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Peruvian Sign Language translator for people with hearing and/or communication disabilities using a convolutional neural network

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Abstract*– Promoting the social inclusion of people with deafness and/or communication disabilities is a priority for many countries. For this reason, considerable emphasis is currently being given to machine learning (ML) and deep learning (DL) techniques for sign language recognition and translation, as they can be a significant contribution to the social inclusion of the deaf and/or deafened community. Thus, the present research proposes the development of a translator of Peruvian Sign Language (PSL) for the recognition and translation of static signs belonging to PSL through a convolutional neural network (CNN). These signs are the numbers from 0 to 9 and the letters of the alphabet except J, Ñ and Z because they are represented with movable signs and the letters O and W because they are very similar to the numbers "0" and "6". To achieve the development of the translator, a balanced database for PSL was built from scratch, consisting of 700 images for each static sign, for a total of 22400 images. These images have a dimension of 80x80 pixels that go through a preprocessing stage, 3 convolutional layers, filters, kernels, ReLu and MaxPooling activation functions. Experimental results show that the translator recognizes static PSL signs with an accuracy of 90%, 86% and 81% for training, validation and testing respectively.

Keywords-- Sign language recognition; deep learning; neural network; convolutional neuronal network

I. Introduction

Sign language is the form of communication for people with hearing or speech problems, where movements or expressions of the human body are used to interact with the environment and be understood [1]–[3]. Sign languages are specific to each country, in some cases they are similar, but they always vary between them. According to the World Federation of Deaf People there are more than 300 sign languages around the world [4]–[6].

Sign language is divided into two types. The first type is the dynamic sign, these signs feature hand movement in their representation. And the second type is the static sign, this sign does not present any movement and presents fewer problems than the dynamic sign in recognition based on computer vision [7]–[9].

According to the World Health Organization (WHO) around 432 million adults, representing more than 5% worldwide, have presented hearing loss. In addition, it is estimated that by 2050 more than 700 million people present with hearing loss [6].

Peru is one of the countries that continuously seeks to eliminate the obstacles that prevent communication with deaf people, as it is a major limitation to exercise the basic right to education. Therefore, it seeks to promote the teaching and dissemination of PSL so that deaf people can access education with equal opportunities, in accordance with Law No. 29935 that grants official recognition to this language [10]. In fact, the INEI in 2017, records 232176 people with hearing difficulties, of which only 8790 have knowledge in PSL. Also, according to the Ombudsman's Office in 2019, it was recorded that 76% of public institutions and 83% of private institutions do not have the required conditions to provide educational services to deaf students. There are also many complaints about the communication barriers faced by deaf people in education, health, and other services due to the lack of qualified PSL interpreters [11].

In addition, people with this condition are underrepresented in academia, with only 587 and 350 primary and secondary school students respectively in 2019 [11]. Therefore, new technologies based on artificial intelligence (AI) could be of great help for the communication of non-hearing people with hearing people. Due to this lack of insertion in the socialsphere, a basic level PSL translator using AI is developed. Thisproposal seeks to help non-hearing people in their communication with other people to have a better integration. Considering that the present research is a starting point since it recognizes and translates basic PSL static gestures.

In that sense, the present research seeks to improve the accuracy of PSL recognition by applying a CNN. This is because it has been the most used technique for the recognition and translation of sign language.

On the one hand, to be able to do this type of recognition, it was started with data collection, in this case images of the Peruvian static signs of the numbers and letters of the alphabet. The reason for this was because there is not much research for the recognition and translation of the signs belonging to the PSL. In fact, studies carried out in [2], [12], [13] show that the sign languages of African countries, such as Arabic and Ethiopian, are mostly addressed. Likewise, these researches do not precisely detail whether the data collection was manual or automatic. Lastly, researches such as [2], [14] show that the

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overfitting problem has not been solved, that it is necessary to solve it so that the CNN model can correctly generalize data that it has not seen before for its correct recognition and translation.

On the other hand, the present research is developed with the purpose of recognizing and translating basic static signs of the PSL, for which, firstly, data capture was carried out automatically by programming to optimize data collection. In this way, it was possible to automatically capture, for CNN training, 80x80 pixel images of the static signs of the numbers from 0 to 9 and the letters of the alphabet in PSL except for J, Ñ and Z for being signs dynamic and the letters O and W for being very similar with the numbers "0" and "6", differentiating according to the context of the communication. Finally, compared to [2], [14], the overfitting problem has been solved to develop a CNN model that correctly recognizes the static signals of the PSL.

The present research is organized as follows: Related work in Section II, where a review of different articles on sign recognition accuracy by applying a CNN is conducted; methodology in Section III, detailing which PSL signs are recognized, the characteristics of the images and the development of the CNN; results in Section IV, where the results of accuracy in training, validation and testing are analyzed; and conclusions in Section V.

II. State of Art

Sign languages are the primary means of communication for people who are totally deaf or hard of hearing. These languages vary from country to country and language to language. In recent decades, image-based ML and DL have been employed for recognition and translation of hand signs in the form of text or audio to assist non-hearing people in their communication with others, whether they are proficient in sign language of non-hearing people [15]–[17]. Thus, with the advancement of AI and computer vision. The most used techniques for sign language recognition and translation are shown below.

On the one hand, a review article for sign language recognition and identification is presented in [18], which indicates, in this compilation of different studies, that webcams and digital cameras have been mostly used for data acquisition (image or video). It also mentions that, for the same data set, the ML algorithms KNN, SVM and CNN obtained an accuracy of 75%, 72% and 97.12% respectively. However, Amharic alphabet sign recognition, as mentioned in [19], obtained an average accuracy of 80.82% and 98.06% using ANN and SVM respectively. Also, [19] mentions that, for different sign language datasets, the most employed DL algorithms were CNNs, with which a minimum accuracy of 93.17% and a maximum accuracy of 99.3% were obtained.

On the other hand, [12] presents an Ethiopian sign language recognition system (ETHSL) that translates this language into Amharic using a CNN. This system handles ETHSL images as input and Amharic text as output. The execution time was minimized by adjusting the images to a suitable size, achieving98.5% training, 95.59% validation and 98.3% testing accuracy. However, in [20] for Indian Sign Language (ISL) recognition where a total of 35,000 images consisting of 100 static images of ISL signs from different users were used, higher training accuracy was achieved for both color (99.72%) and grayscale (99.90%) images using a CNN. Furthermore, in [14], a CNN model for recognition of Bengali Sign Language (BdSL) digits0 to 9 was built with only 1075 images, of which 860 (80%) were used for training and 215 (20%) for validation, achieving95.35% and 94.88% accuracy in training and validation.

Unlike previous studies that used a CNN, the study in [13] employs a variant of this, which is known as Faster R-CNN for Arabic Sign Language (ArSL) recognition. This technique was used because it uses a Region Proposal Network (RPN) and a Region of Interest (ROI) of the image to improve performance by reducing the processing time required by the network. The RPN output contains 2 important aspects: the bounding box coordinates and the score indicating whether a hand exists. The proposed regions generated by RPN are transmitted to the ROI clustering layer along with the feature map generated by the feature extraction networks: VGG-16 and ResNet-18. As results, both models provide an accuracy of about 93% with a slightly higher advantage for ResNet-18. Also, in [21] a variant of CNN known as R-CNN was employed for Turkish Sign Language (TSL) detection and recognition achieving an average accuracy of 99.7%, very acceptable for conventional methods applied in TSL. On the other hand, in [22] a faster R-CNN was used for the recognition of only 3 classes (a, peace and hello) in Indonesian Sign Language, achieving 100% accuracy for each of the classes.

Currently, this DL algorithm called CNN, has become a very popular choice for classification tasks. However, they also suffer from some problems, such as overfitting problem [23]–[25], high variance during prediction and prediction. To overcome these problems, in [23] the part of the gesture is detected using the binary threshold-based background separation method, the contour part is extracted, the hand region is segmented, and finally the images are resized for CNN training. On the other hand, in [25], VGG-16 was used over VGG-19 to improve feature extraction and decrease overfitting. In contrast, [24] only mentions that a dedicated study was carried out to avoid overfitting but does not mention the technique or techniques used to avoid said overfitting.

In summary in the studies shown above, there are gaps, such as a lack of research and/or a database related to PSL, since CNNs have mostly been developed for the recognition and translation of sign languages of African countries, such as Arab and Ethiopian. With the research conducted, it is analyzed that the best alternative solution to this problem is to design the PSL translator for people with hearing and/or communication disabilities using a CNN, since it considerably minimizes the manual gesture classification error rate, achieving in some cases an accuracy of up to more than 95% in the recognition of sign language.

III. METHODOLOGY

The present work performs the recognition and translation of the static signs belonging to the PSL by means of a CNN. These signs are the numbers from 0 to 9, the letters of the alphabet except J, Ñ and Z that are represented with movable signs and the letters O and W because they are very similar to the numbers "0" and "6 ", taking as reference the Guide for the learning of the Peruvian Sign Language proposed by the General Directorate of Special Basic Education (DIGEBE) [26].

Thus, the development process of the PSL translator is divided into parts, as shown in Fig. 1. Data collection, image preprocessing, CNN construction, training, validation and testing.

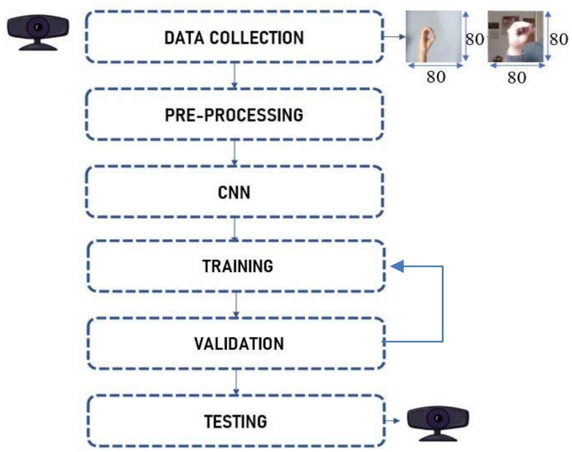

Fig. 1 Process of the Peruvian sign language translator.

A. Data Collection

Initially, a numbers-only database with RGB images of size 80x80 pixels was generated. This balanced database of 7000 images that is made up of 700 samples for each class, that is, 700 images for each sign that represent the numbers from 0 to 9 in PSL. In this way, for the recognition and translation of these numbers, the following are used: 500 images for each of the 10 classes (5000) for network training, 150 images for each of the 10 classes (1500) for validation and 50 images for each of the 10 classes (500) for the test.

Secondly, the previous database was modified, obtaining a new one conformed by the images of the static signs of the above-mentioned numbers and the letters of the alphabet in PSL except J, Ñ and Z for being dynamic signs and the letters O and W for being very similar with the numbers "0" and "6". However, these signs can be recognized as "O" or "W" depending on the context of the communication. Thus, a total balanced database of 22,400 consisting of 700 samples (images) was generated for each class. Thus, for recognition and translation, 500 images from each of the 32 classes (16,000) are used for training, 100 images from each of the 32 classes (3,200) for validation and 100 images from each of the 32 classes (3,200) for testing.

These images were obtained through photographs taken of 2 participants, through an algorithm carried out in Python in the PyCharm environment and Visual Studio Code using the OpenCV and MediaPipe libraries, as in [27] we took the photographs and delimited obtaining the region of interest (ROI) automatically, to have a better recognition because we only focus on the hand sign made by the participant as can be seen in Fig. 2. These captures are made on a uniform background and non-uniform with artificial and natural light, with a webcam built into the laptop and an ANTRYX camera model RK355 connected to the computer.

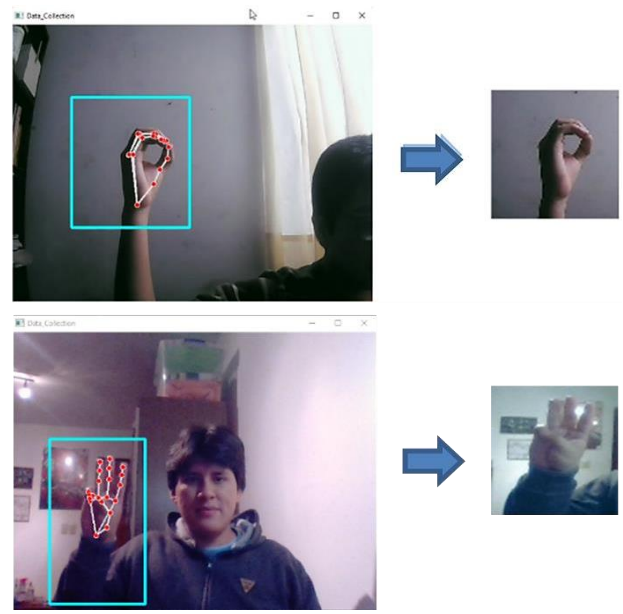

Fig. 2 Data Collection.

B. Pre-processing

Secondly, the images go through a pre-processing stage to obtain better results. This stage consists of rescaling of the image to move the pixels from 0 - 255 to 0 - 1. In addition, as can be seen in Fig.3, the images are tilted and zoomed with a random factor with values in the range from 0 to 0.1 and, in addition, they are randomly inverted horizontally to achieve a better training of the network.

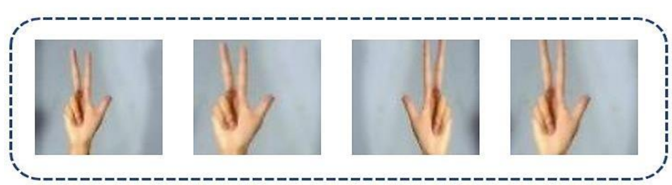

Fig. 3 Preprocessing of data set.

C. CNN

Third, as in [28], [29], our convolutional neural network architecture will present a convolution layer, a MaxPooling layer, and a ReLu activation function as shown in Fig. 4.

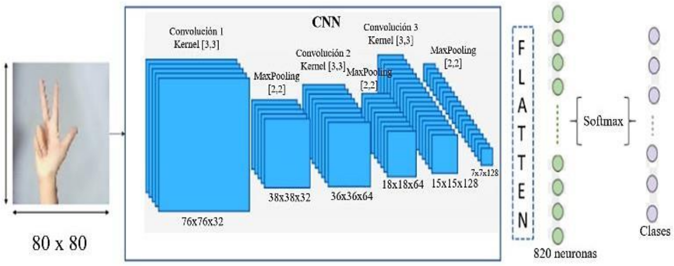

Fig. 4 CNN architecture.

The first convolutional layer receives the input image of 80x80 pixels, this first convolution has 32 filters in the convolution output, a 3x3 Kernel and a ReLu activation function. This layer has no fill, so 76x76x32 images are obtained. Then, a 2x2 MaxPooling is performed at the output of the first convolution, obtaining 38x38x32 dimensions. The second convolutional layer presents 64 filters in the output, and presents a 3x3 Kernel matrix, a ReLu activation function and this convolution also has no filling, obtaining an output of 36x36x64. A 2x2 MaxPooling is applied to this second convolution, reducing the dimensions to 18x18x32. Finally, the third convolutional layer presents 128 filters in the output, a 4x4 Kernel is applied, a ReLu activation function and no filler in the image, obtaining the dimensions of 15x15x128, which will go through a last MaxPooling of 2x2 having a final dimension of 7x7x128.

Then, the final array was flattened using the Flatten function to obtain a one-dimensional array. This matrix will connect with 820 neurons, where the softmax function was then used. This softmax function helped us to give the probability distribution to our outputs, which in this case are each of the signs of the PSL.

D. Training, Validation and Test

Fourth, the training is done with a learning rate of 0.00005 and 100 epochs. The hyperparameters (learning rate, number of layers, number of neurons, and core size) were adjusted to obtain the best metrics in the validation set. These parameters were defined by trial and error, obtaining the best results with these values.

This model is programmed in Python in the PyCharm and Visual Studio C environment, where the model is executedand stored with the respective weights. The final model is evaluated on the test set.

IV. Results

To evaluate the performance of the PSL Translator, two experiments have been carried out. The first one consisted in the development of a CNN for the recognition and translation of 10 classes of static signs (numbers from 0 to 9), which achieved an accuracy of 97% for training with losses of 0.0809: while, for validation, an accuracy of 96.5% with lossesof 0.1607 and for testing, an accuracy of 72% with losses of 1.05, as shown in Table 1.

TABLE I
Training and Validation of the CNN for the Recognition of Numbers 0 to 9 In PLS

Metric	Training	Validation	Test
Loss	0.0809	0.1607	1.0519
Accuracy	0.97	0.965	0.7212

In this way, the values obtained in the training and validation of the network are analyzed, and it is observed that this first CNN model over-fits the training data (Fig. 5).

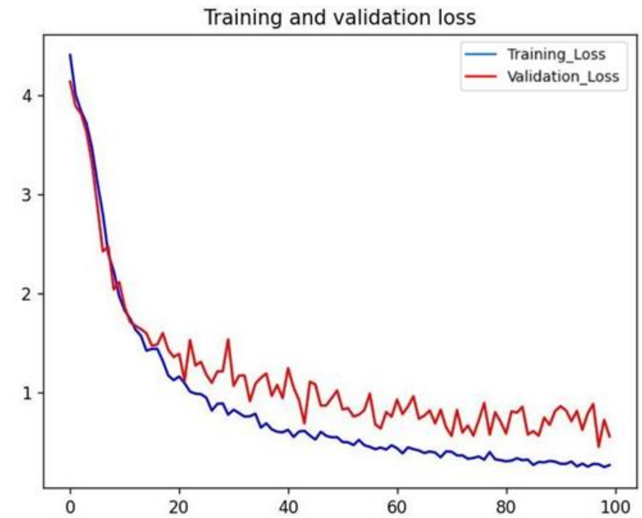

Fig. 5 Epochal losses during training and validation with overfitting.

This overfitting is important to solve because it does not require high accuracy on the training set but being able to develop a CNN model that generalizes correctly to a test set (data that it has not seen before) for correct recognition. Therefore, in the second experiment, an overfitting regularization technique from the open source TensorFlow Keras library was used. In addition, images of the letters of the alphabet in PSL except J, Ñ and Z and the letters O and W were added to the database because they are very similar with the numbers "0" and "6". Thus, CNN was developed for the recognition and translation of 32 static sign classes, with which an accuracy of 90% was achieved for training with losses of 0.8065. While, for validation, an accuracy of 86% with losses of 0.8939 and for testing, an accuracy of 81% with losses of 1.13 as shown in Table 2.

TABLE II
Training and Validation of the Cnn for the Recognition of Numbers 0 to 9 and the Letters of the Alphabet in PLS without Considering The J, Ñ, Z, O and W

Metric	Training	Validation	Test
Loss	0.8065	0.8939	1.13
Accuracy	0.90	0.86	0.81

Finally, Fig. 6 shows that the overfitting problem is solved and Fig. 7 shows that in the testing stage a high probability of recognition of the static PSL signs with which the CNN model was developed is obtained, although the average accuracy in the test was 81%, since only two classes "2" and "V", which are represented by similar gestures in this sign language, have alow percentage of recognition.

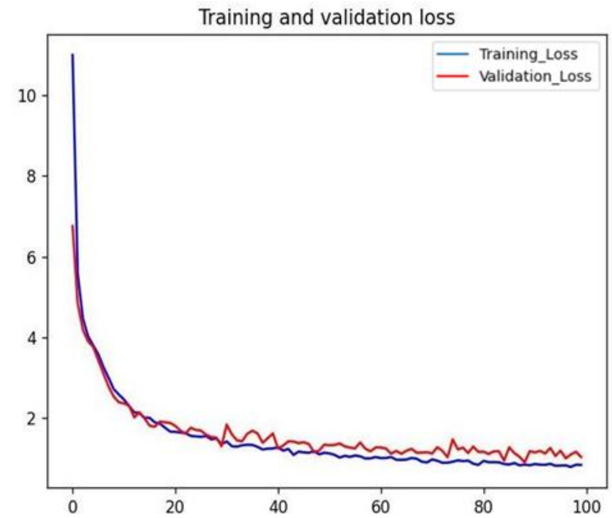

Fig. 6 Epochal losses during training and validation without overfitting

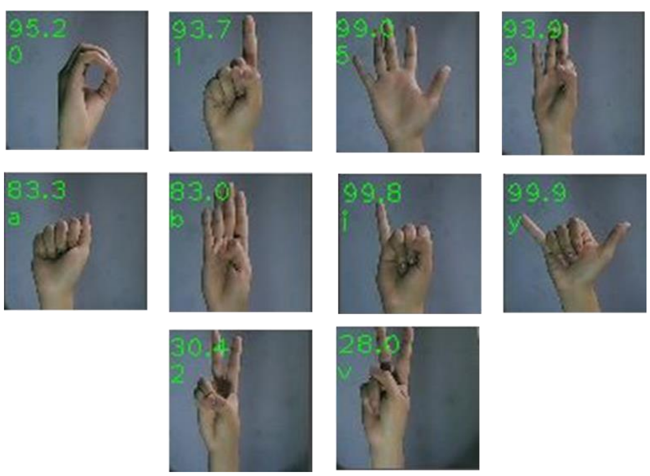

Fig. 7 Probability of recognition and textual translation of the numbers from O to 9 and the letters of the alphabet in PSL without considering the J, Ñ and Z and the letters O and W due to the similarity with the numbers "0" and "6".

Thus, it was possible to obtain a CNN model without overfitting with accuracy losses of 0.90 and 0.86 in training and validation respectively, able to generalize the knowledge to recognize with good accuracy (81%) the static PSL signs mentioned above, in a test stage with images that the network has never seen before. Unlike the study in [10], where the accuracy percentages in training and validation are high (95.35% and 94.88%), as the overfitting problem was not solved, since the accuracy losses in these 2 stages were 12.38% and 26.13% respectively.

V. Conclusions

Since PSL is not widely used and/or mastered by non-disabled people, several countries are looking for different ways to remove this social barrier that prevents access to basic services such as education and healthcare for people with hearing and/or communication disabilities. With the advance in software technological tools for the recognition of different signs using neural networks, a basic level PSL Translator is developed using a CNN that recognizes and translates to text format basic static gestures of PSL, being these, the numbers from O to 9 and the alphabet, except the letters J, Ñ and Z for being dynamic gestures and the letters O and W for being very similar to the numbers O and 6, but that can be understood with the signs of these numbers according to the context in which the communication is taking place. Therefore, the CNN was designed for the recognition and textual translation of the static gestures mentioned above, with a balanced database of 22400 images, of which 71.43% were used for network training and 14.28% for validation and testing, achieving an accuracy of 90%, 86% and 81% for training, validation and testing respectively.

As future work, it is proposed to extend the database by adding the letters O and W that were not considered in the database because they are very similar to the numbers O and 6 considering the confusion matrix technique to show the classes that are confused with others. Furthermore, it is proposed to add everyday sentences that can be represented with static signs in PSL and to investigate how the CNN could be trained to learn dynamic signs as well, thus obtaining a much more complete PSL database.

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