An Inclusive AI-Based Game for LIBRAS Learning Developed Through University Extension

Italo Firmino da Silva[1], João José Sebastião[1], Ruan Pablo da Silva Soares[1], Beatriz Schuelter Tartare[1], Gabriel Feltes dos Santos[1], Maria Eduarda Winkel de Mello Vianna[1], Sheila Filipe Pereira Oliveira[1], Talita Alves Borges Caneda[1], Alison R Panisson[1]

[1]Federal University of Santa Catarina (UFSC) – Brazil
{italo.silva,j.sebastiao,ruan.r.p.s}@grad.ufsc.br,
{beatriz.schuelter,gabriel.feltes}@grad.ufsc.br,
maria.vianna@grad.ufsc.br, sheilapo0410@gmail.com,
{borges.talita,alison.panisson}@ufsc.br

Abstract. *This paper presents IRIS, a university extension project developed within a Computer Engineering program that explores the use of artificial intelligence in the development of educational and inclusive digital games. As part of the project, students design and implement games that apply AI techniques to socially relevant contexts. This paper focuses on one of the project outcomes: an inclusive game inspired by the traditional Hangman game aimed at supporting the learning of Brazilian Sign Language (LIBRAS). The game employs computer vision and artificial intelligence to recognize LIBRAS signs captured by a camera, enabling sign-based interaction instead of text input. The paper describes the main technical aspects of this game and the associated extension activities, highlighting the potential of AI-driven game development in Computer Engineering education and inclusive learning initiatives.*

1. Introduction

University extension is a fundamental dimension of higher education in Brazil and, together with teaching and research, composes an inseparable triad established by the 1988 Brazilian Constitution [Gimenez et al. 2024]. This principle reinforces the idea that academic formation should integrate theoretical learning, knowledge production, and social engagement in a continuous and articulated process. Within this perspective, extension connects the university to society, enabling academic knowledge to be applied and transformed through real-world interactions [Oliveira et al. 2024].

Situated in this context, this paper presents IRIS[1], a university extension project developed within a Computer Engineering program and organized as part of the Artificial Intelligence Academic League[2] of the Federal University of Santa Catarina (UFSC). The project is designed to promote a synergic integration of the three university pillars by engaging students in the conception, development, and dissemination of AI-based interactive systems with social relevance. Classroom knowledge provides the technical foundation, research activities support experimentation and innovation, and extension materializes these efforts through concrete artifacts and collaborative actions with external communities.

[1]The IRIS institutional video is available in `https://youtu.be/FIo9qCIdMeU`
[2]`https://ligaia.ufsc.br/`

IRIS adopts a student-led and collaborative approach, in which participants work in multidisciplinary teams and are encouraged to explore technologies that often go beyond the formal curriculum, such as advanced Artificial Intelligence (AI) techniques, Computer Vision (CV) and Human–Computer Interaction (HAI). This structure fosters autonomy, peer learning, and research-oriented thinking, while grounding technical development in extension demands and social responsibility. The project thus serves simultaneously as a learning environment, a space for applied research, and a channel for social engagement.

This paper focuses on one outcome of the IRIS project: an inclusive digital game inspired by the traditional Hangman game to support the learning of Brazilian Sign Language (LIBRAS). The game employs CV and AI to recognize hand signs captured by a camera, enabling sign-based interaction and reducing reliance on text input. By detailing both the extension context and the main technical aspects of the game, the paper demonstrates how collaborative extension practices can transform AI-based game development into a tool for inclusion, student formation, and societal impact.

2. Background

In this section, we present the main concepts related to this work, establishing the theoretical foundation for the proposed approach. We first introduce AI and CV, which enable the automatic interpretation of visual information and support sign-based interaction. Next, we briefly discuss Brazilian Sign Language (LIBRAS), highlighting its role in inclusive communication and education. Finally, we present the Hangman game as an educational tool, whose effectiveness in vocabulary learning motivates its use as an interactive framework for integrating CV-based LIBRAS recognition.

2.1. Artificial Intelligence and Computer Vision

AI is commonly refereed as a field focused on building computers that improve automatically through experience, representing an intersection between computer science and statistics [Jordan and Mitchell 2015]. Machine Learning (ML), a core part of AI, uses the increasing availability of data to support decision-making in several areas, including health care and education [Jordan and Mitchell 2015].

A major application of these techniques is CV, where Deep Learning (DL) methods have consistently outperformed traditional algorithms [Voulodimos et al. 2018]. DL is especially effective for tasks like object detection and human pose estimation [Voulodimos et al. 2018]. However, these models often rely on billions of parameters, making them difficult to deploy on devices with limited resources, such as mobile phones or web browsers [Gou et al. 2021]. These models require high computational power and large storage space, creating a need for model compression and acceleration [Gou et al. 2021].

To address these challenges, we use a combination of modern tools and optimization strategies to develop the proposed games. We use Next.js to manage the application and MediaPipe [Lugaresi et al. 2019] for real-time hand tracking. MediaPipe is highly effective for this purpose because it accurately extracts hand key points, allowing for stable recognition even in resource-limited environments [Li and Hsieh 2025]. Instead of processing all pixels, the system identifies 21 spatial landmarks, which enables Feature Engineering to calculate geometric relationships, such as finger angles and distances, making the system more robust [Li and Hsieh 2025].

To ensure efficient execution on the client side, we apply Knowledge Distillation. This technique, originally described as a way to transfer knowledge from a large "teacher" model to a smaller "student" one [Hinton et al. 2015], effectively reduces model size while maintaining good accuracy [Gou et al. 2021]. The resulting lightweight model is executed directly in the browser via TensorFlow.js, following *Edge Computing* principles to guarantee low latency and user privacy [Filho et al. 2022]. Finally, MongoDB is used to store statistics data with low memory consumption.

2.2. Brazilian Sign Language (LIBRAS)

Brazilian Sign Language (LIBRAS) is a natural, independent linguistic system that emerges from the cultural experience of the deaf community, possessing its own complex and autonomous grammar [Brito 2010]. Because it is a visual-spatial language rather than an auditory-oral one, CV serves as the essential backbone for AI-driven accessibility. Unlike speech-to-text models, where accuracy is measured by word error rates, LIBRAS recognition depends on the model's capacity to classify high-dimensional spatial data, specifically handshapes, movement, orientation, and even intuitive markers (facial expressions and torso posture).

LIBRAS does not follow the phonetic or syntactic structures of Portuguese; instead, it utilizes a three-dimensional signing space to represent objects, abstract concepts, and psychological phenomena [Brito 2010]. The bridge between LIBRAS and written Brazilian Portuguese is often facilitated through dactylology (the manual alphabet). While not the core of the language, dactylology allows for a lexical exchange, enabling deaf individuals to spell out names or technical terms that lack a specific sign. This bilingual proficiency is vital for accessibility, acting as a "lexical bridge" that allows the community to navigate oral-based environments while maintaining the linguistic integrity of their native sign language.

2.3. Hangman Game

Hangman is a word-guessing game in which players reveal a hidden word by proposing letters, while incorrect guesses result in progressive visual feedback. Beyond entertainment, the game has been widely adopted in educational contexts due to its effectiveness in supporting vocabulary learning, spelling, pronunciation, and learner concentration [Munikasari et al. 2021]. The literature has reported positive outcomes from the use of Hangman as a teaching strategy. [Hidayat et al. 2015] demonstrated that students exposed to Hangman-based activities achieved significant improvements in vocabulary mastery, highlighting the game's effectiveness across different educational levels. Also, it is emphasized that Hangman increases learner motivation, reduces monotony, and promotes both competition and cooperation in the learning process [Munikasari et al. 2021].

Given this evidence, Hangman represents a suitable choice for learning LIBRAS. The game naturally reinforces memorization, visual recognition, and incremental recall, core aspects of sign language acquisition [Morett 2015]. By integrating LIBRAS sign recognition into a game already validated by educational literature, the proposed approach combines pedagogical effectiveness with an engaging and accessible interaction model.

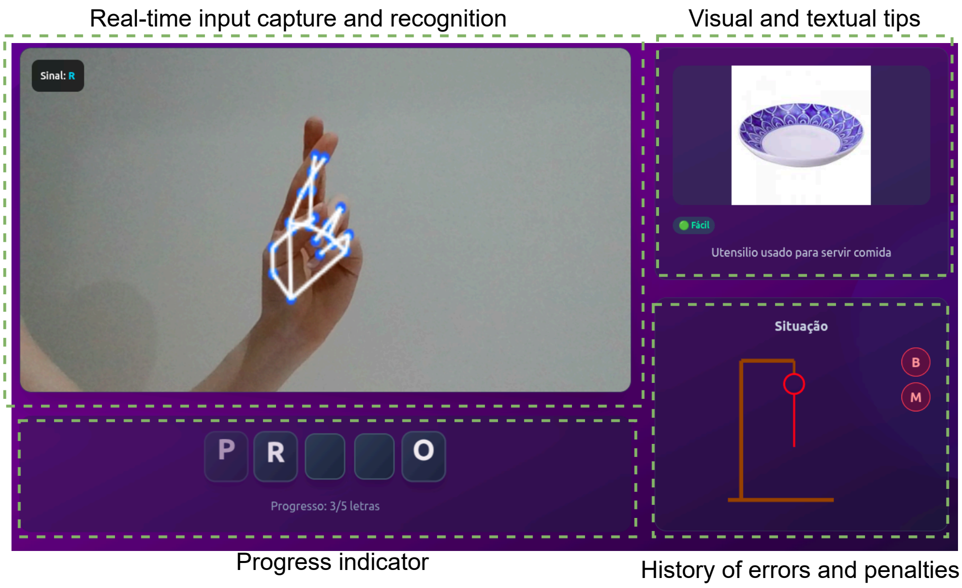


Figure 1. Hangman Using Libras Interface.

3. Related Work

In this section, a literature review was conducted regarding the inclusion of Brazilian Sign Language (LIBRAS) in technology focused on Machine Learning. Initially, technological methods for teaching LIBRAS are discussed, followed by an analysis of gamification based playful strategies. This work integrates these approaches by exploring the use of gamified technological tools for the teaching and learning process of signs.

Manual sign processing has been studied in various technological contexts. In [Alaghband et al. 2023], the authors review methodologies ranging from hardware-based solutions to computer vision systems using Machine Learning algorithms such as Random Forest Classification (RFC). The authors also point out the lack of robust datasets and practical applications, highlighting the need for new tools, such as the one proposed in our study. In line with this need, several recent studies have developed educational support technologies based on AI and computer vision for sign language learning in inclusive educational contexts.

In the context of LIBRAS, in [Rego et al. 2025], the authors proposed a multimodal approach combining positional, kinematic, and spectral data (FFT) for sign recognition, obtaining 92% accuracy and F1-score on the MINDS-Libras dataset. Similarly, in [Ruiz et al. 2023], the authors evaluated manual and non-manual descriptors such as gaze and head orientation using BiLSTM and Transformer models, reaching up to 94.33% accuracy on the LIBRAS Corpus. The effectiveness of compact representations is also evident in other languages; for instance, in [Soukaina et al. 2025], the authors achieved 98.5% accuracy in American Sign Language (ASL) by using handcrafted geometric features (medians and heights) with a Random Forest classifier to prioritize low computational complexity. Additionally, in [Papadimitriou et al. 2025], the authors developed the SL-ReDu platform for Greek Sign Language (GSL), utilizing MediaPipe Holistic and architectures such as ResNet2+1D and BiLSTM to achieve 99.44% accuracy in isolated signs and 75.22% in continuous fingerspelling.

Beyond approaches focused on sign recognition technologies and educational tools, several studies have explored gamification as a strategy for LIBRAS teaching and learning, seeking to increase the engagement, motivation, and active participation of deaf and hearing students. Among the analyzed works, in [Lee et al. 2021], the authors developed a digital ASL recognition prototype integrating Leap Motion, LSTM, and k-NN in a "Whack-a-Mole" style educational game, allowing students to practice the 26 letters of the alphabet in real-time with an average accuracy of 99.44%, using a proprietary dataset of 2,600 samples collected from real participants. Additionally, in [Medronha et al. 2024], the authors proposed LERMO, a web game for LIBRAS finger-spelling training that uses MediaPipe to extract 21 hand landmarks and a Multilayer Perceptron (MLP) classifier for sign recognition, reaching 89.88% accuracy on a proprietary dataset with real-time execution and multi-frame analysis to reduce noise.

Moreover, a branch based on Applied Linguistics investigates gamification as a learning mediator: in [Santana et al. 2022], the authors conclude that playful experiences favor engagement in LIBRAS learning; in [Silva et al. 2023], the authors demonstrate academic performance gains via visual pedagogy; and in [Brito et al. 2024], the authors emphasize deaf culture, warning that technological inequality hinders full digital inclusion.

Related works address computer vision–based techniques for fingerspelling recognition as well as gamification strategies to support sign language learning. However, many existing solutions depend on computationally complex models, specialized sensors, or architectures that limit their applicability in lightweight, web-based educational environments. In contrast, the present work focuses on the design of an educational game for learning LIBRAS fingerspelling that integrates computer vision and gamification with an emphasis on efficiency, accessibility, and practical deployment. By adopting publicly available datasets and prioritizing compact models suitable for web execution, this approach seeks to bridge the gap between technically effective sign recognition methods and their use in inclusive, scalable educational applications.

4. Iris Project

The Interactive Sign Recognition Interface (IRIS) is a university outreach project developed within the scope of an Artificial Intelligence Academic League in the Computer Engineering program. The project is aligned with the National Guidelines for Extension in Brazilian Higher Education [CNE 2018], which define extension as an interdisciplinary, scientific, and technological process that promotes a transformative interaction between the university and society.

By operating within an academic league, the project fosters a student-led environment that encourages autonomy and social responsibility. This structure allows participants to engage in Service Learning, a format in which students collaborate with community partners while developing professional, technical, and social competencies [Schultes et al. 2025]. Although we present here a sub-project focused on LIBRAS recognition, the project's framework is conceived for broader interdisciplinary applications, including future developments in biomechanics and motor rehabilitation in collaboration with healthcare-related programs.

Within this context, IRIS establishes a strong synergy between teaching, research, and extension. Students apply knowledge acquired in the classroom to real-world problems while simultaneously engaging in peer learning, teaching other group members who may not yet be familiar with the techniques required for each project. In many cases, the knowledge demanded by the projects, such as advanced CV methods, human-computer interaction design, or inclusive game mechanics, is not formally covered in the Computer Engineering curriculum. This gap motivates students to actively seek new knowledge, fostering self-directed learning, research skills, and technical autonomy.

The extensionist nature of IRIS is ultimately materialized through the development of interactive games and systems. These products often support transversal research initiatives while also serving as concrete artifacts for extension activities, such as promoting the Computer Engineering program, disseminating emerging technologies, encouraging the learning of sign languages and social inclusion (as exemplified in this paper), motivating physical activity, and raising public awareness about the social impact of AI.

5. The Game - Hangman using LIBRAS

The development of "Hangman using LIBRAS" is a practical application of the IRIS Project's goals. More than a technical demonstration, the game was conceived as a pedagogical instrument to reduce communication barriers by applying academic knowledge to community needs [Schultes et al. 2025].

As illustrated in the interface in Figure 1, the game was designed not only as an entertaining activity but also as a demonstrative platform for the application of sophisticated sign recognition technologies. The real-time input capture and recognition module highlights the system's ability to process hand signs interactively, serving as the technological core of the game. At the same time, pedagogical and inclusion-oriented design choices are reflected in the presence of visual and textual tips, which support learning and accessibility, as well as in the progress indicator, which provides continuous feedback to the player. Finally, the ludic context of the hangman game is reinforced through the history of errors and penalties, linking gameplay mechanics with user awareness and engagement in an intuitive and educational manner. This section describes the project's design philosophy and technical architecture.

5.1. Design Rationale and Social Responsibility

The design choices in the game were driven by the need for an accessible and secure tool suitable for diverse social contexts. The involvement of a multidisciplinary and diverse team, including members of the Deaf community, neurodivergent participants, and LIBRAS interpreters, ensured that the user experience and pedagogical strategies were validated throughout the development.

A central concern was ensuring that the technology could be deployed in environments with limited resources, such as public schools, while strictly adhering to data protection regulations such as the Brazilian LGPD [Brasil 2018]. Beyond security and compliance, the system was designed to be easily accessed and available to everyone, a requirement that directly motivated the adoption of a web-based application architecture. This social responsibility also guided the use of Edge Computing, ensuring that sensitive visual data are processed locally, with no transmission or external storage, thereby enabling secure, low-cost, and widely accessible deployment.

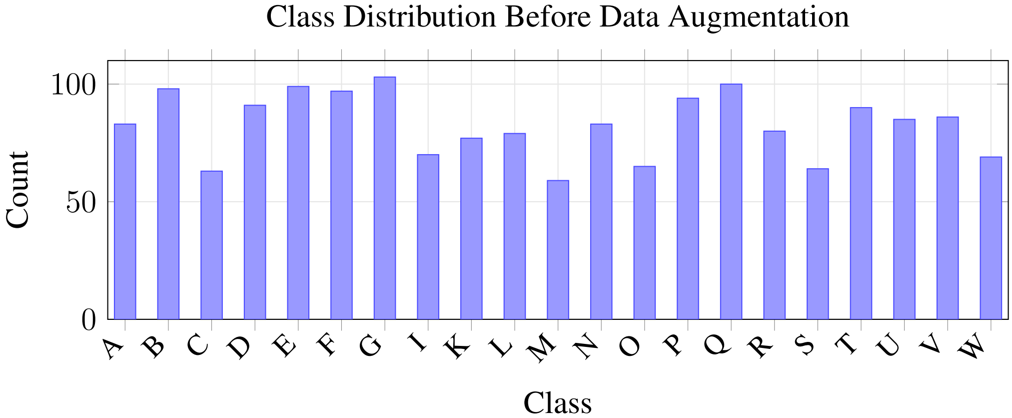


Figure 2. Distribution of samples per class before data augmentation.

5.2. LIBRAS Dataset

The proposed approach relies on an open dataset of static LIBRAS hand signs, hosted on the Roboflow platform [LIBRAS-Roboflow 2025]. The dataset contains 1735 images of hands representing different letters of the Brazilian Sign Language alphabet. The distribution of classes can be seen in the Figure 2.

A relevant characteristic of this dataset is its high variability. Images were captured under diverse real-world conditions, including different camera angles, lighting variations, hand-to-camera distances, partial occlusions, and heterogeneous backgrounds as shown in Figure 3. Although such variability introduces noise, it plays a strategic role in improving model robustness.

By training on this heterogeneous data, the model learns to prioritize the intrinsic geometric features of each sign rather than relying on environmental cues. This results in better generalization and makes the approach suitable for practical deployment in uncontrolled, web-based, and public interaction scenarios.

Figure 3. Sign for letter 'E' under different light intensity.

5.3. The Computer Vision Approach

The proposed system adopts a two-phase architecture designed to reconcile recognition accuracy with the strict constraints of web-based interactive applications. The approach separates intelligence creation from deployment by combining an offline training pipeline, responsible for building and optimizing the recognition model, with an online inference architecture, which executes entirely on the user's device. This separation enables efficient development while ensuring low latency, privacy preservation, and platform independence.

5.3.1. Offline Training Pipeline

The offline phase is executed in a Python-based environment and is responsible for transforming raw visual data into a compact and accurate sign recognition model. This pipeline is composed of a sequence of orchestrated steps. First, a data curation and augmentation process is applied to the LIBRAS static sign dataset discussed in Section 5.2. The dataset is balanced to ensure an equal number of samples per letter, reducing class bias. Synthetic samples are then generated through geometric transformations such as rotation and scaling, increasing data diversity. After data augmentation, each class had 150 samples.

Next, the feature engineering stage constructs a hybrid input vector of 84 features to represent hand posture. This vector is composed of the 63 raw spatial components (x, y, z coordinates) from the 21 detected landmarks [Lugaresi et al. 2019], augmented by 21 engineered geometric descriptors. These additional descriptors, comprising relative distances and joint angles, provide the model with essential scale and rotation invariance, as illustrated in Figure 5. This set includes distances from landmarks to the wrist (Figure 5a), tip inter-finger distances (Figure 5b), and joint angles (Figure 5c). Additionally, global hand metrics such as hand dimensions (height x width x depth) (Figure 5d) and inter-MCP distances (Figure 5e) are incorporate. By combining direct spatial data with these derived geometric relationships, the Random Forest model captures both the global positioning and the subtle finger configurations, achieving an accuracy of 99.21%.

To enable efficient deployment, the knowledge of the model is transferred to a lightweight neural network using a knowledge distillation strategy [Hinton et al. 2015]. Instead of learning directly from hard labels, the light model is trained to mimic the probabilistic outputs of the main model, effectively compressing the learned decision boundaries into a much smaller model with minimal performance loss.

Finally, the lightweight model and the associated normalization parameters are exported and converted to the TensorFlow.js format, making them suitable for execution directly within a web browser, when the game application runs. Figure 4 illustrates the training pipeline.

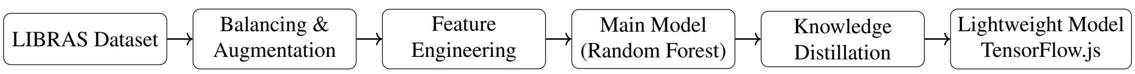
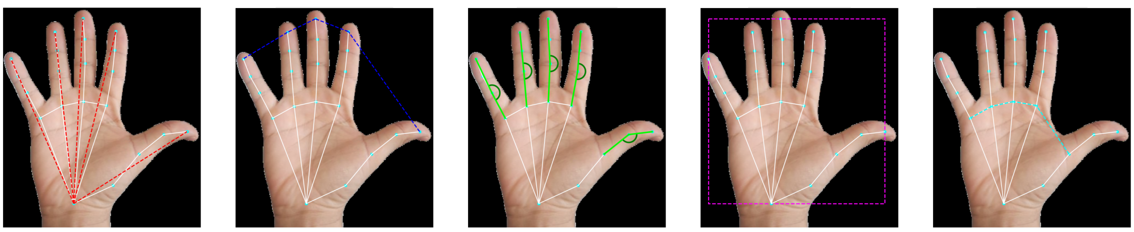


Figure 4. Pipeline used to train the lightweight sign recognition model.



(a) (b) (c) (d) (e)

Figure 5. Geometric Feature Engineering.

5.3.2. Online Inference Architecture

Using the lightweight model, the online inference phase is executed entirely on the client side, ensuring low latency and eliminating the need to transmit visual data to external servers. This design choice enhances responsiveness and preserves user privacy.

During gameplay, the technical process begins with real-time video capture from the user's webcam. The MediaPipe library [Lugaresi et al. 2019] runs locally in the browser and detects the user's hand, extracting the same 21 landmarks used during training. These landmarks are then processed by a JavaScript-based feature engineering module, which reconstructs the identical set of 84 geometric features defined in the offline phase.

Before inference, the features are normalized using the parameters exported during training. The normalized feature vector is then passed to the lightweight model running in TensorFlow.js, which predicts the corresponding LIBRAS letter in real time. The predicted letter is immediately forwarded to the Hangman game logic, updating the interface and providing instant feedback to the user.

This architecture allows seamless integration between CV, AI, and game mechanics, resulting in an interactive and responsive learning experience fully executed within the web browser. Figure 6 illustrates the inference pipeline executed during gameplay.

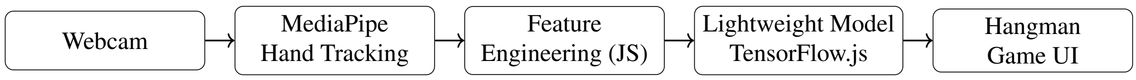


Figure 6. Client-side inference architecture executed entirely in the web browser.

5.4. Empirical Evaluation

The proposed architecture was empirically evaluated with the objective of assessing both its recognition performance and its suitability for deployment in web-based interactive applications. The evaluation focused on classification accuracy and model footprint, which are critical factors for real-time sign recognition systems running entirely in the browser. The final approach achieved an accuracy of 98.57% on the test dataset, demonstrating that the knowledge distillation process preserved a high level of recognition performance despite the aggressive model compression. This result indicates that the proposed architecture is capable of recognizing static hand signs, even when executed under the computational constraints of client-side environments.

In terms of efficiency, the resulting model presents a significantly reduced size. The complete payload required for web deployment, including the neural network weights and normalization parameters, amounts to approximately 44 KB, representing a reduction of nearly 99% compared to the original model, which occupied around 13 MB. This drastic size reduction directly impacts loading time, bandwidth consumption, and memory usage, making the solution particularly suitable for deployment on low-end devices and in scenarios with limited network connectivity. Beyond raw performance metrics, these results highlight the practical feasibility of executing complex sign recognition models entirely within the web browser. By avoiding server-side inference, the approach reduces latency and enhances user privacy, as no visual data needs to be transmitted to external services. Such characteristics are especially relevant for accessibility-oriented applications, where responsiveness and data protection are essential.

Although the current evaluation focuses on static LIBRAS signs, it successfully validates the proposed architecture and establishes a robust foundation for future extensions. In particular, the achieved results suggest that the same design principles can be extended to more challenging scenarios, such as the recognition of dynamic signs and continuous sign sequences, without compromising real-time execution or usability.

5.5. Subjective Evaluation

The proposed Hangman usign LIBRAS game was publicly exhibited during the university's *Doors Open* event[3], an outreach initiative in which prospective students and visitors are invited to explore academic programs and projects being developed by university academics. The game was installed in shared hallway spaces, allowing spontaneous interaction by attendees with diverse backgrounds, ages, and levels of familiarity with both CV systems and LIBRAS.

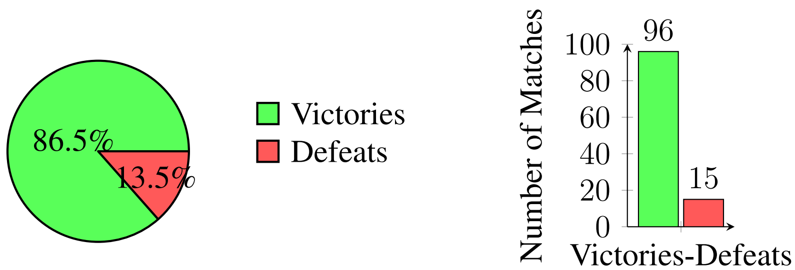


Figure 7. Success rate and result distribution of players.

From a subjective perspective, the overall reception of the game was notably positive. Visitors demonstrated curiosity and engagement, frequently approaching the installation without prior explanation and quickly understanding the gameplay mechanics. This ease of adoption suggests that the interface and interaction model were intuitive, even for users without previous exposure to sign-based systems. Figure 7 summarizes the overall outcome of the matches played during the event. A success rate of 86.5% was observed, indicating that most participants were able to complete the game successfully. Informal observations during the exhibition revealed that successful outcomes often generated visible satisfaction, encouragement among peers, and repeated attempts, reinforcing the game's playful and motivational character. Also, the relatively low defeat rate (13.5%) did not lead to frustration; instead, unsuccessful attempts were commonly perceived as part of the challenge, frequently followed by immediate retries.

In addition to overall performance, Figure 8 provides insight into the subjective difficulty perceived by players when producing specific LIBRAS signs. Certain letters, such as F, G, and N, concentrated a higher number of incorrect recognitions. During the exhibition, these letters were often associated with hesitation, repeated signs, or requests for clarification from nearby monitors. This behavior suggests that errors were not solely due to system limitations, but also to variability in how users executed signs, particularly under informal and non-controlled conditions. Figure 9 shows the number of errors per match, indicating that players committed few errors during gameplay.

[3] `https://portasabertas.ara.ufsc.br/`

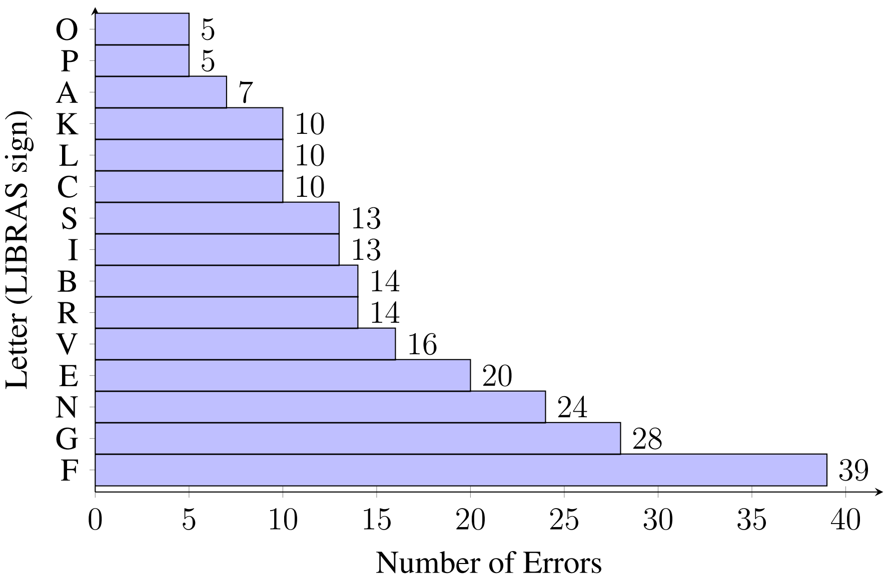


Figure 8. Frequency of incorrect letter during gameplay.

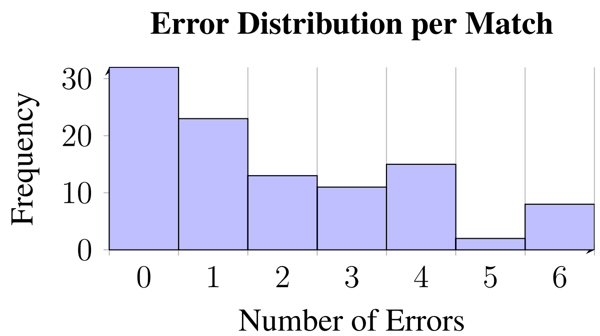


Figure 9. Distribution of errors per match.

Importantly, many participants verbally expressed interest in the educational and inclusive potential of the game, especially its use as a playful introduction to LIBRAS and assistive technologies. The combination of CV, AI, and a familiar game metaphor facilitated communication with visitors, helping demystify complex technical concepts and fostering discussion about accessibility, innovation, and technology.

Overall, the subjective evaluation conducted during the Doors Open event indicates that the proposed system is not only technically functional but also engaging, accessible, and well-suited for public-facing and educational contexts. The positive reception, high success rate, and constructive user behavior observed during errors reinforce the potential of vision-based games as effective tools for outreach, learning, and inclusion.

6. Conclusion

This paper presented IRIS, a university extension project that integrates teaching, research, and extension through the collaborative development of AI-based educational and inclusive digital games within a Computer Engineering program. Focusing on the Hangman using LIBRAS game, we demonstrated how CV and AI can be translated into a socially relevant artifact that supports LIBRAS learning while remaining accessible, privacy-preserving, and suitable for deployment in real-world contexts.

The “Hangman using LIBRAS” game is publicly available at the link `https://forca-com-libras.vercel.app/`.

From a technical perspective, the proposed architecture achieved high recognition accuracy with a lightweight, browser-executable model, validating the feasibility of edge-based sign recognition for inclusive applications. From an extension standpoint, the project fostered student autonomy, peer learning, and engagement with diverse communities, reinforcing the role of extension as a space for multidimensional student formation and social impact. The positive reception observed during public exhibition further highlights the potential of game-based, AI-driven approaches as effective tools for outreach, accessibility, and dialogue between the university and society.

Overall, IRIS illustrates how collaborative extension initiatives can bridge advanced computing research and education with concrete social demands. As future work, the project aims to expand toward dynamic LIBRAS recognition, broader datasets, and deeper collaboration with educational and healthcare partners.

References

Alaghband, M., Maghroor, H. R., and Garibay, I. (2023). A survey on sign language literature. *Machine Learning with Applications*, 14:100504.

Brasil (2018). Lei geral de proteção de dados pessoais (lgpd) – lei nº 13.709. Brazilian General Data Protection Law.

Brito, C. C. d. et al. (2024). Gamificação: uso de estratégias de ensino/aprendizagem na educação de pessoas surdas.

Brito, L. F. (2010). *Por uma gramática de línguas de sinais*. TB - Edições Tempo Brasileiro, Rio de Janeiro, 2. ed. edition. Originalmente publicado em 1995.

CNE (2018). *Resolução Nº 7, de 18 de dezembro de 2018: Estabelece as Diretrizes para a Extensão na Educação Superior Brasileira*. Diário Oficial da União, Brasília, 19 de dezembro de 2018, Seção 1, pp. 49-50.

Filho, R. R., Bittencourt, L. F., Porter, B., and Costa, F. M. (2022). Exploiting the potential of the edge-cloud continuum with self-distributing systems. In *2022 IEEE/ACM 15th International Conference on Utility and Cloud Computing (UCC)*, pages 255–260.

Gimenez, A. M. N., de Oliveira Gavira, M., and Bonacelli, M. B. M. (2024). The three fundamental university missions: Brazilian challenges. *International Higher Education*, (120).

Gou, J. et al. (2021). Knowledge distillation: A survey. *International Journal of Computer Vision*, 129:1789–1819.

Hidayat, E. W. et al. (2015). Increasing vocabulary mastery of the seventh grade students through hangman game. *Unpublished Thesis. Palu: Universitas Tadulako*.

Hinton, G., Vinyals, O., and Dean, J. (2015). Distilling the knowledge in a neural network. *arXiv preprint arXiv:1503.02531*. Accessed: 2026-02-03.

Jordan, M. I. and Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245):255–260.

Lee, C. K., Ng, K. K., Chen, C.-H., Lau, H. C., Chung, S. Y., and Tsoi, T. (2021). American sign language recognition and training method with recurrent neural network. *Expert Systems with Applications*, 167:114403.

Li, H.-H. and Hsieh, C.-C. (2025). Dynamic hand gesture recognition using mediapipe and transformer. *Engineering Proceedings*, 108(1):22.

LIBRAS-Roboflow (2025). Alfabeto em libras. `https://universe.roboflow.com/libras-gglhu/alfabeto-em-libras-qrvnw-te3gf`. Acessado em 10 de setembro de 2025. Licença: CC BY 4.0. Alfabeto em LIBRAS com as letras que não apresentam movimento.

Lugaresi, C., Tang, J., Nash, H., McClanahan, C., Uboweja, E., Hays, M., Zhang, F., Chang, C.-L., Yong, M. G., Lee, J., Chang, W.-T., Hua, W., Georg, M., and Grundmann, M. (2019). Mediapipe: A framework for perceiving and processing reality. *arXiv preprint arXiv:1906.08172*.

Medronha, A., Lima, L., Claudio, J., Kupssinskü, L., and Barros, R. C. (2024). Lermo: A novel web game for ai-enhanced sign language recognition. *The Thirty-Eighth AAAI Conference on Artificial Intelligence (AAAI-24)*, 38:23352–23359.

Morett, L. M. (2015). Lending a hand to signed language acquisition: Enactment and iconicity enhance sign recall in hearing adult american sign language learners. *Journal of Cognitive Psychology*, 27(3):251–276.

Munikasari, M., Sudarsono, S., and Riyanti, D. (2021). The effectiveness of using hangman game to strengthen young learners'vocabulary. *Journal of English Education Program*, 2(1).

Oliveira, D. d. S., Bernet, R., and Hoyos, D. d. M. (2024). The transformative integration of university extension and education in communities. *Seven Editora*, 576:82.

Papadimitriou, K., Potamianos, G., Sapountzaki, G., Goulas, T., Efthimiou, E., Fotinea, S.-E., and Maragos, P. (2025). Greek sign language recognition for an education platform. *Universal Access in the Information Society*, 24(1):51–68.

Rego, R. C., de Morais, L. M., and Almeida, W. M. (2025). Brazilian sign language recognition using deep learning based on fast fourier transform and kinematic features. *IEEE Access*, 13:202875–202892.

Ruiz, D. S., Olvera-López, J. A., and Olmos-Pineda, I. (2023). Word level sign language recognition via handcrafted features. *IEEE Latin America Transactions*, 21(7):839–848.

Santana, D. J., Batista, D. M., et al. (2022). A gamificação no processo de ensino-aprendizagem de libras com l1: vivências no campo de estágio.

Schultes, M.-T., Graf, D., Holzer, J., Schober, B., and Spiel, C. (2025). Implementation and evaluation of service learning at higher education institutions. *Evaluation and Program Planning*, 112:102622.

Silva, L. G. d. et al. (2023). Gamificação e o impacto no ensino-aprendizagem de libras para surdos e ouvintes.

Soukaina, C. M., Mohammed, M., and Mohamed, R. (2025). Geometric feature-based machine learning for efficient hand sign gesture recognition. *Statistics, Optimization & Information Computing*, 13(5):2027–2043.

Voulodimos, A. et al. (2018). Deep learning for computer vision: A brief review. *Computational Intelligence and Neuroscience*, 2018.