Prototype of real-time Mexican sign language classifier

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ABSTRACT

Mexican sign language (MSL) is the language used by the deaf community in Mexico. Like Spanish, it has its own distinct grammar, syntax, and vocabulary. However, instead of relying on sounds, MSL conveys meaning through gestures, facial expressions, and body movement. This research proposes the creation of an image dataset of the MSL alphabet for real-time sign detection. A neural network model was developed to recognize these signs, achieving an accuracy of approximately 60%. Although this result is modest, the study establishes a foundation for future work that could facilitate communication for MSL users or lead to the development of educational applications for language learning.

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1. INTRODUCTION

Hearing impairment is a condition that affects a person’s ability to perceive sound [1]. It ranges from mild hearing loss to profound deafness and can be caused by various factors, including genetics, disease, injury, or aging [2]. Individuals with hearing disabilities face unique daily challenges, such as difficulties with communication, accessing information, and full participation in society.

To overcome these barriers, many deaf individuals use sign language, a visual communication system that employs manual gestures, facial expressions, and body postures. As a natural language with its own grammar and syntax, it is fundamental to the cultural identity of deaf communities [3]. Since each country typically has its own distinct sign language [4], the primary one used by the deaf community in Mexico is Mexican sign language (MSL).

MSL is a rich and complex language that enables deaf individuals to fully express their ideas, emotions, and experiences [5]. However, the widespread lack of MSL knowledge among the hearing population creates communication barriers, limiting the inclusion of deaf individuals in various aspects of social life [6].

Specialized software plays a crucial role in addressing this challenge. Digital platforms can bridge the communication gap between hearing and deaf individuals through real-time translation tools, sign language dictionaries, and educational resources [7]. Furthermore, software can facilitate the creation of virtual learning environments for MSL [8], enabling broader access to language acquisition and fostering more effective communication with the deaf community.

This study details the development of an algorithm for recognizing letters of the MSL alphabet. A dataset of sign images was created for model training and evaluation. The proposed classification model is based on a neural network architecture.

2. RELATED WORK

The following are some studies on sign languages. Initially, research on sign languages other than Mexico's is analyzed. Later, studies related to MSL are discussed.

Antunes *et al.* [9] outlines a framework to support the recognition and interaction of sign language, aiming to serve as a "de facto" standard for use in computer vision. This study highlights the importance of reassessing the needs of the deaf community and the effective use of sign languages as a powerful tool for computational processing. Although it does not concentrate on real-time sign classification, it offers guidelines for developing applications for such purposes.

Guerrero-Balaguera and Pérez-Holguín [10] details the design of a system intended to enhance communication and interaction for individuals with severe hearing disabilities. The system employs artificial vision techniques to identify static signs of Colombian sign language (CSL). The process consists of four phases: image capture, preprocessing, feature extraction, and recognition. During preprocessing, the sign is extracted from the background through a threshold segmentation process, followed by morphological operations to remove noise. In the feature extraction phase, two vectors are generated to describe the hand shape used in the sign. Recognition is conducted using a multilayer perceptron (MLP) artificial neural network (ANN), which acts as a classifier. The results show that the system recognizes 23 static signs of CSL with an accuracy of 98.15%

Riveros and Inostroza [11] aimed to develop a gesture recognition system by implementing image processing and segmentation algorithms using OpenCV libraries with a programming language through a digital camera. The experiment tested only four letters of the alphabet under both controlled and uncontrolled conditions, as well as in low artificial light. The system achieved an overall performance of 90%. The research concludes that hand gesture recognition is vital due to its expressiveness but presents challenges such as segmentation ambiguity and spatiotemporal variability, particularly due to the hand's morphological complexity.

Ortiz-Farfán and Camargo-Mendoza [12] describes the creation of software for CSL recognition aimed at deaf individuals. Machine learning serves as the foundation for the system. Currently, there is no public repository containing images or videos of these signs, nor the necessary information to achieve this goal, which represents one of the main obstacles to starting the project. Therefore, the construction of such a repository was initiated. The repository was utilized as training data to develop an efficient computational model capable of predicting the meaning of new images. The system's performance was evaluated using classification metrics and by comparing different models. The results demonstrate that it is possible to provide new tools for deaf individuals to facilitate communication with people who do not know sign language. After selecting the best models, tests were conducted with new images similar to those in training, and it was observed that the most effective model achieved a success rate of approximately 68% across 22 classes.

Pathan *et al.* [13] employs artificial intelligence to recognize sign language, specifically American sign language (ASL), using images from a dataset titled "Finger Spelling, A." The method incorporates two layers of image processing: in the first layer, images are processed in their entirety for training, while in the second layer, hand landmarks are extracted. A multi-headed convolutional neural network (CNN) model is proposed and evaluated with 30% of the dataset to train these two layers. To mitigate overfitting, data augmentation and dynamic learning rate reduction techniques are implemented. This configuration achieves a test accuracy of 98.981%, which could aid in developing efficient communication systems for the deaf-mute community.

Previous studies concentrate on various sign languages, including Colombian, American, and Chilean. While some report very high accuracy and others yield lower results, it is crucial to recognize that the signs in each language differ, making direct comparisons inequitable. Nevertheless, these studies provide valuable references for identifying strengths and addressing weaknesses in MSL recognition.

Romero [14], progress is presented towards developing a system capable of translating words in MSL by recognizing them based on the 3D trajectory of hand movements using a Kinect sensor. A corpus of 53 words was created, focusing solely on words from eleven semantic fields. To eliminate potential inconsistencies and noise in the extracted patterns, intermediate points were added, and the KNN algorithm was employed for filtering. Additionally, the descriptor method used divides the pattern into two sections according to the peak of its trajectory, and through the arithmetic mean, the representative 3D positions of both sections are obtained. From the general pattern, width, height, depth, and orientation are also extracted. For word classification, a MLP ANN was utilized, trained with the backpropagation algorithm. The system was validated using the K-fold cross validation method, achieving an average precision rate of 93.46%.

Sánchez *et al.* [15] introduces the first architecture that utilizes facial features as grammatical indicators to create a real-time MSL-to-written Spanish interpreter. The model employs MediaPipe, an open-source library, to extract facial landmarks, body positioning, and hand movements. Three 2D CNNs are utilized to individually encode and extract patterns. These networks converge into a MLP for classification. Ultimately, a hidden markov model (HMM) is employed to predict the most probable sequence of words based on a preloaded knowledge base. The experiments yielded a 94.9% accuracy ($\sigma = 0.07$) for 75 isolated words and 94.1% accuracy ($\sigma = 0.09$) for 20 MSL sentences in a medical context. Given that this approach depends on camera inputs and that even with a limited number of examples, a reasonable generalization is achieved, this architecture could potentially be scalable to other sign languages and provide efficient communication solutions for millions of individuals with hearing impairments.

Hernández-de-la-Luz *et al.* [16] presents an analysis of technologies and an architecture for a prototype of an MSL interpreter, supported by 3D motion capture devices, aimed at laying the groundwork for developing an interpreter that would significantly enhance the quality of life for deaf individuals by facilitating communication with the broader society. The three classification algorithms employed achieved over 95% accuracy in predictions, indicating high acceptance levels for recognizing static signs of the MSL alphabet. The study confirms the effectiveness and strong performance of the leap motion controller and the chosen feature set.

This research addresses a notable gap in the literature: while most studies focus on translating signs that represent full concepts, a practical, accessible solution for real-world use remains underexplored. Building a comprehensive dataset for all MSL signs is inherently challenging, and many existing approaches rely on specialized hardware such as Microsoft Kinect or leap motion controllers. In contrast, this work pursues a more practical and widely accessible alternative, a smartphone-based application that uses only the device’s built-in camera and operating system. This approach prioritizes mobility, simplicity, and broad usability. Furthermore, the study specifically targets fingerspelling as a foundational entry point, aiming to develop educational technology to support MSL learning.

3. BACKGROUND

3.1. Deaf person

Deafness constitutes a profound auditory condition characterized by anatomical or physiological alterations, which disrupts communication based on spoken language. Contemporary understanding frames it not as a binary state but as a spectrum of hearing loss, where the capacity to perceive sounds; from environmental cues to linguistic information, is compromised to varying degrees [17].

Deafness is etiologically categorized as either congenital or acquired. Congenital deafness primarily stems from genetic anomalies that disrupt the development or physiology of the auditory system, including its neural pathways. In contrast, acquired deafness can manifest at any stage of life, from infancy to late adulthood [17], [18].

3.2. Mexican sign language

In Mexico, MSL serves as the primary mode of communication for both deaf and hearing individuals. MSL is a spatially organized language articulated through specific bodily movements. Its articulation is constrained by a three-dimensional signing space, defined by vertical, horizontal, and sagittal (proximal-distal) planes. The vertical plane extends from the waist to the top of the head, and the horizontal plane spans the width of the body at elbow height when the arms are bent. Signs produced outside this delineated space are typically perceived as exaggerated or emphatic [19].

The structure of sign language comprises several key components [20]: the most significant is the manual sign itself. This is complemented by non-manual markers, including gestural and oral movements, gaze, and the rhythm of hand articulation, all of which are essential for expressiveness and meaning. Another prominent component in MSL is dactylology, which involves the recodification of writing through a manual alphabet (see Figure 1), where handshapes represent the letters of the Latin script.

The typology of signs is based on two parameters: the number of hands employed (one or two) and the simultaneity of their movement [19]: this yields four distinct categories: (i) unimanual signs, articulated with a single hand; (ii) asymmetrical bimanual signs, where both hands move simultaneously but unequally; (iii) symmetrical bimanual signs, characterized by both hands performing mirroring movements (either identical or inversely proportional) at the same time; and (iv) compound signs, which consist of a sequence of at least two simpler signs or three configurational elements.

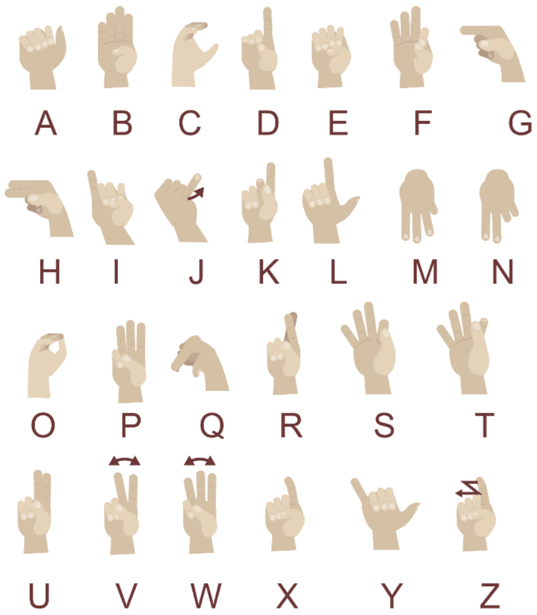

Figure 1. Mexican sign language (dactylology). Source: Image taken from [21]

4. METHOD

This section outlines the methods and procedures employed in this research, beginning with the creation of a sign dataset and followed by the development of a predictive model for sign recognition.

4.1. Dataset

The MSL image dataset was created due to the absence of any existing datasets in public databases. There are limited datasets available online for training and testing [22]. The considered letters were A, B, C, D, E, F, G, H, I, J, K, L, M, N, Ñ, O, P, Q, R, S, T, U, V, W, X, Y, Z-a total of 27 letters. An algorithm was developed to capture images of hands performing each sign. For every sign in the alphabet, 100 images were collected (see Figure 2), resulting in a total dataset of 2,900 images. Examples of the captured sign images can be seen in Figure 2, where Figures 2(a)-(c) represent letters L, S, and R, respectively. These images were then organized into categories corresponding to their respective letters.

(a) (b) (c)

Figure 2. Captured sign images for the dataset; (a) Letter L, (b) Letter S, and (c) Letter R

Next, the images were annotated using the Labelme library [23]. Polygonal annotations were drawn to delineate the region of interest-namely, the hand performing the sign-as shown in Figure 3. These segmentation masks were then exported in JSON format. Following annotation, the dataset was partitioned into training and validation sets. All images have a resolution of 640×640 pixels.

Figure 3. Image segmentation

4.2. Materials

YOLO [24] is an acronym for “You Only Look Once”, is a real-time object detection system that uses deep learning techniques. YOLO enables a computer to identify and locate objects within an image or video in real-time. This research employs YOLO for sign detection.

YOLO applies a single neural network to the entire image. This network divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted based on the predicted probabilities.

The model offers several advantages over classifier-based systems. It analyzes the entire image at once during testing, meaning its predictions consider the global context of the image. Additionally, it performs predictions in a single network evaluation, unlike region-based convolutional neural networks (R-CNN), which require thousands of evaluations for a single image. This makes YOLO extremely fast, being over 1,000 times faster than R-CNN and 100 times faster than fast R-CNN.

YOLO has a wide range of applications, including: (i) Autonomous vehicles: to detect other vehicles, pedestrians, traffic signs, and objects in the environment. (ii) Surveillance: To detect suspicious activities or individuals in specific locations. (iii) Robotics: to allow robots to interact more intelligently with the real world. (iv) Augmented reality: to overlay virtual objects in real-world settings.

The following describes the neural network configuration used in YOLO: (i) Input layer: the images used for training are 640x640 pixels with three RGB channels. (ii) Output layer: the segmentation task generates a segmentation map, where each pixel in the image is classified into a specific category. In this case, 27 letters, one per category. (iii) Intermediate layers: the SiLU (Swish) activation function is used, known for its ability to enhance gradient flow and nonlinear representations. The output layer applies a Sigmoid activation function, as it is designed for binary classification, aligning with the need to predict whether a sign is present in a specific location in the image (a “yes” or “no” decision).

The following describes setup for the training: The model will be trained for 100 full cycles on the defined dataset, meaning the epochs are set to 100. Batch size = 2, meaning two images are processed per training iteration. A pretrained YOLOv8 medium model is used for segmentation as a starting point. The YOLO version used is YOLOv8m (medium) [25], which offers a balance between accuracy and speed. There are smaller versions (e.g., YOLOv8n) and larger versions (e.g., YOLOv8x). The tests were conducted on a home computer with the following specifications: AMD Ryzen 7 3700 with Radeon Vega Mobile Gfx 2.3 GHz, 12 GB RAM, and Windows 10 operating system.

5. EXPERIMENT

5.1. Description

The objective of the experiment was to evaluate the neural network’s accuracy in detecting individual letters of the alphabet. Each letter was presented sequentially to the computer’s camera to measure its specific detection rate. The letters used were A, B, C, D, E, F, G, H, I, J, K, L, M, N, Ñ, O, P, Q, R, S, T, U, V, W, X, Y, Z, totaling 27 letters. Digraphs (combinations of two letters representing a single sound), such as CH, LL, or RR, were not considered [26] since they are already formed by the included letters.

5.2. Results

Figure 4 shows the sign detection algorithm in operation. The image displays the detection of the letter “A” with 60% reliability. Table 1 presents the results of the alphabet letter identification. It displays the letter, whether it was identified, and its detection percentage. As shown, 16 out of 27 letters were successfully identified, resulting in a 59.26% performance rate.

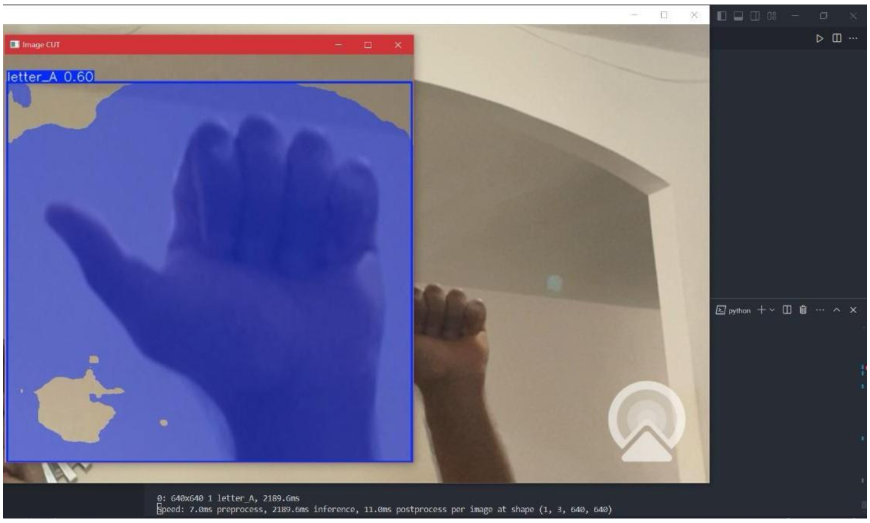

Figure 4. Sign detection algorithm

Table 1. Percentage of the letter identification

Letter	Ident.	%	Letter	Ident.	%	Letter	Ident.	%	Letter	Ident.	%
A	Yes	70	I	Yes	77	P	Yes	69	X	Yes	62
B	Yes	63	J	Yes	59	Q	No	-	Y	No	-
C	No	-	K	No	-	R	Yes	66	Z	No	-
D	Yes	55	L	Yes	78	S	No	-			
E	Yes	88	M	Yes	80	T	Yes	84			
F	Yes	83	N	Yes	89	U	Yes	73			
G	Yes	60	Ñ	No	-	V	No	-			
H	No	-	O	No	-	W	No	-			

The main errors occurred with signs that involve movement, such as: (i) K (up and down movement). (ii) Ñ (a swinging movement of the letter N). (iii) Q (movement from bottom to top). (iv) Z (traced in the air). Other signs also involve movement but were correctly identified: (i) J (starts like “I” and then curves into a “U” shape). (ii) X (resembles pulling a trigger with a backward motion).

The algorithm struggles with similar-looking signs, such as: H and T, S and T, V and U, W and U, Ñ and N, H and G. Signs that were not detected and do not involve movement include C, H, O, S, V, W, Y. When excluding moving signs, both correctly and incorrectly detected, the performance improves to 14/23 = 60.87%. For the identified letters, the average identification percentage was 72.2%, with a standard deviation of 10.51.

5.3. Discussion

The analysis of the results indicates a model accuracy of approximately 60%. This performance level suggests a partial capability for sign detection, revealing a clear opportunity for enhancement. A primary challenge identified is the YOLO architecture’s inherent difficulty with motion-based signs. As time and spatial context are crucial for accurate recognition of dynamic gestures, these signs were frequently misclassified or missed. Notably, the correct detection of letters ‘J’ and ‘K’-which involve movement-appears to be an exception attributable to distinct, static features in their final formation that prevent confusion with other signs.

Furthermore, the model exhibited classification errors between signs with high visual similarity, indicating insufficient feature discrimination in the current configuration. To address these limitations, fine-tuning the neural network’s hyperparameters and architecture is essential. Other studies have encountered similar challenges with detecting moving signs. For instance, omitted moving signs (J and Z) from ASL in their experiments to address this issue [13].

6. CONCLUSION

This research presents a novel dataset of manually formed signs for MSL, with the objective of predicting signs from video input. The initial phase of the project focuses on the detection of alphabet letters. To this end, a predictive model based on neural networks was developed using the YOLO open-source real-time object detection framework.

The creation of this dedicated MSL dataset is essential, as sign languages are country-specific; consequently, datasets from other nations are not directly applicable to the Mexican context. The model achieved a sign detection accuracy of approximately 60%. While this performance is not optimal, the findings establish a foundational benchmark and highlight clear avenues for improvement, including both strengths and limitations of the current approach.

The results revealed successful detection of certain letters, whereas others were missed due to inter-letter visual similarity or the presence of motion within the sign. The latter poses a significant challenge, as the accurate recognition of dynamic signs depends on temporal and spatial features, which complicate video-based object detection. Addressing this limitation is critical for advancing the system.

Despite its current scope being limited to the alphabet, this research holds considerable value. Fingerspelling serves as a fundamental communication tool with deaf individuals, providing a basic yet effective means of interaction for those not proficient in the full lexicon of MSL signs.

Future work will focus on the following directions: (i) conducting extended training and rigorous testing with the dataset to evaluate and refine the model's robustness. (ii) implementing architectural support for motion modeling, as many MSL signs representing full concepts require the interpretation of complex hand trajectories and facial expressions.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [ARN], upon reasonable request.

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