

# **REAL-TIME HAND GESTURE RECOGNITION USING MEDIAPIPE AND ARTIFICIAL NEURAL NETWORKS**

DISSERTATION REPORT

*Submitted by*

**SAJIN XAVIER**

**KH.SC.P2MCA21022**

Under the guidance of

DR. MAYA L. PAI

Asst. Professor Senior Grade

Department of Computer Science and IT

*in partial fulfillment of the requirements of the degree of*

**TWO YEAR MASTER OF COMPUTER APPLICATIONS**



DEPARTMENT OF COMPUTER SCIENCE AND IT

SCHOOL OF COMPUTING

**AMRITA VISHWA VIDYAPEETHAM**

KOCHI CAMPUS (INDIA)

May - 2023

DEPARTMENT OF COMPUTER SCIENCE AND IT

SCHOOL OF COMPUTING  
**AMRITA VISHWA VIDYAPEETHAM**  
KOCHI CAMPUS



## BONAFIDE CERTIFICATE

This is to certify that the thesis entitled “**Real-time Hand Gesture Recognition using Mediapipe and Artificial Neural Networks**” submitted by **Sajin Xavier, Reg. No: KH.SC.P2MCA21022** for the award of the **Degree of Two Year Master Of Computer Applications** under the **Faculty of Artificial intelligence and Computing** is a bonafide record of the work carried out by them under my guidance and supervision at the Department of Computer Science and IT, School of Computing, Amrita Vishwa Vidyapeetham, Kochi Campus.

**Dr. Maya L Pai**(Research Advisor)  
Asst. Professor (Senior Grade)  
Department of Computer Science and IT,  
School of Computing,  
Amrita Vishwa Vidyapeetham,  
Kochi Campus , India

**Dr. Vimina E R**  
Head of the Department,  
Department of Computer Science and IT,  
School of Computing,  
Amrita Vishwa Vidyapeetham,  
Kochi Campus

Date:

**Internal Examiner**

**External Examiner**

DEPARTMENT OF COMPUTER SCIENCE AND IT  
SCHOOL OF COMPUTING  
**AMRITA VISHWA VIDYAPEETHAM**  
KOCHI CAMPUS

**DECLARATION**

I, **Sajin Xavier**, Reg. No: **KH.SC.P2MCA21022** hereby declare that this thesis entitled “**Real-time Hand Gesture Recognition using Mediapipe and Artificial Neural Networks**” is the record of the original work done by us under the guidance of **Dr. Maya L. Pai**, Asst. Professor Senior Grade, Department of Computer Science and IT, Amrita Vishwa Vidyapeetham, Kochi Campus. To the best of my knowledge, this work has not formed the basis for the award of any degree/diploma/associate ship/fellowship or a similar award to any candidate in any University.

**Place:**

**Sajin Xavier**

**Date:**

**(Signature of student)**

Signature of the Guide  
**Dr. Maya L. Pai**  
Asst. Professor Senior Grade,  
Department of Computer Science and IT  
School of Computing  
Amrita Vishwa Vidyapeetham  
Kochi Campus, India

## ACKNOWLEDGEMENTS

I would like to express my gratitude to all who have helped me directly or indirectly in my research work. To start with, I thank the Almighty for all the blessings showered on me during the tenure of my research.

I offer my humble salutations at the lotus feet of **Sri Mata Amritanandamayi** Devi, who is the guiding light of this Research work.

I am much obliged to **Dr. U. Krishnakumar**, Director, Amrita Vishwa Vidyapeetham- Kochi Campus for giving me the opportunity to complete my work.

I express my sincere thanks to **Dr. Vimina E R**, Head of the Department, Dept. of Computer Science & IT, for her valuable support and encouragement. I also express my deep gratitude to my guide, **Dr. Maya L Pai**, for providing me the opportunity to work under her guidance as well as for rendering help and support that I required to complete this research successfully.

I extend special thanks to all the faculty members for the facilities and valuable guidance that was provided to me for the completion of my dissertation work.

Finally, I wish to express my sincere thanks to my family, friends who had contributed a lot towards my work and my mental well-being during this period.

**Sajin Xavier (KH.SC.P2MCA21022)**

# INDEX

|                                       | Page No. |
|---------------------------------------|----------|
| Abstract                              | 6        |
| Chapter 1: Introduction:              | 7        |
| Chapter 2: Related Works:             | 8        |
| Chapter 3: Tools and Techniques       | 11       |
| 3.1: Dataset                          | 11       |
| 3.2: Mediapipe                        | 12       |
| 3.3: ANN                              | 12       |
| Chapter 4: Proposed Model             | 13       |
| Chapter 5: Results and Discussion     | 16       |
| Chapter 6: Conclusion and Future Work | 19       |
| References                            | 20       |
| Appendix:                             | 22       |

## **ABSTRACT**

Hand gestures are an important form of communication, especially for individuals who use American Sign Language (ASL) to communicate. In this study, we explored the use of hand gesture recognition using a dataset of 135,000 images, with 27 classes representing the letters A to Z and the space character. We used the MediaPipe framework and an Artificial Neural Network (ANN) with four hidden layers for building a gesture recognition system. Also to prevent overfitting, two dropout layers. The Rectified Linear Unit (ReLU) activation function was used in the input and hidden layers, while the sigmoid function was used in the output layer to predict probabilities for each class and obtained an accuracy of 99%, indicating the effectiveness of this approach for hand gesture recognition. This study has important implications for improving communication for individuals who use ASL and may lead to the development of more advanced gesture recognition systems which will be beneficial to those who are deaf or dumb.

# 1. INTRODUCTION

Hand gesture recognition using Neural Networks (NN) is an exciting area of study and development in computer vision and human-computer interaction. NN aims to create systems that can interpret human hand gestures into commands or actions that are meaningful to the user.

Due to the ability to automatically recognize complicated patterns and connections between data, neural networks are well suited for tasks involving hand gesture recognition. This is crucial for hand gesture recognition because the movements and positions of the hand and fingers can exhibit a wide range of variations and are challenging to programmatically capture.

Collecting information on hand positions and movements is the first step in using neural networks to recognize hand gestures. Either a narrow range of gestures or a variety of gestures can be recognized by the network. Once trained, the network can be used to instantly categorize new hand gestures.

Hand gesture recognition powered by neural networks is used in virtual reality, video games, sign language interpretation, robotics, and other applications. As a result, technology may improve human-machine collaboration by providing more straightforward and organic ways for people to interact with machines.

## 2. RELATED WORKS

Hand gesture recognition has been a popular topic in recent times due to its numerous applicability across several fields. The following research papers discuss different approaches to recognize hand movements using NN and other techniques.

Gadekallu et al. [1] proposed a Harris Hawks optimized Convolutional Neural Networks (CNN) for hand gesture recognition resulting in an accuracy of 100% and outperformed other CNN-based models. Similarly, Buckley et al. [2] put forward a CNN-based sign language recognition system that achieved 89% accuracy for single and double-handed gestures. For modeling Indian Sign Language, Singh [3] presented a 3D-CNN based dynamic gesture identification technique and also used depth information to increase recognition accuracy to 88.24%. Sharma et al. [4] used image processing and feature extraction techniques for hand gesture recognition and significantly higher accuracy has been found. Gnanapriya et al. [5] presents a novel approach for recognizing hand gestures in real-time. The proposed method is based on a hybrid deep learning model that combines CNN and Long Short-Term Memory (LSTM) networks. Spatial feature extraction is done using the CNN from the hand gesture images, and to identify temporal dependencies, the LSTM is utilized between consecutive frames of the video. In difficult lighting and backdrop conditions, Bakheet et al. [6] presented a reliable hand gesture identification approach that makes use of several shape-oriented visual cues and achieves 93% accuracy. Pisharady et al. [7] studied recent methods using Red Green Blue (RGB) and Red Green Blue Depth (RGB-D) cameras and databases in vision-based hand gesture recognition in their study. They provided insights into the challenges and future directions of hand gesture recognition. Pugeault et al. [8] suggested an ASL fingerspelling recognition technique that could execute in real time. Islam et al. [9] proposed a static hand gesture recognition approach using CNN with data augmentation, achieving accuracy of 97.12%. A method for hand gesture identification based on CNN was suggested by Zhan [10], achieving average accuracy of 98.76% and demonstrating its potential for real-time applications. The article by Simion et al. [11] provides a comprehensive review of the contemporary methods used in vision-based hand gesture recognition and serves as a valuable resource for researchers working in this field. The proposed method by Athira et al. [12] involves extracting the hand region from the video frames using skin color segmentation, and then obtaining the features using Local Binary Pattern



(LBP) and Discrete Cosine Transform (DCT). A Support Vector Machine (SVM) classifier is then fed the collected features to perform recognition. The proposed method is tested on a dataset of 10 Indian Sign Language (ISL) gestures performed by 20 different signers, and achieves an average recognition accuracy of 91.37%. Shah et al. [13] discuss the various components of a hand gesture recognition system and compare different techniques used for hand segmentation, feature extraction, and classification. The paper also covers the use of deep learning in hand gesture recognition and provides a comparison of various CNN architectures for this task. Yeshe et al. [14] propose a method that uses a webcam to capture the hand gestures and then processes the video frames to recognize the gestures. The main steps involved in the method include image preprocessing, feature extraction, and gesture recognition using an ANN classifier. The authors use a dataset of 10 different hand gestures and report an accuracy of 93.67% using the proposed method [14]. Noraini et al. [15] reviews various techniques that have been developed for hand gesture recognition, including traditional computer vision-based approaches, machine learning-based approaches, and hybrid approaches which discuss the advantages and limitations of each technique and provide insights into their performance in different scenarios. Grime et al. [16] put forward a method for recognizing ISL gestures using Principal Component Analysis (PCA) features. The proposed system involves acquiring the hand gesture images, segmenting the hand region, extracting the features using PCA, and classifying the gestures using a SVM classifier. The PCA features reduce the quantitative nature of the attribute space and increase the identification efficiency [16]. The outcomes of the experiments show that the suggested system works well in recognizing 21 ISL gestures with an accuracy of 95.45%. Oudah et al. [17] presents a review of hand gesture recognition techniques based on computer vision and discusses various approaches including traditional machine learning, deep learning, and hybrid methods for hand gesture recognition. The review also includes a detailed analysis of the datasets used in the studies, as well as the evaluation metrics employed. Sharma et al. 's [18] system utilizes OpenCV and Python programming language to detect and recognize hand gestures and is tested on a dataset of ten hand gestures and achieved an accuracy of 95% for gesture recognition. Rafiqul et al. [19] provides a comprehensive literature review on hand gesture recognition, covering various techniques and algorithms used in the field. The review highlights the importance of hand gesture recognition in human-computer interaction and identifies challenges faced by researchers, such as dealing with variations in lighting, backgrounds, and hand orientations. The Study by Aashni et al. [20] presents a hand gesture recognition system based on the background subtraction method and contour analysis. The system utilizes a webcam to capture hand gestures and processes the images using OpenCV libraries in Python. The paper reports an average recognition accuracy of 85% for the

developed system, demonstrating the potential of vision-based hand gesture recognition in practical applications [20].

Overall, the reviewed studies demonstrated the effectiveness of NN-based approaches for hand gesture recognition, and highlighted the importance of data preprocessing, feature extraction, and augmentation techniques to improve recognition accuracy.

This paper makes an analysis of hand gesture recognition using MediaPipe and ANN. The strategy combines data gathering, pre-processing, setting up the ANN, and creating the model.

### 3. TOOLS & TECHNIQUES

The dataset, MediaPipe, and ANN settings that were employed are described in this section.

#### 3.1. Dataset

The dataset used in this study for identification of hand movements using ANN consists of 135,000 images representing 27 classes of ASL hand gestures. The classes range from A to Z, including a space character, and each class has around 5,000 images. The dataset was obtained from Kaggle [33] <https://www.kaggle.com/datasets/kapillondhe/american-sign-language> and only includes right hand gestures. To increase the number of samples, left hand gestures were created by flipping the right hand gesture images. The dataset provides a comprehensive collection of ASL hand gestures and is suitable for training and evaluating deep learning models for hand gesture recognition. With the increasing demand for gesture-based systems, this dataset can contribute significantly to the development of robust and accurate hand gesture recognition models. Fig.1 displays an illustration of each of the 26 alphabet hand movements.

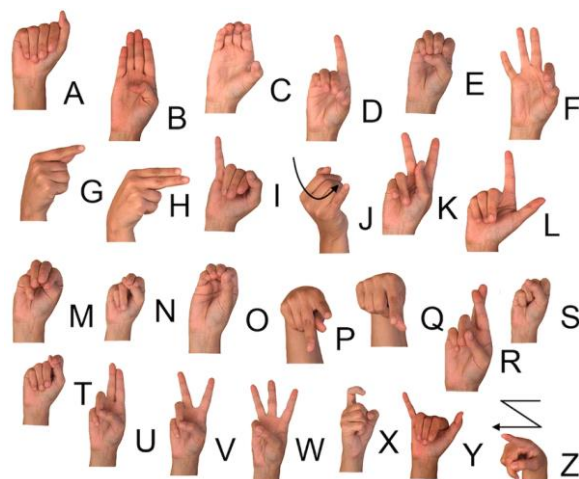


Fig. 1. ASL alphabets (Source:[https://www.researchgate.net/figure/The-symbols-of-alphabets-in-ASL-fingerspelling-23\\_fig1\\_351655963](https://www.researchgate.net/figure/The-symbols-of-alphabets-in-ASL-fingerspelling-23_fig1_351655963))

### 3.2. *MediaPipe*

MediaPipe is a free source cross-platform framework that provides a wide range of pre-built solutions for various computer vision and machine learning tasks, including hand gesture recognition.

In hand gesture recognition, MediaPipe uses a neural network-based algorithm to detect and track 21 specific landmarks or key points on the hand, including fingertips, knuckles, and wrist. These landmarks are detected by examining the video feed from a camera and with the help of several machine learning and computer vision techniques.

### 3.3. *ANN*

An ANN is a type of machine learning model that is inspired by the structure and function of the human brain. ANNs consist of a large number of interconnected processing nodes, or neurons, that work together to process and classify input data.

## 4. PROPOSED MODEL

The flowchart describes the process of creating a dataset for identification of hand movements using the MediaPipe framework. The input to the process is an image of a hand, which is processed by the MediaPipe framework to extract the landmarks of the hand. The landmarks consist of 21 points on the hand, each with an (x,y) coordinate.

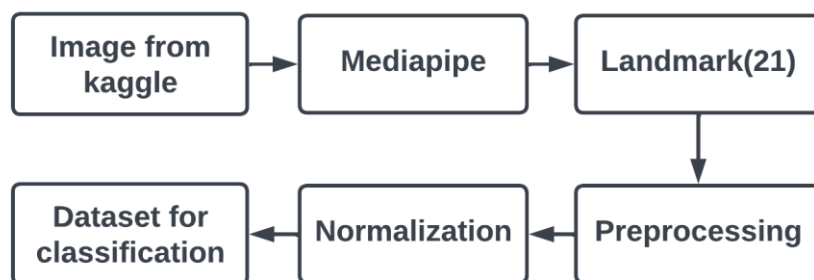


Fig. 2. Dataset Preparation for Analysis

The next step is preprocessing, which involves subtracting the coordinates of the wrist landmark from every other landmark to form an array. This array is then flattened into a one-dimensional array.

After preprocessing, the array is normalized by subtracting every value in the array with the highest value in the array. This results in a dataset that can be utilized to create a machine learning model for hand gesture recognition. Figure 2 shows the flowchart from image to dataset.

Figure 3 shows the flowchart you provided outlines a typical machine learning workflow that involves building an ANN model to make predictions or classifications based on a given dataset. Here is a brief description of each step:

The first step is to collect or obtain the dataset that will be used to train and test the ANN model. This dataset will contain various features or variables that are relevant to the problem being solved, as well as a target variable that the model will try to predict or classify.

The ANN architecture is composed of 1 input layer, 3 hidden layers, and 1 output layer, with 2 dropout layers incorporated to prevent overfitting. The activation function used is the ReLU, except for the output layer where the sigmoid function is employed to predict the probability of each class. The input layer of the ANN has an input dimension of 42, and the ReLU activation function is applied, as it performs better than the tanh and sigmoid functions in the input and hidden layers. The ReLU function is chosen due to the fact that it is a simple and mathematically structured non-linear activation function that can model complex relationships between inputs and outputs. ReLU activation functions are also present in the next 3 hidden layers as well and the output layer comprises 27 nodes, with each representing the classes of the ASL. The sigmoid function is employed as the activation function in the output layer, which is well-suited for binary classification problems and can provide accurate predictions using the probability of each class. Dropout layers have been added to the model to reduce overfitting, a common problem in deep learning models. The dropout technique randomly removes some of the neurons during training, which forces the model to learn redundant representations and increases its generalization ability. Before training the model, the dataset is usually divided into training sets and testing sets in a 70:30 ratio. The training set is used to train the ANN model, while the testing set is used to evaluate its performance and generalization ability.

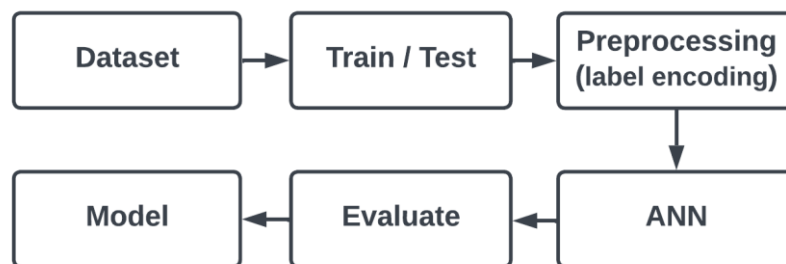


Fig. 3. ANN Model

The dataset may require preprocessing before it can be used to train the ANN model. This may involve label encoding to improve the quality and relevance of the input data.

Once the data is ready, an ANN model is built using a chosen architecture and algorithm. This model is designed to recognize the patterns and relationships between the input features and the target variable, by adjusting its weights and biases during training.

After the model is trained, it is evaluated using the testing set to measure its performance metrics, such as accuracy, precision, recall, or F1-score. This step is crucial to ensure that the model can

generalize well to new and unseen data, and to identify any potential overfitting or underfitting issues.

If the model performance is satisfactory, predictions can be made using it or classifications on new data. The final model may also be saved and reused for future tasks or applications.

Overall, this flowchart represents a typical supervised learning pipeline for building an ANN model, which can be used in different fields such as image identification, Natural Language Processing (NLP), or predictive analytics.

## 5. RESULTS AND DISCUSSION

The experiment's outcomes are discussed in this section. Based on the Figure 4 provided, both the test and train models stopped after 4 epochs. It is also noteworthy that the accuracy of the test model improved at a faster rate compared to the train model. The test model has a comparatively lower loss than the train model. This indicates that the model has performed well in generalizing unseen data, as it was able to achieve good accuracy while minimizing loss.

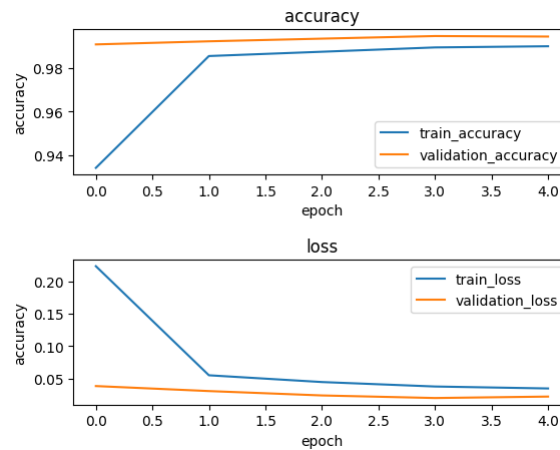


Fig. 4. Accuracy and Loss of ANN Model

In Figure 5., the confusion matrix provides a detailed understanding of the performance of identification of the hand gesture model. The diagonal values of the matrix displays the correctly classified tuples, whereas the off-diagonal values represent the incorrectly classified tuples. A higher diagonal value indicates a better performance of the model. However, it is observed that the 'N' gesture has relatively lower performance because it is sometimes confused with the 'M' gesture. On the other hand, gestures 'B', 'H', and 'K' have performed better.



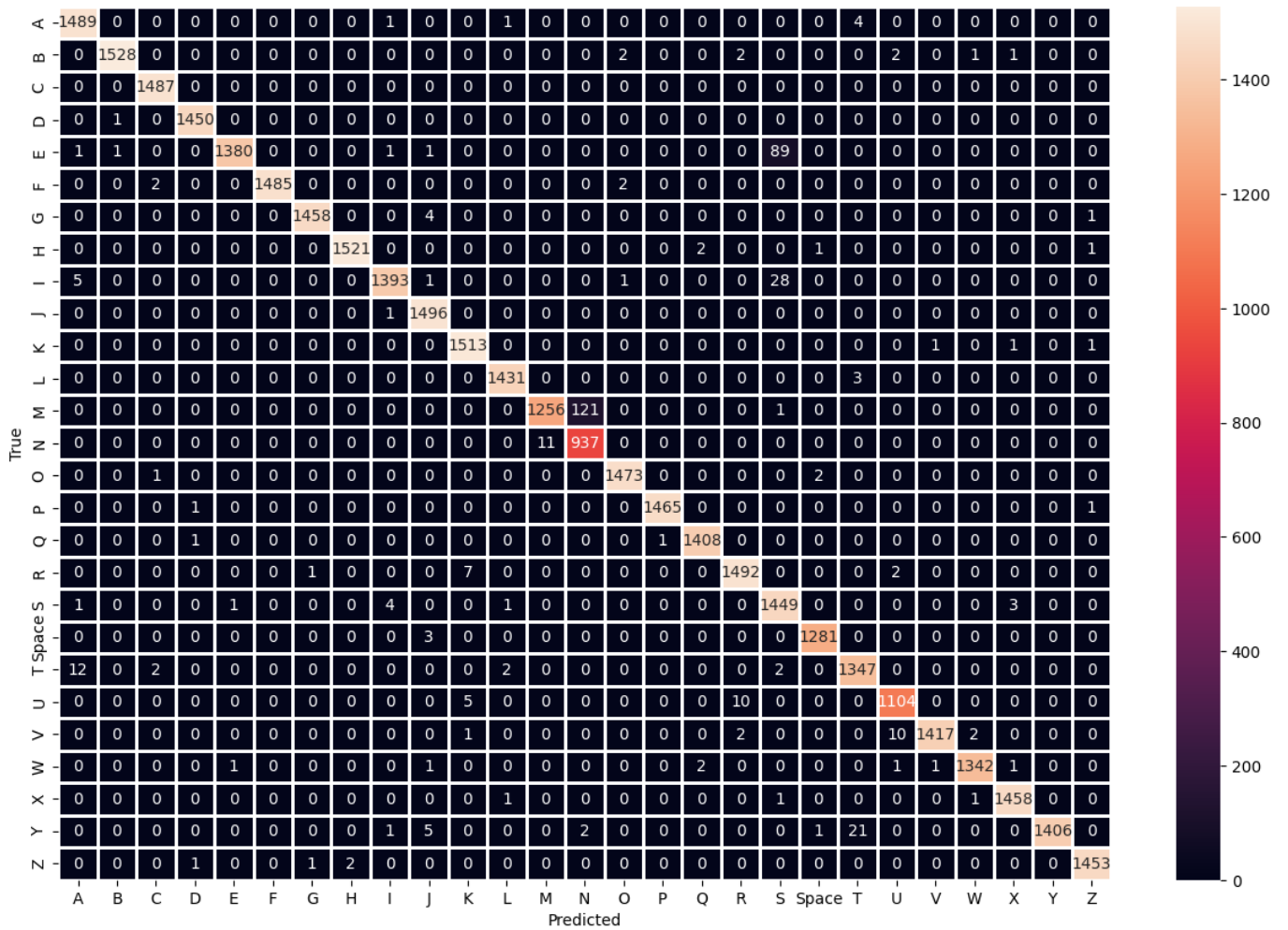


Fig. 5. Confusion Matrix of Recognition Model

According to the experiments conducted, the proposed hand gesture recognition system achieved an impressive accuracy of 99%. Table 1. shows the classification result.

TABLE I  
Classification Result

| Performance Measure | ANN Model |
|---------------------|-----------|
| <i>Precision</i>    | 0.99      |
| <i>Recall</i>       | 0.99      |
| <i>F1-Score</i>     | 0.99      |

|                        |     |
|------------------------|-----|
| <b><i>Accuracy</i></b> | 99% |
|------------------------|-----|

Additionally, the precision, recall, and F1 score were also calculated to evaluate the performance of the model. The precision score, which represents the ratio of correctly predicted positive observations to the total predicted positive observations, was found to be 0.99. The recall score, which represents the ratio of correctly predicted positive observations to the total actual positive observations, was also found to be 0.99. Finally, The harmonic mean of recall and accuracy, or the F1 score, was discovered to be 0.99 as well. These results demonstrate that the proposed system is highly accurate and precise in recognizing hand gestures of ASL. From Table 1., it is clear that the proposed model gives an accuracy of 99% which is better than other models [14, 3].

## **6. CONCLUSION AND FUTURE WORK**

In conclusion, this study aimed to develop a hand gesture recognition system using artificial neural networks and the MediaPipe library for the ASL alphabet. The dataset contained 135,000 images of right hand gestures, with each of the 27 classes having around 5,000 datasets.

The proposed system utilized a NN architecture with one input layer, four hidden layers, and one output layer with 27 nodes representing each class of ASL. The ReLU activation function was utilized for input and hidden layers, and the sigmoid function for the output layer to predict the probability of each class accurately. Two dropout layers were included to prevent overfitting.

The outcomes of the study showed that the system obtained an accuracy of 99%, which shows the efficiency of the suggested method. The precision, recall, and F1 score of the system were also evaluated, and the results indicate high performance across all metrics.

This study provides an efficient and accurate method for recognizing hand gestures in ASL, which could be useful in various applications such as improving accessibility for the hearing-impaired community or enhancing human-computer interaction.

## REFERENCES

1. Thippa Reddy Gadekallu et al. Hand gesture recognition based on a Harris Hawks optimized Convolution Neural Network. 2022;vol. 100,pp. 1-13,107836.
2. Neil Buckley, Lewis Sherrett, Emanuele Lindo Secco. A CNN sign language recognition system with single & double-handed gestures. 2021; IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC) | 978-1-6654-2463-9/21, DOI: 10.1109/COMPSAC51774.2021.00173
3. Singh D.K., 3D-CNN based Dynamic Gesture Recognition for Indian Sign Language Modeling. *Procedia Computer Science* 2021; vol. 189,pp. 76-83
4. Ashish Sharma, Anmol Mittal, Savitoy Singh, Vasudev Awatramani. Hand Gesture Recognition using Image Processing and Feature Extraction Techniques. *Procedia Computer Science* 2020; vol. 173, pp. 181-190.
5. S. Gnanapriya and K. Rahimunnisa, "A hybrid deep learning model for real time hand gestures recognition," *Intelligent Automation & Soft Computing*, vol. 36, no.1, pp. 1105–1119, 2023.
6. Samy Bakheet and Ayoub Al-Hamadi. Robust hand gesture recognition using multiple shape-oriented visual cues. 2021.
7. Pramod Kumar Pisharady, Martin Saerbeck. Recent methods and databases in vision-based hand gesture recognition: A review. *Computer Vision and Image Understanding*, 2015; vol. 141, pp. 152–165
8. N. Pugeault and R. Bowden, "Spelling it out: Real-time ASL fingerspelling recognition", *Proc. IEEE Int. Conf. Comput. Vis. Workshops (ICCV Workshops)*, pp. 1114-1119, Nov. 2011.
9. M. Z. Islam, M. S. Hossain, R. UI Islam and K. Andersson, "Static hand gesture recognition using convolutional neural network with data augmentation", 2019 Joint 8th International Conference on Informatics Electronics and Vision ICIEV 2019 and 3rd International Conference on Imaging Vision and Pattern Recognition icIVPR 2019 with International Conference on Activity and Behavior Computing ABC 2019, pp. 324-329, 2019.
10. F. Zhan, "Hand gesture recognition with convolution neural networks", 2019 IEEE 20th International Conference on Information Reuse and Integration for Data Science (IRI), pp. 295-298, 2019.
11. G. Simion, V. Gui, and M. Ottesteanu. Vision Based Hand Gesture Recognition: A Review. 2012; vol. 4(6), pp.275-282.
12. P.K. Athira et al. A signer independent sign language recognition with co-articulation elimination from live videos: an indian scenario, *J. King Saud Univ. – Comput. Inf. Sci.* (2019); vol. 34(3), pp. 771-781
13. Pranit Shah, Krishna Pandya, Harsh Shah, Jay Gandhi, "Survey on Vision based Hand Gesture Recognition", *International Journal of Computer Sciences and Engineering*, 2019, Vol.7, Issue.5, pp.281-288.
14. Mayur Yeshi, Pradeep Kale, Bhushan Yeshi, Vinod Sonawane. Hand gesture recognition for human-computer interaction. 2016, vol. 1(8), pp.9-14
15. Noraini Mohamed, Mumtaz Begum Mustafa, Nazean Jomhari. A Review of the Hand Gesture System: Current Progress and Future Directions, 2017, vol. 20, pp. 1-19.
16. Mr. Girme R B., Prof. Marathe V R. Indian Sign Language Recognition System Using PCA Features, Vol. 5, Issue 10, pp.1192-1197.
17. Oudah, M.; Al-Naji, A.; Chahl, J. Hand gesture recognition based on computer vision: A review of techniques. *J. Imaging* 2020, vol. 6(73), pp. 1-29.
18. Surya Narayan Sharma, Dr. A Rengarajan. "Hand Gesture Recognition using OpenCV and Python" Published in *International Journal of Trend in Scientific Research and Development (IJTSRD)*, Vol. 5, Issue-2, February 2021, pp. 346-352.
19. Rafiqul Zaman Khan and Noor Adnan Ibraheem. Hand Gesture Recognition: A Literature Review, *International Journal of Artificial Intelligence & Applications*, 2012, vol. 3(4): pp. 161-174.
20. Aashni P Haria, Archanasri Subramanian, Nivedhitha Asokkumar, Shristi Poddar, Jyothi S Nayak. Hand Gesture Recognition System, *International Journal of Emerging Trends & Technology in Computer Science(IJCTT)*, 2017, vol. 47(4): pp. 209-212.

21. Yannick Jacob, Sotiris Manitsaris, Fabien Moutarde. Hand gesture recognition for driver vehicle interaction, Yannick Jacob, Sotiris Manitsaris, Fabien Moutarde, Gautam Lele, Laetitia Pradere. Hand gesture recognition for driver vehicle interaction. IEEE Computer Society Workshop on Observing and understanding hands in action (Hands 2015) of 28th IEEE conf. on Computer Vision and Pattern Recognition (CVPR'2015), Jun 2015, Boston, United States. Ffhal-01256263.
22. Tiago Cardoso, João Delgado, José Barata. Hand Gesture Recognition towards Enhancing Accessibility, *Procedia Computer Science* (2015), vol. 67, pp. 419-429.
23. Ashutosh Samantaray, Sanjaya Kumar Nayak, Ashis Kumar Mishra "Hand Gesture Recognition using Computer Vision", *International Journal of Scientific & Engineering Research*, Volume 4, Issue 6, June 2013 ISSN 2229-5518.
24. Vishal Nayakwadi, N. B. Pokale. Natural Hand Gestures Recognition System for Intelligent HCI: A Survey, 2013, vol. 3 Issue- 1, pp. 10-19.
25. Padmanabh D. Deshpande, Sudhir S. Kanade "Recognition of Indian Sign Language using SVM classifier" Published in *International Journal of Trend in Scientific Research and Development (IJTSRD)*, ISSN: 2456-6470, Vol. 2, Issue-3, April 2018, pp.1053-1058.
26. Madhuri Sharma, Ranjna Pal, Ashok Kumar Sahoo. INDIAN SIGN LANGUAGE RECOGNITION USING NEURAL NETWORKS AND KNN CLASSIFIERS, *Asian Research Publishing Network (ARPN)*, 2014, vol. 9, Issue- 8, pp. 1255-1259.
27. Dinesh Dattatraya Rankhamb, Prof. S. C. Mhamane. Recognition of Indian Sign Language using SVM Classifier, *Journal of Emerging Technologies and Innovative Research*, 2021, vol. 8, Issue- 9, pp. 119-125.
28. Simion, G., Gui, V., & Otesteanu, M. (2011). A brief review of vision based hand gesture recognition. *Proceedings of the 10th WSEAS International Conference on Circuits, Systems, Electronics, Control, Signal Processing, and Proceedings of the 7th WSEAS International Conference on Applied and Theoretical Mechanics, CSECS/MECHANICS'11*, World Scientific and Engineering Academy and Society (WSEAS), Stevens Point, Wisconsin, USA, pp. 181-188.
29. B. Nandwana, S. Tazi, S. Trivedi, D. Kumar, S. K. Vipparthi, A survey paper on hand gesture recognition, *Proc. of the International Conference on Communication Systems and Network Technologies (CSNT)*, 2017, Nagpur, India, pp. 147-152.
30. S. S. Rautaray and A. Agrawal, "A Vision based Hand Gesture Interface for Controlling VLC Media Player," *International Journal of Computer Applications*, Oct. 2010., vol. 10, no. 7, pp. 11–16.
31. Tomasz Kapuscinski, Mariusz Oszust, Marian Wysocki, Dawid Warchol. Recognition of Hand Gestures Observed by Depth Cameras, *International Journal of Advanced Robotic Systems*, 2015, DOI: 10.5772/60091
32. Vishal Bhame, R. Sreemathy, Hrushikesh Dhumal. Vision based Calculator for Speech and Hearing Impaired using Hand Gesture Recognition, *International Journal of Engineering Research & Technology (IJERT)*, 2014, Vol. 3 Issue 6, pp. 632-635.
33. <https://www.kaggle.com/datasets/kapillondhe/american-sign-language>
34. [https://www.researchgate.net/figure/The-symbols-of-alphabets-in-ASL-fingerspelling-23\\_fig1\\_351655963](https://www.researchgate.net/figure/The-symbols-of-alphabets-in-ASL-fingerspelling-23_fig1_351655963)

# **APPENDIX**

**16** %  
SIMILARITY INDEX

**10** %  
INTERNET SOURCES

**9** %  
PUBLICATIONS

**9** %  
STUDENT PAPERS

---

PRIMARY SOURCES

---

- |          |  |            |
|----------|--|------------|
| <b>1</b> | <b>Advances in Intelligent Systems and Computing, 2016.</b><br>Publication   | <b>2</b> % |
| <b>2</b> | <b>researchspace.auckland.ac.nz</b><br>Internet Source   | <b>1</b> % |
| <b>3</b> | <b>Submitted to University of South Australia</b><br>Student Paper   | <b>1</b> % |
| <b>4</b> | <b>Deepak K. Dalakoti, Armin Wehrfritz, Bruno Savard, Marc S. Day, John B. Bell, Evatt R. Hawkes. "An a priori evaluation of a principal component and artificial neural network based combustion model in diesel engine conditions", Proceedings of the Combustion Institute, 2021</b><br>Publication | <b>1</b> % |
| <b>5</b> | <b>Submitted to Georgia Institute of Technology Main Campus</b><br>Student Paper   |            |
- 
-

# Plagiarism Report

## ORIGINALITY REPORT

**15** %  
SIMILARITY INDEX

**11** %  
INTERNET SOURCES

**9** %  
PUBLICATIONS

**6** %  
STUDENT PAPERS

## PRIMARY SOURCES

|          |   |            |
|----------|---|------------|
| <b>1</b> | <a href="https://researchspace.auckland.ac.nz">researchspace.auckland.ac.nz</a><br>Internet Source  | <b>1</b> % |
| <b>2</b> | Deepak K. Dalakoti, Armin Wehrfritz, Bruno Savard, Marc S. Day, John B. Bell, Evatt R. Hawkes. "An a priori evaluation of a principal component and artificial neural network based combustion model in diesel engine conditions", Proceedings of the Combustion Institute, 2021<br>Publication | <b>1</b> % |
| <b>3</b> | Submitted to University of Liverpool<br>Student Paper   | <b>1</b> % |
| <b>4</b> | <a href="http://www.mdpi.com">www.mdpi.com</a><br>Internet Source   | <b>1</b> % |
| <b>5</b> | Submitted to Kaohsiung Medical University<br>Student Paper  | <b>1</b> % |
| <b>6</b> | <a href="http://www.amrita.edu">www.amrita.edu</a><br>Internet Source   | <b>1</b> % |

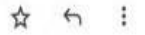


## Paper Submission Mail :



**14th ICCCNT 2023** <14thiccncnt2023@easychair.org>  
to me ▾

Fri, Apr 28, 5:50 PM



Dear authors,

We received your submission to 14th **ICCCNT** 2023 (14th International Conference on Computing Communication and Networking Technologies -2023):

Authors : Sajin Xavier, Vaisakh B and Dr. Maya L. Pai

Title : Real-time Hand Gesture Recognition using MediaPipe and Artificial Neural Networks  
Number : 888

The submission was uploaded by Sajin Xavier  
<[sajinxaviersanchez@gmail.com](mailto:sajinxaviersanchez@gmail.com)>. You can access it via the 14th **ICCCNT**  
2023 EasyChair Web page

<https://easychair.org/conferences/?conf=14thiccncnt2023>

Thank you for submitting to 14th **ICCCNT** 2023.

Best regards,  
EasyChair for 14th **ICCCNT** 2023.