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Comparative Evaluation and Utilization of Convolutional Neural Network Architectures for Irish Sign Language Recognition

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Abstract. Irish Sign Language (ISL) stands as a preferred mode of communication used by the deaf and hard-of-hearing community in Ireland. With its unique grammar, syntax, and lexicon, ISL plays a pivotal role in facilitating communication for thousands of individuals, reflecting centuries of cultural heritage and linguistic development. An estimated 5,000 Deaf individuals utilize ISL, with an additional 40,000 hearing individuals, spanning from regular to occasional users, also engaging with Irish Sign Language. Despite its cultural and linguistic importance, ISL faces numerous challenges in terms of technical accessibility. The exclusion of sign languages from modern language technologies places the deaf or hard-of-hearing individuals at a disadvantage, exacerbating the barrier to human-to-human communication and further marginalizing an already under-resourced linguistic subset. This necessitates innovative approaches and technologies to enhance its utilization and promote inclusivity. This research is concerned with evaluating the performance of various deep neural network architectures in the recognition of sign language by utilizing and evaluating state-of-the-art architectures for the recognition of sign language, in particular Irish Sign Language. This research is part of research progress towards the development of an automatic computational annotation system for Irish Sign Language. Notably, the Densenet architecture performed better than other architectures in ISL alphabet recognition with an average accuracy of 99\%. Our findings illustrate the potential of sophisticated deep neural networks to overcome constraints relating to the scarcity of ISL-specific data. This contribution provides the potential to further develop natural language processing tools and technologies for Irish Sign Language, which may alleviate the lack of technical communicative accessibility and inclusion for the deaf and hard-of-hearing community in Ireland.

Keywords: Irish Sign Language, Deep Neural Network Architectures, Sign Language Recognition

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1 Introduction

Sign Languages (SLs), conveyed through visual gestures within a three-dimensional signing space and lacking a written form, constitute the primary means of communication for many deaf and hard-of-hearing communities in their everyday interactions. The tendency of current natural language processing and machine translation technologies to disregard sign languages further complicates the communication hurdles experienced by approximately 72 million deaf individuals worldwide (Murtagh, 2020; Murtagh et al., 2022). Irish Sign Language (ISL), like all sign languages, is a visual gestural language without any aural or written form, serving as the indigenous language of the Irish Deaf Community and the preferred means of communication for deaf and hard-of-hearing individuals in Ireland (Irish Sign Language). With its visual and spatial characteristics, ISL possesses a distinct grammar. In recent years, advancements in artificial intelligence technologies have presented opportunities to address communication barriers faced by sign language users, within the domain of sign language processing (Scientific Publications, Project Easier; SignON Project - Sign Language Translation Mobile Application). However, achieving precise recognition solely with a standard camera input, without the support of sensors or multiple cameras, remains a significant challenge. The development of Human-Computer Interaction is closely tied to progress in computer vision, with recognition emerging as an active area of exploration. The oversight of incorporating sign languages into modern technologies has hindered the development of accessible information and services for the ISL community. Additionally, the scarcity of comprehensive datasets required for training and evaluating AI models poses further challenges to ISL computational processing. This research aims to analyze and compare the effectiveness of advanced neural network frameworks in identifying and classifying ISL hand gestures. The research work in progress seeks to provide a comparative assessment of neural network architectures and advance our understanding of ISL processing using AI. Ultimately, these efforts are a work in progress, towards the development of a computational system that will automatically annotate sign language data, which has the potential to enhance communication accessibility for the ISL community.

The primary contribution of this research is to offer a comprehensive investigation of the various deep neural network frameworks used to recognize Irish Sign Language. The structure of the paper is outlined as follows: Section 2 provides an overview of pertinent research in sign language recognition. Section 3 presents the proposed methodology, encompassing the description of the dataset, techniques for data augmentation, and the architectures proposed. Section 4 elaborates on the experimental findings, and Sections 5-6 conclude with discussions and conclusions, respectively.

2 Related Work

In recent times, deep learning approaches have significantly outperformed traditional machine learning techniques across various fields, notably demonstrating superior capabilities in computer vision and natural language processing. Prominent deep learning architectures applied to sign language processing in computer vision include Convolutional Neural Networks (CNNs), Deep Belief Networks (DBNs), Autoencoders (AEs), Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Recursive Neural Network (RNN) variations such as Long Short-Term Memory (LSTM) units and Gated Recurrent Units (GRUs). In this section, we look at some advancements in sign language recognition.

Fowley et al. (Fowley & Ventresque, 2022) address the challenge of sparse training datasets in Sign Language Recognition (SLR) by employing synthetic data generated via a Blender-based framework to augment their training dataset. They used a pre-trained convolutional neural network fine-tuned on these synthetic images, achieving a notable increase in recognition accuracy. Specifically, they tested the model using real recordings from the ISL-HS corpus (Oliveira et al., 2017), a collection of Irish Sign Language fingerspelling signs. This approach resulted in an accuracy of 71% using skeletal wireframe images for training, a significant improvement compared to the state-of-the-art models which previously achieved up to 62% accuracy with natural datasets. This study exemplifies the potential of synthetic data in enhancing the performance and robustness of computer vision models in SLR applications. De Coster et al. (De Coster et al., 2021) presents a novel approach to Isolated Sign Recognition using a Video Transformer Network (VTN) enhanced by pose flow and self-attention mechanisms. Their research focuses on the AUTSL dataset (DATASETS – Computer Vision and Machine Learning Laboratory), comprising 36,302 samples across 226 sign categories, captured purely in RGB, to address the challenges posed by limited labeled data. By incorporating per-frame human pose key points extracted via OpenPose and hand crops to better capture hand shapes, the authors significantly improve the recognition accuracy. The traditional VTN achieves 82% accuracy, but by pre-extracting hand shapes and adding body pose information, the accuracy is boosted to 92% on the test set. This improvement highlights the efficacy of their multi-modal input strategy in enhancing the VTN's performance for isolated sign recognition. Barbhuiya et al. (Barbhuiya et al., 2021) employs convolutional neural networks (CNNs) for feature extraction and classification. Their research, guided by the utilization of pre-trained CNN models like "AlexNet" and "VGG-16," unveils a tailored architecture adept at discerning discriminative features from a rich tapestry of sign language images. Through rigorous quantitative assessments, they unveil a remarkable achievement: an accuracy rate soaring to 98% in sign language classification. These findings underscore not only the efficacy of CNN-based methodologies but also their potential for real-world applications within sign language recognition systems. Parallel to this exploration, Wadhawan et al. (Wadhawan & Kumar, 2020) delve into the robust modeling of static signs within the context of sign language recognition. Armed with a dataset comprising 35,000 sign images representing 100 static signs, their study navigates through an intricate web of CNN models, each an avenue towards enhanced accuracy. Their findings reveal a notable training accuracy of 99%, a testament to the meticulous refinement of their proposed system and its superiority over previous methodologies. Sevli et al. (Sevli & Kemaloğlu, 2020) explore the classification of Turkish sign language digits, weaving a narrative of meticulous experimentation and optimization. Their study, anchored by a meticulously developed CNN model, traverses through various optimization techniques, ultimately unveiling the Adam optimizer as the harbinger of success. With training and testing accuracy reaching 98%, respectively, their findings redefine the landscape of sign language digit classification. Meanwhile, Sharma et al. (Sharma & Singh, 2021) embarks on a quest for innovation, presenting a deep learning-based CNN model tailored specifically for gesture-based sign language recognition. Through meticulous comparisons with established architectures, their model emerges triumphant, boasting outstanding accuracy rates of 98% on both Indian and American Sign Language datasets. These findings herald a new era in the field, where diverse gestures are classified with unprecedented precision and efficiency. Oliveira et al. (Oliveira et al., n.d.) capture the essence of Irish Sign Language (ISL) through a rich collection of videos. These videos serve as the foundation of their exploration into Irish Sign Language recognition, revealing a remarkable recognition accuracy of 95% through the principal component analysis. Their findings offer profound insights into the intricacies of sign language recognition, illuminating pathways toward enhanced communication accessibility and inclusion.

Despite the success of deep learning architectures in surpassing traditional methods for sign language recognition, there is a notable absence of in-depth studies directly comparing algorithms specifically for Irish Sign Language (ISL). While extensive research has been conducted and continues to progress within the realm of sign languages such as American Sign Language (ASL), British Sign Language (BSL), Indian Sign Language (ISL), and others, the focus on Irish Sign Language (ISL) remains limited. Consequently, the aim of this research is to offer a comprehensive comparison of state-of-the-art deep learning architectures for Irish sign language recognition, addressing this gap in the literature. The evaluation highlights each model's performance with bespoke hyperparameters, highlighting their respective capabilities and limits, and assisting in determining the best framework for sign language recognition. Moreover, we integrate dynamic image analysis alongside static image recognition for Irish Sign Language. By incorporating dynamic gestures, this study expands the scope of sign language recognition beyond static handshapes, thus capturing a more comprehensive range of linguistic expressions.

3 Proposed Methodology

In this section, the architectures employed for sign language recognition, along with pertinent details pertaining to the dataset are elucidated.

3.1 Dataset

In this study, we utilized Marlon Oliveira's et al. Irish Sign Language hand-shape dataset (ISL-HS) (Oliveira et al., 2017), which features authentic hand-shape images providing a valuable starting point for our research. The ISL alphabet comprises 23 static gestures, corresponding to characters from the English alphabet alongside 3 dynamic gestures (J, X, and Z). Following the documentation provided with the original dataset, the authors recorded brief videos. Six individuals (three males and three females) were tasked with performing finger spelling of the ISL alphabet, with each shape captured thrice. The execution of each of the 23 static gestures involved transitioning the arm from a vertical to a horizontal position, aimed at incorporating rotation as a variation to train classifiers for robust sign rotation angle recognition. However, for the dynamic gestures, no arm rotation was involved; only the motion of the gesture itself was captured. Subsequently, the videos were converted into frames, which were then converted to grayscale and had the background removed using a pixel value threshold, resulting in frames containing only the arm and hand. The videos were recorded at 30 frames per second (fps) and a resolution of 640x480 pixels, yielding a total of 468 videos. From these videos, a total of 52,688 frames were extracted for static shapes and 5,426 frames for dynamic gestures, resulting in a total of 58,114 frames. For our study, we utilized both static and dynamic shape images. F1 displays sample images extracted from the Irish Sign Language dataset, while Figure 2 illustrates the distribution of files among the different alphabets. Additionally, Table 1 provides counts for each alphabet, further enhancing the comprehensiveness of the dataset analysis.

Table 1. Distribution of Alphabets among each Persons

A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**
2107	2325	2278	2347	2442	2231	2373	2349	2273
J	**K**	**L**	**M**	**N**	**O**	**P**	**Q**	**R**
2055	2203	2273	2168	2051	2267	2358	2426	2249
S	**T**	**U**	**V**	**W**	**X**	**Y**	**Z**	
2246	2422	2340	2312	2417	1443	2231	1928	

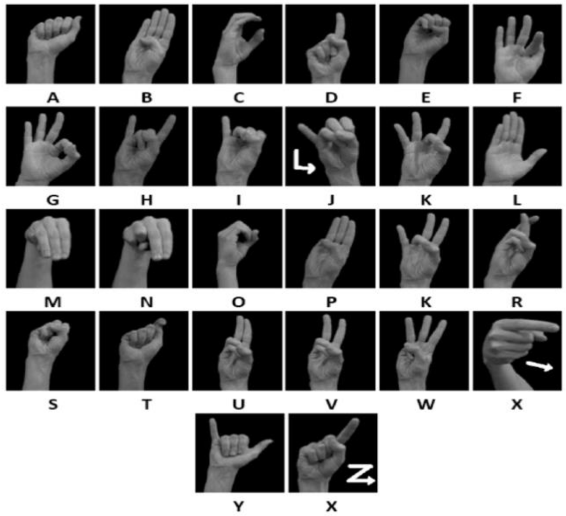

Fig. 1. Sample Images from Irish Sign Language Dataset

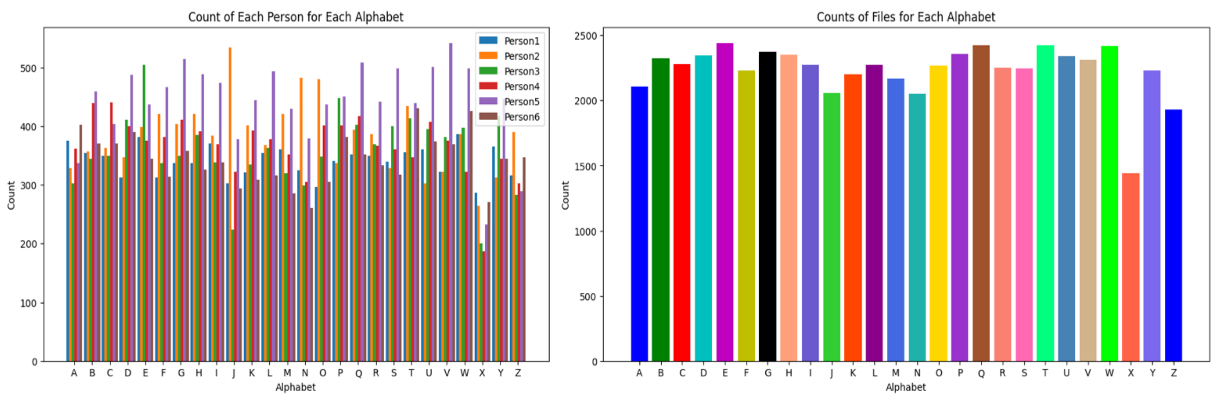

Fig. 2. Graphical Representation Depicting the Distribution of Files Among Different Alphabets

3.2 Data Augmentation

In our data preparation approach, we implemented image rescaling as the sole data augmentation technique, using the ImageDataGenerator class in Keras. The data augmentation function was used to configure separate generators for the training, validation, and testing datasets, focusing primarily on the essential step of pixel value normalization through rescaling. This method ensures the dataset is appropriately conditioned for efficient model training. Key parameters were meticulously chosen to optimize the data processing workflow. Images are resized to the uniform dimensions of 160x120 pixels, suitable for the model's input requirements. For training and validation purposes, the batch size is set at 32, balancing computational efficiency with the model's learning capabilities. Additionally, the class mode is configured as 'categorical', facilitating the handling of labels in a one-hot encoded format for multi-class classification tasks. Distinctively, for the testing dataset, the batch size is set to 1. This configuration allows for the sequential processing of images, ensuring there is no shuffling and thus preserving the original order of the data for accurate evaluation. This careful attention to detail in setting up the testing dataset underscores the precision required in evaluating model performance, emphasizing the significance of tailored dataset preparation for successful model training and evaluation. Table 2 pretrains the total number of training, validation, and testing images used.

Table 2. Number of Images for Training, Validation and Testing Dataset

Dataset	Number of Images	Training	Validation	Testing
ISL-HS (Oliveira et al.2017)	58114	38811	10585	8718

3.3 Proposed Architectures

Numerous deep learning algorithms are available, with CNN being particularly prominent. Researchers predominantly favor CNN for image classification tasks due to its capability to accept an image as input and provide a probability value or class label as output. Consequently, CNN architecture has been widely adopted to address challenges in image classification. In our study, a variety of CNN architectures served as the foundational frameworks for sign language classification, as detailed in Table 3.

Table 3. Model Architectures and Parameters

Author	Architecture	Size	Parameters
VGG (Simonyan & Zisserman, 2014)	VGG-16	528	138.4 M
	VGG-19	549	143.3 M
Resnet (He et al., 2016)	Resnet 50 V2	98	25.6 M
	Resnet 101 V2	171	44.7 M
	Resnet 152 V2	232	60.4 M
Xception (Chollet, 2017)	Xception	88	22.9 M
Densenet (Huang et al., 2016)	Densenet 121	33	8.1 M
	Densenet 201	80	20.2 M
	Densenet 169	57	14.3 M
Inception (Szegedy et al., 2015, 2016)	Inception Resnet V2	215	55.9 M
	Inception V3	92	23.9 M
Mobilenet (Howard et al., 2017; Sandler et al., 2018)	Mobile net	16	4.3 M
	Mobile net V2	14	3.5 M
Nasnet (Zoph et al. 2017)	Nasnet Mobile	23	5.3 M
	Nasnet Large	343	88.9 M
ConvNext (Liu et al., 2022)	ConvNext Tiny	109	28.6 M
	ConvNext Small	192	50.2 M
	ConvNext Base	338	88.5 M
	ConvNext Large	755	197.7 M
	ConvNext X-Large	1310	350.1 M

4 Experimental Results

4.1 Model Hyperparameters

Deep learning architectures are instantiated utilizing the TensorFlow and Keras libraries. Keras offers ImageNet based weights tailored for integration with these pre-trained models. Furthermore, image augmentation techniques are applied, with the training epoch set to 20. Employing a learning rate of 0.001, a batch size of 32 is utilized, and optimization is achieved through the ADAM optimizer while employing the "categorical cross-entropy" loss function. The SoftMax activation function is applied to the models. To expedite processing, the resolution is standardized to 160x120. Execution of Python scripts is conducted on Google Collab, leveraging the Tesla K80 GPU for enhanced computational efficiency.

4.2 Rationale for Model Selection and Uniform Parameters

In this research, the selection of deep neural network architectures was directly influenced by their demonstrated success in various image recognition tasks, highlighting their potential applicability to Irish Sign Language (ISL) recognition. These models, known for their robust performance in handling complex image data, were chosen based on their historical effectiveness, suggesting their suitability for ISL recognition tasks. To ensure a fair and controlled comparison across all architectures, uniform hyperparameters were maintained for each model which includes consistent batch sizes, input image resolutions, and the use of standardized optimizers and loss functions. Such uniformity in experimental conditions was aimed at isolating the architectural differences in performance outcomes, thus providing a clear basis for evaluating each model’s efficacy in recognizing ISL gestures.

4.3 Evaluation Metrics

Accuracy, precision, recall, and F1-Score were used in the appraisal of the framework's performance.

- **Recall**: It is the measure of how the model and algorithm predict True positives where TP stands for True Positive and FN stands for False Negative.

$$Recall = \frac{TP}{TP + FN}$$

- **Precision**: It is determined by the ratio of properly identified true negative samples to the total number of outcomes, which includes both true negative and false positive results.

$$Precison = \frac{TN}{TN + FP}$$

- **Accuracy**: The accuracy of the model is determined by the proportion of its predictions that are confirmed by testing.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

- **F1-Score**: It is a technique that is used to combine the accuracy and recall of the model and is also the harmonic combination of the model's recall and precision.

$$F1\ Score = \frac{2TP}{2TP + FP + FN}$$

4.4 Results

In our research, we employed cutting-edge deep learning models, including VGG, Inception, Densenet, Xception, Resnet, Nasnet, Mobile Net, Efficient net, and ConvNext to analyze the Irish Sign Language handshape dataset. Densenet 201 achieved a remarkable performance, obtaining an accuracy rate of 99% and confirming its ability in sign language recognition on the test dataset. This analysis demonstrates that Densenet architectures outperform alternative models in critical parameters like as F1 score, accuracy, recall, and precision, notably in the domain of sign language recognition. Figure 3 depicts the confusion metrics, showcasing the performance metrics on the ISL-HS data set. Table 4, on the other hand, presents a summary of the performance metrics for the analyzed architectures against the dataset. This table encapsulates the valuable insights gleaned from our exploration of deep learning architectures.

Table 4. Evaluation Metrics

Model	Architecture	Accuracy	Precision	Recall	F1-Score
VGG	VGG-16	83.32	85	84	83
	VGG-19	78.80	79	78	78
Inception	Resnet V2	95.66	96	96	96
	InceptionV3	97.08	97	97	97
Densenet	Densenet 121	97.05	97	97	97
	Densenet 201	99.10	99	99	99
	Densenet 169	98.42	98	98	98
Resnet	Resnet 50 V2	98.35	98	98	98
	Resnet 101 V2	98.36	99	99	99
	Resnet 152 V2	98.43	98	98	98
Nasnet	Mobile	92.96	92	92	92
	Large	94.01	94	94	94
Mobile Net	Mobile Net	96.10	96	96	96

	Mobile Net V2	98.21	98	98	98
ConvNext	ConvNext Tiny	60.10	59	59	59
	ConvNext Small	65.27	64	63	64
	ConvNext Base	92.52	91	91	91
	ConvNext Large	91.33	91	91	91
	ConvNext Large	93.10	92	92	92
Xception	Xception	98.14	98	98	98

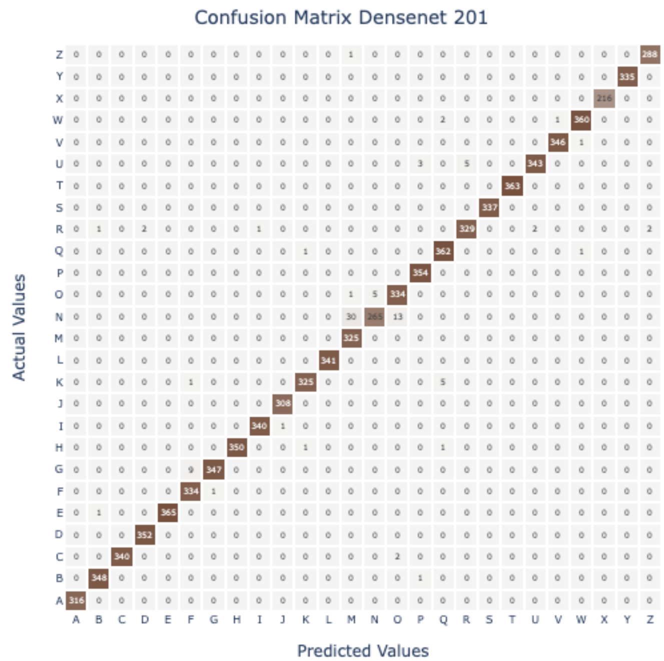

Fig. 3. Confusion Matrix illustrating the Performance Metrics on the ISH-HS Dataset

5 Discussion

Our research investigates the effectiveness of advanced deep learning models for Irish Sign Language (ISL) recognition, emphasizing not only technological innovation but also the broader societal, cultural, and ethical dimensions. By integrating insights from linguistics, sociology, and accessibility research, we aim to enrich the technological developments, ensuring they are inclusive and respectful of the ISL community's sociolinguistic complexities (O'Connell & Deegan, 2014). We believe that defining sign language communities' terms of reference (SLCTR) would help guide our research to ensure inclusiveness and uphold ethical standards, particularly considering the social vulnerabilities faced by the deaf and hard-of-hearing communities (Harris et al., 2020). These standards are essential as we explore the practical applications that could enhance communication in educational settings, workplaces, and social interactions, thus reducing barriers and promoting inclusivity. Furthermore, the integration of AI technologies into real-world applications can provide on-demand services, significantly improving daily interactions for ISL or any other sign language individuals, and the ethical deployment of these AI technologies demands careful consideration to ensure they respect user privacy and autonomy (Conama, 2013). Community members from the ISL community are actively involved in the research process, providing valuable insights and feedback to ensure the technology meets their needs and respects their cultural and communicative nuances. Commencing with this research as a foundational step for our forthcoming endeavors in automatic computational annotation for Irish Sign Language (ISL) systems, our dedication to advancing AI technologies for ISL recognition remains steadfast. We prioritize the development of adaptable solutions that cater to the evolving linguistic requirements of the ISL community. Our primary objective is to ensure that the research makes substantial contributions to accessible communication technologies, thereby upholding the broader interests and principles of the ISL community. Table 5 provides a comparison with several other cutting-edge sign-language recognition methods that have been discussed in the research literature.

Table 5. Comparison of the Proposed Methodology to Several Baseline Sign Language Recognition Approaches

Author	Sign Language Dataset	Features	Accuracy (%)
Proposed	**Irish**	**Densenet 201**	**99**
(Oliveira et al., n.d.)	Irish	Principal Component Analysis	95
(Sharma & Singh, 2021)	American & Indian	VGG-11,16	98
(Sevli & Kemaloğlu, 2020)	Turkish	CNN	98
(Wadhawan & Kumar, 2020)	Indian	CNN	99
(Barbhuiya et al., 2021)	American	VGG-16, Alex net	98
(Fowley & Ventresque, n.d.)	Irish	CNN	71
(De Coster et al., n.d.)	Turkish	Vision Transformer	92

6 Conclusion

In conclusion, our research marks a crucial initial stride in providing a comprehensive overview of deep learning architectures, with a view to processing sign language, in particular Irish Sign Language. This study establishes a foundational platform for subsequent innovations within this domain, through the application and assessment of diverse deep-learning architectures for image classification in sign language recognition. The notable enhancements in metrics such as accuracy, precision, recall, and F1 score achieved by the Densenet model, relative to other models, highlight the efficacy of these parameters in improving sign language recognition. Additionally, this research may act as a critical benchmarking tool for the efficiency of deep learning models in the computational processing of sign language, presenting a detailed comparative analysis to evaluate performance. In the future, we will explore more intricate challenges focusing on sign language annotation, and the development of a pipeline that will enable us to automatically annotate a sign language dataset. By investigating the efficiency of deep learning frameworks in terms of computer vision, we aim to further bridge the technological gap in sign language recognition, thereby contributing to the broader field of accessible communication technologies.

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