These systems aim to convert hand gestures into audible speech or text, thereby facilitating communication with the general public. Deep learning and neural network advances have improved the accuracy and efficiency of these systems, opening up new avenues for inclusivity and communication enhancement for the speech-impaired [6].

2.LITERATURE SURVEY

For human-computer interaction mouse, keyboard, touch screen, and remote control are most common devices. Although, body language and voice are usually used which is generally known as more effective and flexible [12]. Zhi-Hua Chen et al. [13] claim that the quick

advancement of hardware and software necessitates the need for new forms of HCI. Particularly, gesture and speech recognition have received more considerations in the domain of HCI. Specifically, gesture recognition requires artificial intelligence (AI) or computer vision technology. Real time motion- driven recognition is only among numerous matter that can be researched in computer vision technology. Recognition system's development can be made in a number of means. This field study commonly

aim to improve the accuracy of gesture recognition, encompassing hand, sign, and body movements. Generally speaking, recognition technology can identify many objects for various application, that consists faces, patterns, hand or body motions, and movements. A real-time gesture recognition study conducted in 2013 gained a success rate over 68% for every gesture. This analysis combines a face detector with an optical flow feature [14].

“Shirbate, Shinde, Metkari, Borkar, and Khandge proposed a sign language recognition system using support vector machines in 2007. Authors have trained the model on an Indian sign language (ISL) dataset” [10]. For dataset, the skin portion of the image dataset was segmented. Their primary focus, the classification, involved extracting pertinent features from the skin-segmented images [10]. The model was trained using these extracted features, and image recognition was performed using the trained model [10]. This research paper's system has an accuracy rate of almost 100% [10]. “Kanchan Dabre and Surekha Dholay proposed a machine learning model for sign language interpretation using webcam images” [11]. The authors recognized the hand gestures using Neural network techniques and the Haar Cascade Classifier. This research paper's system has an accuracy rate of 92.68% [11].

SLR provides a means of communication for people having problem in gaining expertise in sign language. It translates a gesture into a widely spoken language, such as English. Nevertheless, that SLR gained significant dedication, there are several problems that still want resolution. Thanks to machine learning techniques, on the basis of data and information, electronic systems capable of decision making. For the classification of algorithms training and testing dataset are required. For evaluating the model, testing dataset is used and the training dataset gives the classifier experiences [15]. Effective techniques for gathering data and classifying it have been developed by numerous writers [16][17]. Considering the data

acquisition method, former work is partitioned into two sections: vision-based approaches and direct measurement methods [16]. Motion data gloves, motion capturing systems, or sensors are the foundation of direct measurement techniques.

Different devices must be used for data acquisition using vision-based methods or direct measurement methods. 83.6% accuracy scored by Light-HMM, 86.7% made by the MSHMM, 97.5% by the SVM, 97% by the Eigen value, and was 100% by the Wavelet Family [18][19][20][21]. Although a variety of models have yielded highly accurate results, accuracy is dependent on many components like, the dataset volume, the devices utilized, images clearness in the dataset depends on the data acquisition methods, etc.

3.PROPOSED MODEL

- Collecting colored images of ASL with OpenCV and a webcam.
- Dataset is trained using the CNN algorithm.
- Streamline model training and evaluation processes, optimizing the number of epochs and batch size for effective convergence.
- Real-time detection using OpenCV.

First, using a webcam and OpenCV to record hand gestures, based on American Sign Language (ASL), having colored dataset of numbers and alphabets was gathered for this study. Colored dataset helps in improving the accuracy and robustness of the ML model. The data is preprocessed using techniques like background subtraction and data augmentation. A custom CNN model is then trained using Tensor flow and Keras, incorporating various layers such as convolutional, pooling and dense layers. Fig. 1 is used to illustrate how the workflow diagram leverages CNN for effective feature extraction and classification. At last, for real-time hand gesture recognition, OpenCV is used along with trained model in which the live webcam is able to detect the hand gestures.

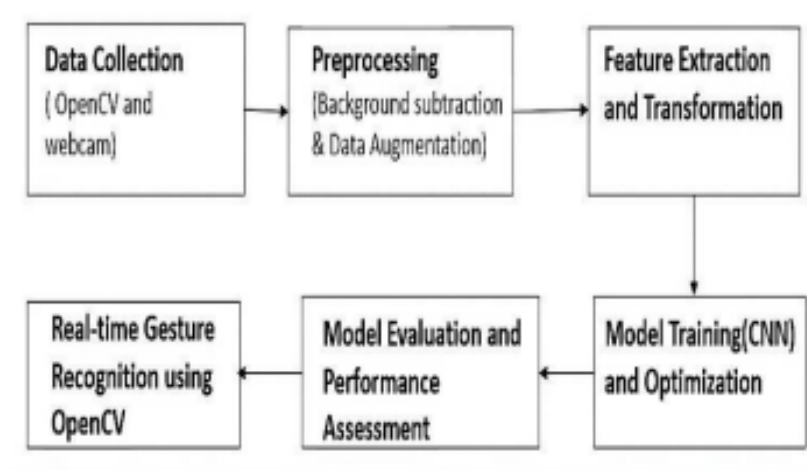


Fig. 1: CNN based system workflow

4.IMPLEMENTATION

For capturing hand gestures in real-time OpenCV library is used and recognizing sign language gestures laptop-based webcam is used. Gathered data is then undergoes to careful preprocessing, along with methodology of background subtraction, for separating the hand gestures from the environment. Furthermore, for enhancing the dataset data augmentation technique is used for differentiating hand gestures instances, consequently increases the robustness of the dataset and following fine quality for classification and model training.



Fig. 2: American Sign Language Dataset

The work sequence for data processing primarily target the background subtraction, an important step for extracting the relevant hand gestures within captured video frames. For further phases of the system this step acts as a critical and important foundation. Furthermore, the dataset is augmented by the usage of data augmentation methodology including image flipping, rotation, shifting which guarantee its range and compatibility for training, precise classification, proficient model for sign language gestures.

Dataset: As shown in Fig. 2, user created dataset is used in this study. It includes 300 images of each gesture of American Sign Language (ASL) that contains numbers from 1 to 10 and alphabets from A to Z.

5.MODEL ANALYSIS AND RESULT

For successful training of CNN model for sign language recognition featured data augmentation and the significant role that chosen dataset plays. For effortless flow of augmented data to the network, Image Data Generator is used for processing that increases the dataset diversity and reduces overfitting tasks. These result highlights the power of CNN in accurately classifying the gestures and emphasizes their relevance in real- world scenarios providing an efficient solution for enhancing communication accessibility for hearing-impairment individuals.

Convolutional Neural Networks (CNNs) used in the recognition of hand gestures with a good accuracy of 98.21% that has been achieved by 25 training epochs. Fig 3. is the result of real-time sign language detection through OpenCV. By utilizing multiple layers of convolution and max pooling, the network architecture is able to capture and extract complex features from colored dataset. Moreover, model distinction capabilities are increased by adding dense layer of rectified linear unit (RELU) empowering the attainment of complex pattern and representation. To reduce overfitting tendencies a dropout layeris integrated that enhances the performance.

Later on, training phase, the model efficiency is evaluated through a real-time testing situation using a web-based implementation. For subsequent analysis, the system successfully captured and preprocessed hand gestures by using background subtraction methodology. System can successfully detect the class labels corresponded with the hand gestures with help of already been trained Convolutional Neural Network (CNN)'s model.

The live stream detection displays the identified labels in real-time providing a smooth user interface to the user. Its acts as a powerful application in promoting communication ease of access for individuals with hearing impairments and show the model's capability of recognizing and interpreting the dynamic hand gestures.

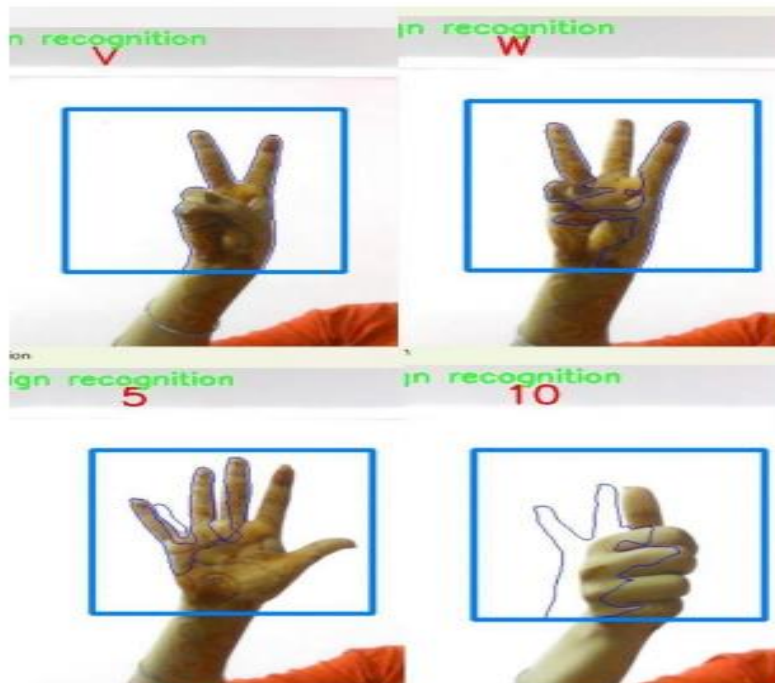


Fig. 3: Real-Time Sign Language Recognition

6.APPLICATION AND FUTURE SCOPE

Application: This system acts as an important instrument to enhance more smooth communication for people having hearing and speech impairment. It can also strengthen early training of sign language, enhance diversity and maintains a supportive environment for children with communication challenges in educational institutions.

Future scope: The relevance and influence of this technology can be greatly expanded by including more sign languages such as regional or international sign languages like American sign language (ASL) and Indian sign Language (ISL). Moreover, by persistently training and diversifying the neural network's dataset. Accuracy and adaptability of model can be improved by allowing it to understand a broader variety of complex hand gestures and signs.

7.CONCLUSION

In this research, a real-time sign language recognition system is developed by using OpenCV technique and deep learning algorithm (CNN). The system's ability to accurately identify and interpret various sign language gestures focus its potential as a reforming tool for improving communication accessibility to user with hearing and speech impairment. The system not only leverages smooth

communication but also fosters an inclusive learning and working environment by leveraging an user-friendly interface and adaptable design. This research forges the way for future advances in the domain of supportive technology, focusing the importance of technological innovation in supporting equitable opportunities uplifting individuals with diverse communication requirements.

8.REFERENCES

[1] Areeb, Qazi Mohammad, Mohammad Nadeem, Roobaea Alroobaea, and Faisal Anwer. "Helping hearing-impaired in emergency situations: A deep learning-based approach. "IEEE Access 10 (2022): 8502-8517.

<https://ieeexplore.ieee.org/abstract/document/9681062>

[2] Real Time Sign Language Detection

<https://www.irjet.net/archives/V9/i4/IRJETV9I4506.pdf>

[3] Munnaluri, Vishal, Vishal Pandey, and Parminder Singh. "Machine Learning based Approach for Indian Sign Language Recognition." In 2022 7th International Conference on Communication and Electronics Systems (ICCES), pp.1128-1132. IEEE, 2022.

<https://ieeexplore.ieee.org/document/9835908>

[4] Chabeb, Y., O. Elghoul, and M. Jemni. "WebSign: A Web-Based Interpreter of Sign Language." In International Conference on Informatics and its Applications, Oujda. 2006.

https://www.researchgate.net/publication/235760500WebSign_A_WebBased_Interpreter_of_Sign_Language

[5] Bhadra, Rajarshi, and Subhajit Kar. "Sign language detection from hand gesture images using deep multi- layered convolution neural network." In 2021 IEEE Second International Conference on Control, Measurement and Instrumentation (CMI), pp. 196-200. IEEE, 2021.

<https://ieeexplore.ieee.org/document/9362897>

[6] Patani, Ayushi N., Varun S. Gawande, Jash V. Gujarathi, Vedant K. Puranik, and Tushar A. Rane. "Methodologies for Sign Language Recognition: A Survey." (2021).

<https://ijisrt.com/assets/upload/files/IJISRT21APR505.p>

[7] Obi, Yulius, Kent Samuel Claudio, Vetri Marvel Budiman, Said Achmad, and Aditya Kurniawan. "Sign language recognition system for communicating to people with disabilities." Procedia Computer Science 216 (2023): 13-20.

<https://www.sciencedirect.com/science/article/pii/S1877>

[8] Rani, Reddygari Sandhya, R. Rumana, and R. Prema. "A Review Paper on Sign Language Recognition for The Deaf and Dumb." International Journal of Engineering Research & Technology 10, no. 10 (2021).

<https://www.ijert.org/a-review-paper-on-sign-language-recognition-for-the-deaf-and-dumb>

[9] Rokade, Rajeshree S., and Dharmpal D. Doye. "Spelled sign word recognition using key frame." IET Image Processing 9, no. 5 (2015): 381-388.

<https://doi.org/10.1049/iet-ipr.2012.0691>

[10] Shirbhate, Prof. Radha, Vedant D. Shinde, Sanam A. Metkari, Pooja U. Borkar, and Mayuri A. Khandge, "Sign Language Recognition Using Machine Learning Algorithm." In 2020 International Research Journal of Engineering and Technology (IRJET), Volume: 07 Issue: 03, 2020.

- [11] Dabre, Kanchan, and Surekha Dholay. "Machine learning model for sign language interpretation using webcam images." In 2014 International Conference on Circuits, Systems, Communication and Information Technology Applications (CSCITA), pp. 317- 321. IEEE, 2014.
- [12] Zhang Q, Xiao S, Yu Z, Zheng H, Wang P. Hand gesture recognition algorithm combining hand-type adaptive algorithm and effective-area ratio for efficient edge computing Journal of Electronic Imaging. 2021;30(6):063026.
- [13] Chen Zh, Kim JT, Liang J, Zhang J, Yuan YB. Real-time hand gesture recognition using finger segmentation. The Scientific World Journal. 2014;2014.
- [14] Bayazit M, Couture-Beil A, Mori G. Real-time Motion-based Gesture Recognition Using the GPU. In: MVA. Citeseer; 2009. p. 9-12
- [15] Rosero-Montalvo, P.D., Godoy-Trujillo, P., Flores-Bosmediano, E., Carrascal-Garcia, J., 12
- Otero-Potosi, S., Benitez-Pereira, H., PeluffoOrdonez, D.H.: Sign Language Recognition Based on Intelligent Glove Using Machine Learning Techniques. 2018 IEEE 3rd Ecuador Tech. Chapters Meet. ETCM 2018. (2018).
- <https://doi.org/10.1109/ETCM.2018.8580268>
- [16] Konstantinidis, D., Dimitropoulos, K., Daras, P.: Sign language recognition based on hand and body skeletal data. 3DTV-Conference. 2018-June, (2018).
- <https://doi.org/10.1109/3DTV.2018.8478467>
- [17] Zheng, L., Liang, B., Jiang, A.: Recent Advances of Deep Learning for Sign Language Recognition. DICTA 2017 - 2017 Int. Conf. Digit. Image Comput. Tech. Appl. 2017- Decem, 1–7 (2017). <https://doi.org/10.1109/DICTA.2017.8227483>
- [18] . Suharjito, Anderson, R., Wiryana, F., Ariesta, M.C., Kusuma, G.P.: Sign Language Recognition Application Systems for Deaf-Mute People: A Review Based on InputProcess Output. Procedia Comput. Sci. 116, 441–448 (2017).

<https://doi.org/10.1016/J.PROCS.2017.10.028>

[19] Liang, Z., Liao, S., Hu, B.: 3D Convolutional Neural Networks for Dynamic Sign Language Recognition. *Comput. J.* 61, 1724–1736 (2018).

<https://doi.org/10.1093/COMJNL/BXY049>.

[20] Kumar, P., Roy, P.P., Dogra, D.P.: Independent Bayesian classifier combination-based sign language recognition using facial expression. *Inf. Sci. (Ny)*. 428, 30–48 (2018).

<https://doi.org/10.1016/J.INS.2017.10.046>

[21] Pigou, L., Van Herreweghe, M., Dambre, J.: Gesture and Sign Language Recognition with Temporal Residual Networks. *Proc. - 2017 IEEE Int. Conf. Comput. Vis. Work. ICCVW 2017*. 2018-Janua, 3086–3093 (2017).

<https://doi.org/10.1109/ICCVW.2017.365>

[22] Thakral, Gagan, Sapna Gambhir, and Nagender Aneja. "Proposed methodology for early detection

of lung cancer with low-dose CT scan using machine learning." In 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON), vol. 1, pp. 662-666. IEEE, 2022.

APPENDIX 2 (PLAGIARISM REPORT)

Sign Lang

ORIGINALITY REPORT

11 %
SIMILARITY INDEX

6 %
INTERNET SOURCES

7 %
PUBLICATIONS

4 %
STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to CSU Northridge Student Paper	2 %
2	link.springer.com Internet Source	1 %
3	"Inventive Systems and Control", Springer Science and Business Media LLC, 2023 Publication	1 %
4	www.ijraset.com Internet Source	1 %
5	pubmed.ncbi.nlm.nih.gov Internet Source	1 %
6	"Proceedings of International Joint Conference on Advances in Computational Intelligence", Springer Science and Business Media LLC, 2023 Publication	1 %
7	Submitted to University of West Attica Student Paper	1 %