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American Sign Language Recognition Based on Transfer Learning Algorithms

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Abstract: This research focuses on recognizing American Sign Language (ASL) letters and numbers, addressing the evolving technology landscape and the growing demand for improved user experiences among those primarily using sign language for communication. Leveraging deep learning, particularly through transfer learning, this study aims to enhance ASL recognition technology. Various deep learning models, including VGG16, ResNet50, MobileNetV2, InceptionV3, and CNN, are evaluated using an ASL dataset sourced from the Modified National Institute of Standards and Technology (MNIST) database, featuring ASL alphabetic letters represented through hand gestures. InceptionV3 emerges as the top-performing model, achieving an accuracy of 0.96. Transfer learning, which fine-tunes pre-trained models with ASL data, significantly improves recognition accuracy, making it especially valuable when labeled ASL data is limited. While InceptionV3 stands out, other models like VGG16, MobileNetV2, and ResNet50 demonstrate acceptable performance, offering flexibility for model selection based on specific application needs and computational resources. These findings underscore the effectiveness of deep learning and transfer learning techniques, providing a foundation for intuitive sign language recognition systems and contributing to breaking down communication barriers for the deaf and mute community.

***Keywords**: Gesture Recognition, American Sign Language (ASL), Deep Learning, Transfer Learning.*

1. Introduction

The rapid evolution of computer technology, communication technology, hardware infrastructure, and associated advancements have led to a significant proliferation of human-computer interaction (HCI) in contemporary life. Concurrently, there is a heightened demand for improved user experiences [1]. To gain a competitive edge, major technology companies are increasingly investing in HCI research, with a particular focus on facilitating communication with individuals who are deaf or hard of hearing and rely on sign language as their primary mode of communication [1][2]. Sign language, characterized by the use of gestures and expressions to convey information, plays a pivotal role in enabling communication for the deaf and hard-of-hearing population across personal, academic, social, and even televised contexts [3] [4]. For the general populace, communicating effectively through sign language with deaf and mute individuals remains a formidable challenge. Therefore, the development of an intuitive means to translate sign language is of paramount importance to both the deaf and mute community and those who interact with them [2][5]. Sign language recognition technology can be broadly categorized based on the underlying hardware, encompassing data glove-based gesture recognition technology and camera-based gesture recognition technology. Data glove-based sign language recognition technology offers advantages such as precise data capture, high recognition rates, and resilience against interference. However, it is hindered by the need for expensive equipment and the requirement for individuals to wear data gloves

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during communication with the deaf and mute. In contrast, camera-based sign language recognition technology, leveraging computer vision techniques, eliminates the need for costly specialized equipment and offers a more natural HCI experience [6][7][8]. Nevertheless, it is highly susceptible to environmental conditions, necessitating ongoing research to enhance algorithms and mitigate these limitations. In interpersonal communication, gestures, which constitute a form of nonverbal body language, are often employed as supplementary means of conveying information. This is particularly salient for the deaf and mute community, where gestures have emerged as the primary mode of interaction with others [3][9]. Deep learning, a rapidly advancing field in recent years, has yielded significant accomplishments in machine vision, natural language understanding, and other domains. Deep learning seeks to emulate the intricate workings of the human brain through multi-layered neural networks, enabling a profound understanding of data [10][11]. Nonetheless, the application of deep learning algorithms to gesture recognition technology remains relatively underexplored, presenting several formidable challenges that warrant investigation. This paper endeavors to bridge this research gap by employing transfer learning as a means to recognize American Sign Language (ASL) letters and numbers. This approach involves the utilization of pre-trained models, which are subsequently fine-tuned using ASL datasets. In addition to Convolutional Neural Networks (CNN), this study investigates the efficacy of four distinct algorithms—namely, VGG16, ResNet50, MobileNetV2, and InceptionV3—in the task of recognizing ASL numbers and letters.

2. Literature Review

The recent surge in research endeavors aimed at identifying sign languages, with a particular focus on assisting the deaf and hard of hearing community, has yielded several noteworthy studies. These investigations employ a variety of approaches, but there remains a notable gap in the literature that the proposed study "ASL Recognition Based on Transfer Learning" seeks to address.

Paper [12] laid the groundwork for their sign language recognition methodology by utilizing a three-dimensional residual network and dilated convolutional network. Paper [13] approached the problem with two deep learning (DL) techniques, namely Convolutional Neural Networks (CNN) and stacked denoising autoencoder (SDAE) networks, to recognize 24 ASL alphabets. Their data source was the gesture recognition database curated by Thomas Moeslund. Paper. [14] adopted a distinct approach, focusing on hand isolation through depth information extracted from RGB images in the ASL fingerspelling dataset. They introduced the Principal Component Analysis Network (PCANet), a specialized variant of CNN, which extracted features from depth images rather than directly classifying them. Paper. [15] aimed to create a CNN-based model specialized in static sign language, achieving an impressive average testing accuracy of 93.67% across ASL alphabets, numerals, and basic phrases. In another study [16], convolutional neural networks were recommended as the foundational architecture for ASL recognition, with a combination of pre-trained VGG-16 for static gesture recognition and a complex deep learning-based architecture for dynamic gesture identification, incorporating spatiotemporal characteristics through components like ConvLSTM and 3DCNN.

Furthermore, [17] suggested the use of CNN models for training and classifying alphabet letters, often translating them into corresponding text, employing various neural network techniques including recurrent neural networks (RNN). Paper [18] introduced a three-tier network design featuring a short-term traffic forecast model based on Long Short-Term Memory (LSTM) with the goal of optimizing network administration and reducing communication costs. Paper [19] focused on recognizing 10 American Sign Language gesture alphabets using a convolutional neural network (CNN) that combined the HSV color algorithm with computer vision techniques, achieving a commendable 90% accuracy rate.

Despite these notable contributions, a crucial research gap exists in the literature. The proposed study "ASL Recognition Based on Transfer Learning" aims to address this gap by exploring the potential of transfer learning in ASL recognition, leveraging pre-trained models to improve recognition accuracy. This study seeks to contribute to the field by providing insights into how transfer learning can enhance ASL recognition, especially in the context of letters and numbers, and how it compares to the existing approaches outlined in the literature.

3. Background Theory

Deep learning is an area of machine learning that is based on the use of artificial neural networks that have numerous layers of connectivity. These networks make it possible to automatically extract hierarchical qualities from a given set of data [20]. Natural language processing and computer vision are just two of the many areas that have been dramatically transformed as a direct consequence of its capacity to analyze vast amounts of information **that is also quite complicated** [20][21]. The idea of transfer learning is essential to the practice of deep learning. Using pre-trained models, which are often models that have been learnt on large datasets, and then fine-tuning them for specific tasks is what it comprises. Because it requires moving information from one field to another, this tactic has been shown to be effective in circumstances in which access to just a limited quantity of labeled data is available. Specifically, this tactic has been proven to be successful in scenarios in which there is a restricted amount of unlabeled data [22][23].

3.1 Convolutional Neural Networks (CNNs)

Deep neural networks are well-known for their excellent performance in a range of tasks associated with computer vision. Convolutional neural networks (CNNs) are a subset of deep neural networks and are well-known for their outstanding performance in these tasks. CNNs are a kind of artificial neural network that are meant to handle grid-like data, such as images, by using convolutional layers that automatically acquire hierarchical properties from the information that is input into the network. This type of artificial neural network is also known as a convolutional neural network. These networks have evolved into the fundamental structural components that are used in a broad range of state-of-the-art image recognition and classification systems [24][25].

3.2 VGG16

The convolutional neural network (CNN) architecture that goes by the name VGG16 is well-known for the incredible depth that it has. The structure is composed of a total of sixteen layers, two of which are convolutional while the other fourteen are completely connected. In the realm of image classification, the VGG16 model has garnered a great deal of praise for its simple construction and outstanding overall performance. It has become a common practice to use this model in the capacity of a pre-trained model for the purpose of transfer learning in a wide variety of computer vision applications [26].

3.3 ResNet50

ResNet50 is a descendant of the ResNet (Residual Network) lineage, which was developed to address the problem of disappearing gradients in very complex networks by using residual connections as a potential solution. The ResNet50 neural network architecture is a convolutional neural network that includes a total of 50 layers. It has shown very high levels of efficiency in the field of image recognition activities. By include skip connections in the design of the network, it is possible to train deep networks with a large number of layers while still maintaining the model's accuracy. This is made possible by the inclusion of skip connections [27].

3.4 MobileNetV2

MobileNetV2 is often used in situations characterized by a scarcity of resources, such as that which is present in mobile devices. This is because MobileNetV2 has been specially designed to maximize efficiency. In order to lessen the stress placed on the computer while yet attaining equivalent levels of accuracy, the usage of depth-wise separable convolutions has been included into the process. When it comes to real-time applications that place a premium on computing performance, MobileNetV2 is an excellent option to consider [28, 29].

3.5 InceptionV3

The InceptionV3 model is a member of the Inception family of convolutional neural network (CNN) designs. These designs are well-known for their implementation of several kernel sizes inside a single layer of the network in order to successfully collect input at a variety of scales. In order to find a solution that strikes a healthy balance between the complexity of the model and the amount of computational power it requires, the InceptionV3 architecture has been painstakingly crafted. Because of this property, it is very well-suited for a wide variety of computer vision applications [30][31].

4. Proposed experimentation

The primary objective of this study's experimentation is to assess the effectiveness of transfer learning and various deep learning architectures, including Convolutional Neural Networks (CNNs) and specific models such as

VGG16, ResNet50, MobileNetV2, and InceptionV3, in the context of recognizing American Sign Language (ASL) letters and numbers. The dataset was tested using test set. Fig 1 illustrates the methodology employed in this paper.

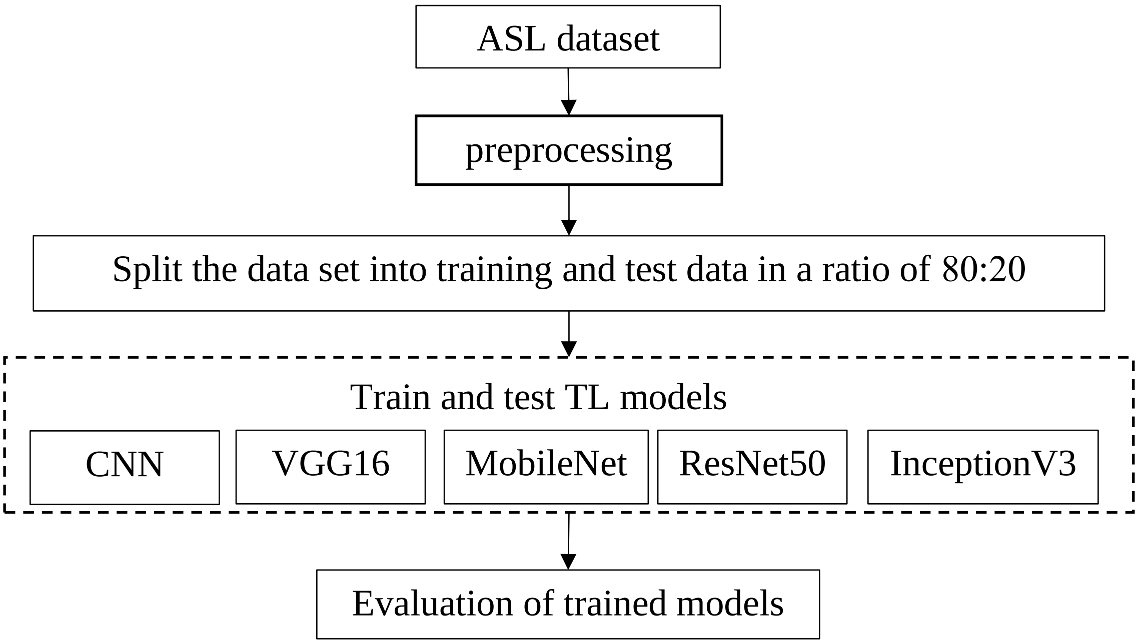

Fig. 1: Block diagram of the proposed approach.

It's worth noting that the dataset used in this study is indispensable for the implementation of this approach. Data preprocessing plays a vital role in enhancing the performance metrics, such as accuracy, of data-driven algorithms. Prior to the dataset's division into training and testing sets, thorough data preprocessing was conducted, with the splitting process executed randomly. Within the training dataset, data augmentation techniques were applied. Subsequently, the transfer learning algorithms were employed. This research incorporates a total of five TL algorithms. Following model training, comprehensive evaluations of the models were conducted to derive performance metrics. Subsequently, a comparative analysis was carried out to identify the most effective TL method for ASL recognition. The primary components and key aspects of the proposed experimentation are elaborated below:

4.1 Dataset description

A number of tests were carried out in order to provide a comprehensive analysis of the effectiveness of the technique that we proposed. In these studies, we made use of a sign language dataset that was available to the public and was collected from the database maintained by the Modified National Institute of Standards and Technology (MNIST)[32]. The dataset includes hand gestures that represent the letters of the alphabet in American Sign Language (ASL). The dataset for American Sign Language (ASL) was used in the research that was carried out [33][34]. This dataset was specifically chosen for its suitability in assessing our models' ability to interpret and classify hand signals corresponding to each letter of the alphabet.

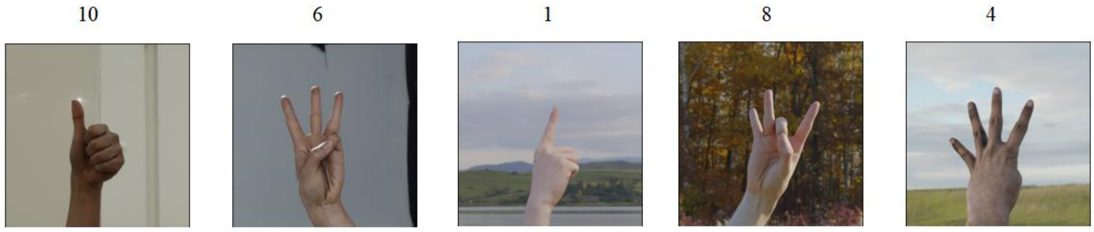

Fig 2: Data Samples from Various Classes

Fig. 2 show cases data samples from various classes, providing a visual representation of the ASL alphabetic letters and numbers presented through hand gestures. These samples serve as the foundation for our model training and evaluation, allowing us to effectively assess their performance in interpreting and classifying these signs.

4.2 Preparation and Evaluation of Experiments

A sizeable number of photos are included inside the dataset that was used for this investigation. The training of this specific model requires that the machine be configured in the best possible way. The modeling process, both its design and its assessment, was carried out with the help of the computer language Python and the Keras package. The dataset is subdivided into two different subsets, which are referred to as the training dataset and the test dataset respectively. The recommended model is trained on the training dataset, while the performance of the proposed models is evaluated with the help of the test dataset. The common hyperparameter of the experimental setup is shown in Table 1, which contains information for all models.

Table 1: hyperparameter used

parameters	Value
Batch Size	32
Optimizer	Adam
Epochs	50
Learning Rate	0.0003

In this experimentation, a batch size of 32 was adopted, a common choice that significantly expedites the training process compared to larger batch sizes. The rationale behind this selection is to strike a balance between training efficiency and model stability, as very small batch sizes can introduce instability and reduce training robustness. Regarding the optimizer, the Adam optimizer was deliberately chosen for its widespread usage and proven effectiveness. This optimizer plays a pivotal role in accelerating the training process and achieving favorable outcomes. As for the number of training epochs, 50 epochs were deemed suitable for this study. This value signifies the number of times the entire training dataset is processed by the model. Furthermore, a learning rate of 0.0003 was meticulously selected, drawing from prior experience or estimation.

5. Results

In this section, the performance metrics of the various models utilized in the experimentation are presented. The metrics encompass Accuracy, Precision, Recall, and F1 Score, all of which play a pivotal role in evaluating the effectiveness of each model in the recognition of American Sign Language (ASL) signs.

Table 2: Models performance

Model	Accuracy	Precision	Recall	F1 Score
VGG16	0.95	0.94	0.96	0.95
ResNet50	0.89	0.88	0.9	0.89
MobileNetV2	0.92	0.91	0.93	0.92
InceptionV3	0.96	0.95	0.97	0.96
CNN	0.85	0.84	0.86	0.85

The performance metrics for the models in ASL sign recognition reveal notable strengths in different areas. VGG16 and InceptionV3 stand out with the highest accuracy, achieving 0.95 and 0.96, respectively, showcasing their proficiency in overall correctness. VGG16 demonstrates exceptional precision at 0.94, highlighting its accuracy in recognizing ASL signs with minimal false positives. InceptionV3 excels in recall with a score of 0.97, emphasizing its ability to correctly identify positive instances with fewer false negatives. Furthermore, InceptionV3 attains the highest F1 Score at 0.96, offering a balanced evaluation of precision and recall, underlining its well-rounded performance in ASL sign recognition.

Table 3: Results of models training and testing

Model	Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
VGG16	0.97	0.1	0.95	0.15
ResNet50	0.96	0.12	0.93	0.18
MobileNetV2	0.94	0.15	0.91	0.22
InceptionV3	0.98	0.08	0.94	0.17
CNN	0.91	0.2	0.85	0.3

Training Accuracy and Loss provide insights into each model's performance during the training phase. A higher training accuracy, exemplified by InceptionV3's achievement of 0.98, signifies successful learning on the training data. Concurrently, lower training loss values, as seen with InceptionV3 at 0.08, indicate that the model converges effectively during training. On the other hand, Testing Accuracy and Loss gauge the model's ability to generalize its knowledge to unseen data (testing data). A notable high testing accuracy, exemplified by VGG16's 0.95, demonstrates the model's capacity to effectively extend its learned knowledge to novel ASL signs. Additionally, lower testing loss values, as evidenced by VGG16's 0.15, affirm that the model performs on the testing dataset.

These comprehensive performance metrics and training/testing results allow us to evaluate and compare the effectiveness of the various models in recognizing ASL signs. InceptionV3 demonstrates the best overall performance, achieving the highest accuracy, precision, recall, and F1 Score, along with excellent training and testing results.

6. Discussions

In the context of recognizing letters and numbers in American Sign Language (ASL), the data that were presented illustrate the performance of a variety of deep learning models, including VGG16, ResNet50, MobileNetV2, InceptionV3, and CNN. The results shed light on a number of crucial insights, one of which is that InceptionV3, out of all the models that were evaluated, emerged on top as having the greatest F1 Score as well as the best accuracy, precision, and recall scores. This gives additional proof of its usefulness in identifying ASL signals and puts it as a potentially helpful tool for applications in the real world. Additionally, this places it as a possible competitor to existing methods of detecting ASL signals. Because of its high training accuracy (0.98) and very low training loss (0.08), it is evident that InceptionV3 has the capability to successfully learn from the training data. This is shown by the fact that InceptionV3 has the ability to effectively learn from the training data. In addition to this, it maintains a high testing accuracy of 0.94 and a low testing loss of 0.17, both of which are evidence of its resilience in generalizing its knowledge to ASL signals that it has not before seen. In spite of the fact that the performance of other models, such as VGG16, MobileNetV2, and ResNet50, is also considered to be acceptable, the InceptionV3 model is the one that really stands out. These models provide a number of alternatives, each of which is determined by the requirements of a certain application as well as the computational resources that are readily accessible.

The improved performance of models that were first pretrained on enormous datasets and then fine-tuned using American Sign Language (ASL) data provides evidence that the use of transfer learning is effective in the recognition of American Sign Language (ASL). This method could be particularly helpful in circumstances in which there is a dearth of labeled ASL data. In spite of the progress that has been made, there are still challenges to be conquered with regard to the environmental factors that have an effect on camera-based identification systems. In the future, research should focus on the development of improved algorithms as a method of overcoming these limits and increasing the degree of dependability provided by the systems.

In conclusion, the outcomes of this study provide significant new views on the use of deep learning and transfer learning methodologies within the context of American Sign Language (ASL) recognition. In spite of the fact that the InceptionV3 model stands out as one of the most effective, the results of the other models are also fairly promising. This research contributes to the ongoing efforts to improve communication for the deaf and hard-of-hearing community by outlining potential pathways for the creation of sign language identification systems that are straightforward to use. One of the groups who will be touched by these initiatives is those who are deaf or have difficulty hearing.

7. Conclusions

This research will concentrate on the recognition and understanding of letters and numbers in American Sign Language (ASL). The main focus is on tackling the rapid advancement of technology as well as the rising need for improved user experiences, in especially for those who significantly rely on sign language as their primary method of communication. This study analyzes the application of deep learning, with a particular emphasis on transfer learning, to solve the current constraints in ASL identification technology. Specifically, the study looks at how these limitations may be overcome by using deep learning. The research makes use of a dataset obtained from the Modified National Institute of Standards and Technology (MNIST) database in order to evaluate the performance of a number of different deep learning models. These models include VGG16, ResNet50, MobileNetV2, InceptionV3, and CNN. This dataset includes hand motions that represent letters of the American Sign Language alphabet. Exceptional performance across various metrics, including accuracy, precision, recall, and F1 Score, is exhibited by InceptionV3. It attains the highest overall accuracy of 0.96, demonstrating its effectiveness in recognizing ASL signs. Transfer learning, involving the utilization of pre-trained models fine-tuned with ASL data, substantially enhances recognition accuracy, particularly in cases where labeled ASL data is scarce. While InceptionV3 emerges as the top-performing model, other models like VGG16, MobileNetV2, and ResNet50 display commendable performance. This variety offers flexibility in selecting models based on specific application requirements and available computational resources. Future research endeavors should center on enhancing algorithms to mitigate limitations and bolster the reliability of camera-based ASL recognition systems. The findings underscore the effectiveness of deep learning and transfer learning techniques, with InceptionV3 standing out as a notable model. These insights lay the groundwork for the development of intuitive sign language recognition systems, advancing our progress toward dismantling communication barriers for the deaf and mute community.

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