REAL-TIME CONTINUOUS SIGN LANGUAGE RECOGNITION SYSTEM FOR GERMAN AND INDIAN LANGUAGES

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1. INTRODUCTION:

Communication is one of the most fundamental human rights, serving as the cornerstone of social interaction, education, personal development, and civic participation. However, for the approximately 70 million deaf individuals worldwide who primarily rely on sign languages as their first language, traditional spoken communication presents significant and persistent barriers. According to the World Health Organization, over 430 million people globally experience disabling hearing loss, with projections indicating this number will rise to over 700 million by 2050. This growing population faces profound challenges in accessing digital services, educational opportunities, and everyday communication technologies that are predominantly designed for spoken languages.[1]

Sign language represents far more than simple gesture-based communication—it constitutes a complete, complex linguistic system with its own grammar, syntax, vocabulary, and cultural nuances. Despite this linguistic richness, sign languages face substantial recognition and integration challenges in mainstream technology. Current estimates suggest that fewer than 10% of hearing parents of deaf children learn sign language, creating immediate communication barriers within families and limiting educational opportunities from early childhood. Additionally, studies indicate that approximately 2.8% of adults in the United States use sign language, with usage rates higher among women and younger adults. The digital divide further exacerbates these communication challenges, as the deaf community remains largely excluded from voice-activated assistants, speech-to-text services, and audio-based interfaces that have become integral to modern life.[3]

Traditional approaches to bridging this communication gap have relied heavily on human interpreters and static gesture recognition systems. However, these solutions face critical limitations in scalability, cost-effectiveness, and availability. Human interpretation services are expensive, not always accessible in remote or underserved areas, and cannot scale to meet the growing demand for inclusive communication technologies. Existing static sign recognition systems typically focus on isolated gestures or single signs rather than the continuous, dynamic nature of natural sign language communication, significantly limiting their practical utility in real-world conversational scenarios.[5]

India, with over 18 million people experiencing hearing disabilities according to the National Association of the Deaf, faces particularly acute challenges in sign language accessibility and recognition. The country's 2011 Census estimated the total deaf population at 50 lakh (5 million), though advocacy organizations suggest higher numbers. Indian Sign Language (ISL) serves as the primary means of communication for the deaf community across India, with an estimated 1 million to 2.7 million users. However, there exists a dire shortage of certified sign language interpreters. As per the Indian Sign Language Research and Training Centre, ~300–325 certified ISL interpreters serve ≈6 million ISL users in India — that's roughly 1 interpreter for every 18,000–20,000 users. This massive gap in accessibility infrastructure has led to significant barriers in **education**, **healthcare**, **employment**, and **social integration** for the hearing-impaired community. In such contexts, scalable, technology-driven solutions have the potential to create transformative impact on social inclusion and accessibility.[7]

Furthermore, the challenges faced by the deaf community extend beyond mere communication barriers. In India, **over 90% of deaf children are born to hearing parents**, and only **5%** of **hearing-impaired children** receive basic schooling. This educational disparity stems largely from the lack of ISL integration in mainstream education systems and the absence of ISL as a recognized first language, creating cognitive delays and reduced literacy levels among deaf children.[10]

Motivated by the urgent need for inclusive communication technologies and the potential for artificial intelligence to bridge existing gaps, this study investigates the development of a comprehensive continuous sign language recognition system. Unlike traditional static gesture recognition approaches that process individual signs in isolation, our research focuses on understanding the continuous, temporal, and contextual nature of sign language communication—including the complex sequential dependencies, co-articulation effects, and grammatical structures that characterize natural sign language discourse.[11]

Recent advances in computer vision and deep learning have demonstrated remarkable progress in human motion analysis, gesture recognition, and temporal sequence modelling. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown promising results in **fingerspelling and isolated sign recognition**. However, the continuous nature of sign language poses significant challenges, leading researchers to explore advanced neural network models such as Transformer architectures for continuous sign language recognition (CSLR). Current challenges in the field include expanding **sign language datasets**, achieving user independence in recognition systems, exploring different input modalities, effectively fusing features, modelling co-articulation, and improving semantic and syntactic understanding.[12]

Building upon these technological foundations, this project aims to develop a state-of-the-art continuous sign language recognition system that can understand the nuanced, sequential nature of sign language communication while maintaining real-time processing capabilities. The system employs advanced deep learning architectures including the **Cross Correlation** and **Temporal Attention** Mechanism, on top of **Resnet-18** for Feature Extraction, and a Bi-directional Long Short-Term Memory (BiLSTM) networks for temporal sequence modelling. Recent research has shown that such approaches can achieve a recognition Word Error Rate (WER) of over 20% across various benchmarks, demonstrating the technical feasibility of real-time sign language recognition systems.[13]

The proposed solution addresses several critical technical challenges in continuous sign language recognition, including temporal segmentation of continuous signing streams, handling variations in signing speed and style across different users, managing occlusion and lighting variations in real-world environments, and achieving robust performance across diverse sign language vocabularies and grammatical structures. Current limitations in existing datasets, including small scale and limited vocabulary, lack of diversity in signers, variability in controlled environments, and absence of multimodal data, present ongoing challenges that this research aims to address.[11]

Fig 1. *Hearing Loss in the Adults of India*

The broader impact of this work extends beyond technical achievement to encompass social inclusion, educational accessibility, and economic opportunity for the deaf and hard-of-hearing community. By providing real-time, accurate sign language interpretation capabilities, the system can facilitate improved access to education, healthcare services, employment opportunities, and social participation for sign language users. Research has shown that unaddressed **hearing loss poses an annual global cost of nearly $980 billion**, highlighting the economic importance of developing effective assistive technologies.[5]

This project holds deep personal significance, inspired by interactions with members of the deaf community who have shared their daily communication challenges and the barriers they face in accessing technology-mediated services. My objective is to create a tool that not only enhances communication accessibility but also promotes greater understanding, acceptance, and inclusion of sign language as a legitimate and rich form of human expression.

By developing this continuous sign language recognition system, this study aims to bridge the persistent communication gap between deaf and hearing communities, foster more inclusive digital environments, and advance the broader goals of universal accessibility in human-computer interaction. This research contributes to the growing field of assistive artificial intelligence while addressing a critical social need that affects millions of individuals worldwide, particularly in countries like India where the gap between the deaf population and available interpretation services remains critically large.[3]

1.1 Aim

The main aim of this project is to build a **real-time**, **AI assisted intelligent system** that can recognize and understand **Sign Language** (**SL**) from **video**, helping bridge gaps in communication for the **deaf and hard-of-hearing** community. The proposed system prioritizes lightweight architecture, **sign language relevance, and accessibility**, making it suitable for deploying in resource-constrained settings such as **micro-controllers**. Delivered via a web-based interface, the system is intended to enable healthcare professionals to rapidly prescribe a CSLR system for deaf and dumb people. This project demonstrates the technical feasibility of such an assistive tool, setting the foundation for future development and validation at scale.

To achieve this, I undertook the entire development pipeline—from data collection and annotation to model training and deployment—ensuring transparency, reproducibility.

1.2 Objective

The following structured objectives guided the project:

- Acquire a relevant dataset for continuous sign language recognition dataset of multiple languages such as German (PHOENIX2014-T), ISL-CSLRT (Indian signs) and CSL (Chinese) datasets of videos annotated with the gloss sentences.
- Select the Best Model: The project begins with a broad review of the latest sign language recognition models. Instead of limiting the choice to one particular architecture, the goal is to identify the model that has performed best on large, standard datasets. This ensures we use an approach that is thoroughly tested and is likely to be robust in real-world applications.
- Train the model with PHOENIX2014-T dataset, After selecting the top-performing model, the next step is to fine-tune or retrain it using the ISL CSLRT dataset. This allows the model to adapt and learn the specific gestures, grammar, and unique features of Indian Sign Language, making it more accurate and reliable for that context.
- Validate the model using standard evaluation metrics, ensuring that the model's predictions align with sign language expectations.
- Design and deploy a web-based interface through which users can upload an image and receive a real-time classification output.
- Throughout the process, maintain ethical standards, especially with respect to sign language data, and reflect on each stage to document personal learning and project direction changes.

1.3 Wider Purpose of The Project and Broader Impact

This project extends beyond technical innovation and academic inquiry—it is fundamentally oriented toward advancing communication accessibility, social inclusion, and digital equity, particularly for communities relying on a **single sign language**. By automating **continuous recognition of Sign Language** through artificial intelligence, the system has the potential to provide real-time interpretation support and bridge linguistic barriers in regions where certified **ISL (Indian Sign Language) interpreters are scarce**.[1]. Although the model achieves high accuracy on standard benchmarks for **German** and **Chinese sign** languages, its performance on **ISL** remains **limited, highlighting** the need for dedicated ISL datasets, culturally informed annotation practices, and tailored model architectures to achieve equitable accessibility for the Indian deaf community.

Deploying the trained model via a **lightweight**, **scalable web-based interface** enables outreach to **educational institutions**, **healthcare facilities**, **public services**, and **community centres**—not only specialized **deaf-service organizations**. This democratization of ISL interpretation can reduce social isolation, educational barriers, and employment discrimination by facilitating immediate communication support for ISL users in everyday interactions.[16]

Focusing on ISL allows the solution to incorporate cultural and grammatical nuances unique to the Indian deaf community. Tailoring the model to ISL enhances recognition accuracy, ensuring that the system's output aligns closely with native signing patterns and regional dialects. This emphasis on a single language **maximizes relevance** and impact within India's diverse **linguistic** landscape.[5]

From a global accessibility standpoint, the system aligns with the United Nations Sustainable Development Goal 4: "**Ensure inclusive and equitable quality education and promote lifelong learning opportunities for all**," and SDG 10: "Reduce inequality within and among countries." Specifically, it addresses targets for inclusive **education**, **equal access** to information and communication technologies, and **empowerment of persons** with **disabilities**. It also supports the **UN Convention** on the Rights of Persons with Disabilities (CRPD), particularly Article 9 on accessibility and Article 21 on freedom of expression and access to information.[6]

The broader societal impact extends to **economic empowerment**: communication barriers significantly affect employment outcomes for deaf individuals, with **lower employment rates** and income levels compared to hearing peers. By providing scalable, **accessible ISL recognition technology**, this system can help narrow these disparities.[8]

Prioritizing deployment through web interfaces with **low computational** requirements ensures compatibility with existing digital infrastructure in resource-constrained settings—such as rural clinics, government offices, and schools—without the need for specialized hardware. This approach emphasizes sustainability and scalability, making the technology accessible to organizations serving the ISL community across India.[9]

Moreover, the system fosters greater awareness and acceptance of ISL as a complete, legitimate linguistic system. Automated recognition and translation can facilitate **two-way**

communication: enabling hearing individuals to **understand ISL** and promoting mutual cultural respect. This dual impact helps break down barriers and promotes broader inclusion of sign language culture.[3]

In essence, this proof-of-concept represents a step toward equitable innovation in communication technology—**leveraging AI** not only to enhance recognition accuracy and speed but also to **bridge systemic** gaps in **accessibility** and **inclusion** for **ISL** users. By centering the needs of a single language community, the project demonstrates how technical solutions can be designed with social impact at their core, **prioritizing cultural relevance**, community needs, and **sustainable deployment** over purely technological advancement.

2. METHODOLOGY AND PROJECT PLANNING

2.1 Overview of Approach:

The methodology for this project was structured around building a **lightweight**, **real-time deep learning** system capable of generating **sentence glosses** using **sign videos** (i.e. Continuous Sign Language Recognition). The project encompassed the full **machine learning pipeline**, including **data collection**, **preprocessing**, **model training**, **interpretability analysis**, and **deployment** via a **web interface**.

2.2 Justification for Deep Learning Approach

The decision to adopt a deep learning-based solution was guided by a comparative evaluation of three primary approaches: classical Techniques, traditional machine learning with handcrafted features, and deep learning.

I. **Classical Techniques**:

   a. **Dynamic Time Warping (DTW)**

   Dynamic Time Warping aligns two temporal sequences by warping their time axes to minimize a cumulative distance. In sign language, DTW compares a signer's input trajectory to stored templates despite variations in speed or duration. A distance matrix between frames is built, and dynamic programming finds the lowest-cost path. Early CSLR systems using DTW achieved up to 84% accuracy on isolated American Sign Language tasks by comparing joint trajectories extracted via computer vision [25]. However, DTW has O(N·M) complexity and struggles with sign-to-sign co-articulation in continuous streams. Enhanced variants (e.g., AF-DTW) impose warping windows and fuse multimodal features, narrowing the gap to HMMs but remaining outpaced by statistical and neural models.

   b. **Finite State Machines (FSM) and Rule-Based Models**

   FSMs represent signs as sequences of discrete states—each a handshape or motion phase—with transitions encoded by linguistic rules. Hierarchical FSMs recognize low-level gestures (handshapes, orientations) then assemble them into word-level signs. While offering clear interpretability, FSMs are brittle under real-world variability: small deviations break state transitions, and co-articulation defies fixed rules. Hybrid FSM–probabilistic systems later added transition probabilities to handle uncertainty, but pure rule-based models gave way by the mid-2010s to statistical approaches.

II. Traditional Machine Learning with Handcrafted Features

a. Support Vector Machines (SVMs) with Handcrafted Features

SVM classifiers combined with engineered descriptors like SIFT, HOG, and geometric hand-landmark features achieved 86–97% accuracy on isolated sign vocabularies. Pipelines used Bag-of-Visual-Words: cluster local features into codebooks, then SVM for multi-class classification [26]. Though computationally efficient and theoretically principled, SVMs falter in continuous recognition, lacking temporal modeling and requiring labor-intensive feature design.

b. Conditional Random Fields (CRF)

CRFs model P(Y|X) over label sequences Y given observations X, capturing temporal dependencies without HMMs' independence assumptions. Linear-chain CRFs achieved spotting rates ≈ 87% and recognition rates ≈ 93% by incorporating local and transition features [27]. Hierarchical CRFs extended this across temporal scales. Deep-structured CRFs, layering CRF atop CNN features, improved robustness but incurred high inference cost for long videos.

c. Hidden Markov Models (HMM)

HMMs dominated early CSLR by modeling signs as hidden state sequences emitting observable features. Training via Baum–Welch and decoding via Viterbi yielded real-time recognition; MIT's system using colored gloves achieved > 99%-word accuracy on a 40-word ASL vocabulary [28]. Yet Markovian assumptions and limited state capacities hindered modeling of rich spatial-temporal patterns; modern methods now embed HMM cues within neural backbones.

III. Deep Learning Methods

Continuous sign language recognition has been transformed by the advent of deep learning, especially through the combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM) networks. CNNs automatically learn hierarchical spatial representations directly from raw image data, eliminating the need for handcrafted features and making them highly effective for analysing complex visual patterns in sign language videos. This automated approach not only improves the consistency of feature extraction but also reduces the dependency on domain expertise for feature engineering.[12]

When CNNs are integrated with RNNs or LSTM layers, the resulting architectures capture both the spatial and temporal dynamics essential for continuous sign language understanding. CNNs extract robust spatial features from each frame, while LSTMs model the sequential dependencies across time, allowing the networks to interpret gestures, transitions, and co-articulation in natural sign language sentences. These hybrid architectures consistently outperform traditional methods in benchmark evaluations.

Key advantages of modern deep learning models for CSLR include:

- **Automated feature extraction**: Deep networks learn meaningful representations, improving recognition reliability and scalability.[28]
- **Superior generalization**: Techniques such as data augmentation and transfer learning enhance performance on diverse signers and previously unseen signs.
- **Real-time inference on lightweight models**: Efficient architectures like Resnet-18 enable deployment on resource-constrained devices, supporting broad accessibility and point-of-care applications.[13]

In this Sub-section, we will discuss various deep learning models, particularly focusing on identifying lightweight, high-performing architectures that can be easily integrated into low-processing systems for practical deployment.

1) CNN+LSTM/RNN

Early Continuous Sign Language Recognition (CSLR) models fused convolutional networks for spatial feature extraction with recurrent units for temporal modelling. The canonical pipeline—exemplified by CNN-LSTM-HMM—first applies a 2D Convolutional Neural Network (e.g., ResNet-based) to each video frame, producing frame-wise embeddings. A bidirectional Long Short-Term Memory (BiLSTM) network then captures temporal context across the sequence, and alignment with target glosses is achieved via Connectionist Temporal Classification (CTC) or hybrid HMMs.

Key contributions in this class include:

- CNN-LSTM-HMM [28]: Introduced end-to-end learning by jointly optimizing CNN spatial encoders, BiLSTM temporal models, and HMM alignment probabilities under CTC loss. Demonstrated feasibility on RWTH-PHOENIX-Weather-2014T, achieving Dev/Test WERs of 24.5%/26.5%.

- VAC (Visual Alignment Constraint) [29]: Enhanced spatial consistency by imposing a visual alignment loss that encourages CNN features to align tightly with gloss boundaries. Improved Dev/Test WERs to 21.5%/22.1%.
- SMKD (Self-Mutual Distillation Learning) [30]: Employed mutual distillation between parallel CNN-LSTM streams to regularize feature representations. Achieved 20.8%/21.0% WER.

Strengths:

1. Mature training paradigms leveraging proven CNN and LSTM modules.
2. Straightforward alignment via CTC yields robust convergence.

Limitations:

- Frame-wise correlation is neglected, causing difficulty modeling fine-grained hand articulations.
- BiLSTM struggles with very long sequences, leading to suboptimal handling of extended sentences or rapid signing.

2) CNN + Transformer Architecture:

Building on the success of transformer architectures in natural language, hybrid CSLR models replaced recurrent modules with multi-head self-attention to capture long-range dependencies more effectively. In these pipelines, a CNN encoder (e.g., I3D pretrained on isolated sign datasets) outputs frame embeddings, which feed into a Transformer encoder–decoder stack. The encoder's self-attention layers aggregate temporal context, and the decoder—often with CTC or autoregressive cross-entropy—generates gloss sequences or spoken-language translations.

Representative models:

- I3D + Seq2Seq Transformer [31]: Frozen I3D extracts spatial features; a six-layer Transformer processes temporal context. Demonstrated gains on RWTH-PHOENIX14, reaching ~19.0% test WER.
- C2ST (Cross-Modal Contextualized Sequence Transduction) [32]: Introduced cross-modal attention between RGB and keypoint streams, yielding Dev/Test WERs of 17.3%/18.9%.

- Vision Transformer (ViT) for CSLR [33]: Applied patch-based tokenization per frame with positional encodings; captured global context via pure transformer layers. Reported ~19.5% test WER.

Innovations:

- Multi-head self-attention offers flexible context aggregation across tens or hundreds of frames—addressing long-sequence modeling limits of BiLSTM.
- Cross-modal fusion (RGB + pose/keypoints) improves robustness by combining appearance and motion cues.

3) CNN+Spatial-Temporal Correlations + BiLSTM

Spatial-Temporal Correlation Networks explicitly model inter-frame feature correlations to capture signer trajectories without external pose supervision. CorrNet introduced compressed correlation maps between adjacent frames; CorrNet+ extended this by multi-scale attention and residual connections, reducing computational complexity from O(W2H2) to O(WH). [34]

Core Concepts:

- Correlation Module: Computes cross-frame feature correlations within local neighborhoods, producing maps that highlight motion patterns (hand trajectories, facial expressions).
- Identification Module: Applies multi-scale dilated convolutions to correlation maps, dynamically constructing human body trajectories and selecting informative spatial regions.
- Temporal Attention: Utilizes parallel depth-wise convolutions at varied dilation rates to model short and long temporal ranges.

Performance:

CorrNet+ achieves Dev/Test WERs of **18.0%/18.2%** on **RWTH-PHOENIX-Weather 2014T**, setting a high bar for single-view, signer-independent recognition.

Impact:

Correlation networks bridge the gap between end-to-end deep learning and explicit motion modeling, offering robust performance without reliance on computationally expensive pose estimation.

2.3 Gantt Chart

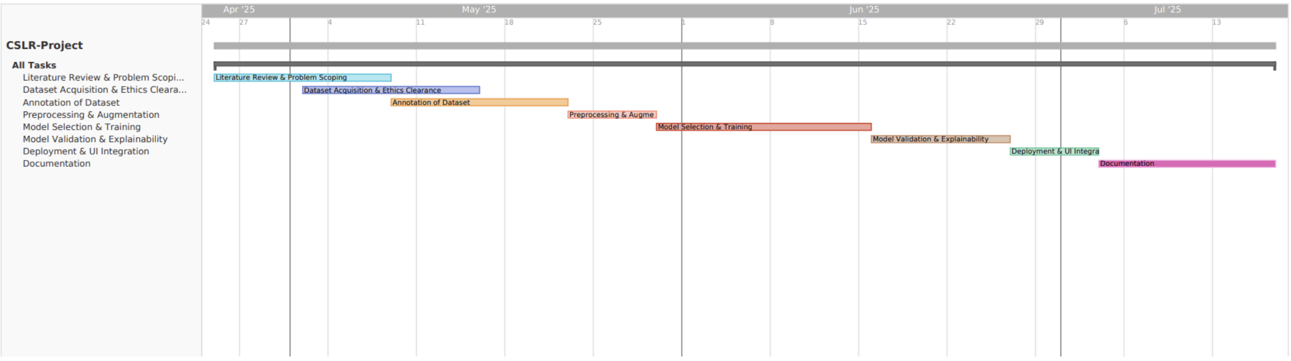


Fig 2 Project Gantt Chart

2.3 Project Plan with Timeline

Week(s):	Task:	Description:	Skills Required:	Key Resources:	Dependencies:
1-2	Literature Review & Problem Scoping	Researching on CSLR, and Sign Language Recognition Methods.	Literature Analysis, domain knowledge	Online research papers with online access and past CSLR papers	None
2-3	Dataset Acquisition & Ethics Clearance	Identifying possible data sources for the CSLR Task like CSL, PHOENIX, ISL CSLRT	Communication, Ethical considerations	Sign Language Videos, Sentence Gloss Labels from CSL, ISL-CSLRT, PHOENIX	Must follow literature review
3-4	Annotation of Dataset	It is already annotated by the signers for each sign language video	None	Especially ISL-CSLRT dataset it annotated by the 7 signers (2 from Residential Deaf school in AP, India and 5 from SASTRA Deemed University, Thanjavur, Tamilnadu	Dataset acquisition from the online sources

5	Preprocessing & Augmentation	Image resizing, normalization, rotation, etc.	Python, OpenCV	Google Colab	Annotated Data
6-7	Model Selection & Training	Selection and training of Sign Language Recognition model (CorrNet+)	PyTorch, CSLR knowledge	Google Colab GPU, PyTorch, CTCdecoder.	Preprocessing
8	Model Selection & Training	Using CorrNet+ (Resnet-18+(correlation+attention) +BiLSTM) with transfer learning	PyTorch, Resnet-18,Correlation and Temporal attention and Followed by BiLSTM.	Google Colab GPU	Training
9	Model Validation & Explainability	Explainability evaluation using WER, and Grad-CAM visualizations.	Model evaluation, visualization	PyTorch, matplotlib	model training
10	Deployment & UI Integration	Creating a real-time interface via Gradio	Backend development, UI, deployment	Gradio, GitHub	All models trained and evaluation completed
11-12	Documentation	Writing technical reports, reflections, and ethical discussions	Technical writing, project review	CREST guidelines, Microsoft Word	All project tasks are complete.
12	Final Edits, Backup & Submission	Format report, organize GitHub	Organizational skills	Git, Word, email	Documentation

3. BACKGROUND RESEARCH

Sign language serves as a visual-gestural language used by deaf and hard-of-hearing communities worldwide, functioning as a complete linguistic system with its own grammar, syntax, and cultural expressions. Unlike spoken languages that rely on auditory channels, sign languages utilize hand gestures, facial expressions, and body movements to convey meaning, making them inherently multimodal communication systems that require sophisticated recognition approaches.

3.1 Communication Challenges and Accessibility Barriers:

The deaf and hard-of-hearing community faces significant communication barriers in mainstream society, where the scarcity of certified sign language interpreters creates obstacles in accessing essential services including healthcare, education, legal assistance, and employment opportunities. Studies indicate that communication barriers contribute to lower employment rates and income levels among deaf individuals compared to their hearing counterparts, highlighting the urgent need for technological solutions that can bridge these linguistic divides[11].

Key Communication Barriers Include:

Interpreter Scarcity: Professional sign language interpreters are limited in availability and costly to employ, particularly in rural or underserved regions where deaf communities may be geographically dispersed.

Institutional Awareness: Many organizations lack understanding of deaf communication needs and fail to provide appropriate accommodations, creating exclusionary environments that limit participation in civic, educational, and professional activities.

Real-time Communication Gaps: The absence of immediate interpretation services in emergency situations, medical appointments, or spontaneous interactions can lead to critical miscommunications with potentially serious consequences.

3.2 Technical Challenges in Sign Language Recognition

Continuous Sign Language Recognition (CSLR) presents unique computational challenges that distinguish it from traditional speech recognition or isolated gesture classification tasks [12].

Temporal Complexity: Unlike isolated sign recognition, continuous signing involves fluid transitions between signs without clear boundaries, requiring models to segment and recognize overlapping gestures within temporal sequences. Co-articulation effects, where preceding and following signs influence the current sign's execution, add additional complexity to pattern recognition.

Spatial-Temporal Dependencies: Sign languages utilize three-dimensional space meaningfully, with hand locations, orientations, and movements carrying linguistic information. Capturing these spatial relationships across temporal sequences demands sophisticated modelling approaches that can handle high-dimensional feature spaces [40].

Multimodal Information Integration: Effective sign language recognition requires simultaneous processing of manual features (hand shapes, movements, positions) and non-manual features (facial expressions, head movements, body posture), each carrying distinct linguistic functions that contribute to overall meaning.

Environmental Variability: Real-world deployment scenarios introduce challenges including varying lighting conditions, camera angles, background clutter, and signer positioning that can significantly impact recognition accuracy compared to controlled laboratory settings .

3.3 Dataset and Resource Limitations

Current sign language recognition research faces critical data scarcity challenges that limit the development of robust recognition systems [11].

Scale Limitations: Existing datasets are often small in scale with limited vocabularies. For instance, popular benchmarks like PHOENIX-2014-T contain approximately 1,200 signs, while comprehensive sign languages encompass tens of thousands of lexical items .

Signer Diversity Constraints: Most datasets feature limited numbers of signers (typically 7-15), resulting in models that may overfit to specific signing styles rather than generalizing across the diverse signing patterns found in real-world communities [11].

Linguistic Bias: The majority of available datasets focus on well-resourced sign languages (German, Chinese, American), while hundreds of national and regional sign languages remain severely under-represented in research contexts .

Annotation Complexity: Creating accurate temporal annotations for continuous signing sequences is **time-intensive** and requires **linguistic expertise**, creating a bottleneck in dataset expansion .

3.4 Dataset Applications and Social Impact

CSLR technology has transformative potential across multiple domains:

Educational Accessibility: Automated Continuous sign language recognition can enable real-time captioning and translation in educational settings, improving access to learning materials and classroom discussions for deaf students.

Healthcare Communication: Medical interpretation systems could provide immediate communication support during healthcare encounters, potentially improving diagnosis accuracy and treatment compliance.

Employment Integration: Recognition technology can facilitate workplace communication, enabling deaf employees to participate more fully in meetings, training sessions, and collaborative activities.

Digital Inclusion: Integration with video conferencing platforms and social media can enhance digital communication accessibility, reduce isolation, and promote social participation.

3.5 Current Research Trajectory

Recent advances in deep learning have accelerated progress in sign language recognition, with CNN-RNN hybrid architectures and attention-based models showing promising results on established benchmarks. However, significant gaps remain between laboratory performance and real-world deployment requirements, particularly for under-resourced sign languages where limited data constrains model development.

The field increasingly recognizes the need for community-centred research approaches that involve **deaf stakeholders** in **system design** and **evaluation**, ensuring that technological developments serve the actual needs and preferences of sign language users rather than imposing external technological frameworks.

Motivation for **AI-Based Proof-of-Concept**

- To bridge communication gaps for the deaf community, particularly in resource-constrained settings, an AI-driven continuous sign language recognition system can assist by:
- Automatically detecting and segmenting Sign Language gestures in real time from video streams.
- With widespread smartphone and tablet use, a lightweight web or mobile deployment enables real-time interpretation support in classrooms, clinics, and public services.

Project Scope

This proof-of-concept project implements a deep learning-based pipeline to:

- Capture live video or uploaded recordings of ISL signing.
- Perform continuous sign recognition by combining a CNN backbone with correlation and temporal attention along with a Bi-LSTM.
- Output the recognized gloss sequences
- Deploy the model using a Python Flask interface to accept user-uploaded images or videos of sign and return sentence glosses results instantly

There are various data sources which are publicly available, each offering unique characteristics and challenges for **continuous sign language recognition** research. This section provides a detailed description of each dataset, the **creative approaches** we employed, and the **challenges** encountered during model development.

4. DATASET COLLECTION

4.1 Dataset Overview

4.1.1 PHOENIX Datasets

RWTH-PHOENIX-Weather 2014: This German sign language dataset contains weather forecast videos from the German public TV station PHOENIX. It includes 386 editions with both gloss notation transcriptions and automatic speech recognition with manual cleaning of the original German speech. The dataset features:

- 9 different signers performing weather forecasts
- 45,760 sign instances across 1,200 different signs
- Videos recorded at 25 fps with 210×260 pixel resolution
- Stationary camera setup with consistent grey background

PHOENIX-2014-T: An extended version of the original PHOENIX dataset that enables end-to-end sign language translation from video input to spoken language. This parallel corpus allows training of complete **translation** systems rather than just **recognition systems**. The dataset has become a standard benchmark for continuous sign language recognition and translation research.

4.1.2 Indian Sign Language Datasets

ISL-CSLRT: The Indian Sign Language dataset for Continuous Sign Language Recognition and Translation represents **one of the limited resources available for ISL** research. This dataset includes video samples capturing various hand gestures representing specific words or phrases, with annotations for both isolated signs and continuous sequences.

It consists only 100 different sentences and sentence gloss for 700 sign videos.

- 7 different signers
- 700 sign instances across 170 different signs(vocabulary size)
- 100 different sentences.

4.2 Creative Approaches and Data Handling

4.2.1 Multi-Modal Data Integration

We employed creative approaches to maximize the utility of available datasets by:

Cross-Dataset Learning: We developed techniques to leverage knowledge from high-resource languages (German, Chinese) to improve performance on lower-resource languages like ISL. This involved transfer learning approaches where models pre-trained on PHOENIX-2014-T were fine-tuned on ISL data.

4.3 Challenges Encountered

4.3.1 Dataset-Specific Challenges

Small Scale and Limited Vocabulary: Most sign language datasets suffer from limited scale and vocabulary coverage. For instance, ISL datasets contain significantly fewer samples compared to spoken language datasets, limiting model generalization.

Lack of Signer Diversity: Many datasets feature a limited number of signers, resulting in models that overfit to specific signing styles. PHOENIX-2014-T includes only 9 signers, while real-world applications require robustness across diverse signing styles.

Controlled Environment Bias: Most datasets are collected in controlled settings (studios, laboratories) with uniform backgrounds and lighting. This creates a significant domain gap when deploying models in real-world scenarios.

Annotation Inconsistencies: Different datasets use varying annotation schemes for glosses, making cross-dataset learning challenging. Some datasets use detailed linguistic annotations while others employ simplified gloss representations.

4.3.2 Technical Challenges

ISL-Specific Challenges: Our experiments revealed a few difficulties with ISL recognition:

- Limited training data compared to German and Chinese sign languages
- Lack of standardized gloss annotation schemes for ISL
- Regional variations in signing style across different parts of India
- Unbalanced glosses in the dataset.

4.3.3 Computational Challenges

Memory and Processing Requirements: Continuous sign language videos require significant memory and computational resources. Processing high-resolution videos with temporal modelling approaches like LSTMs often exceeded available GPU memory constraints. To overcome this, I trained the model on a GPU server instead of simply using with Google Colab.

Real-time Processing: Achieving real-time recognition speeds while maintaining accuracy proved to be quite challenging, particularly for resource-constrained deployment scenarios like mobile devices or embedded systems.

4.4 Ethics and Data Privacy

The development of this continuous sign language recognition (CSLR) system was **conducted** using **exclusively publicly available** datasets, requiring careful adherence to ethical standards and **data privacy protocols** that respect the unique considerations inherent in sign language research.

4.4.1 Ethical Framework and Public Dataset Usage

This research was guided by established ethical principles for sign language communities, particularly the **Sign Language Communities' Terms of Reference (SLCTR)** framework. All datasets utilized (PHOENIX-2014-T [35], and ISL-CSLRT [36]), which were accessed through official distribution channels and used strictly within the terms of their original licensing agreements. Each dataset had undergone appropriate institutional ethical review processes prior to public release, including informed consent procedures with original participants.

We ensured proper academic attribution to all dataset creators and maintained transparency about data sources throughout the research process. The use of these datasets remained within the scope of the original consent frameworks under which participants agreed to have their signing recorded and made available for research purposes.

4.4.2 Privacy Considerations Unique to Sign Language Research

Sign language research presents distinctive privacy challenges that require specialized consideration. As established in research ethics literature, "even techniques for disguising facial features will not hide characteristic signing styles that may lead to inadvertent identification of participants". This heightened identification risk exists because facial expressions convey essential linguistic information in sign languages and individual signing styles are recognizable within sign language communities.

Given these constraints, we implemented strict protocols: all dataset processing was conducted on secure, password-protected systems with access limited to authorized research personnel. Our pipeline was designed to extract only essential features (pose landmarks, cross correlation and temporal attention, temporal sequences) required for model training, minimizing retention of identifiable visual information. All model training was conducted on secured GPU servers with encrypted data transfer protocols.

4.4.3 Cultural Sensitivity and Research Transparency

We acknowledged the limited representation of Indian Sign Language in international research contexts and the vulnerabilities this creates for the ISL community. The small scale of available

ISL [36] datasets (700 videos, 7 signers) compared to international benchmarks highlights both resource scarcity and heightened privacy risks within this linguistic community.

In alignment with ethical research practices, we maintained transparency about significant limitations observed in current sign language recognition technology, particularly regarding poor model performance on ISL data compared to established benchmarks. This honest assessment prevents over-optimistic expectations about system capabilities and acknowledges the preliminary nature of current CSLR technology for practical deployment.

4.4.4 Data Security and Compliance

All computational processing adhered to data minimization principles, retaining only aggregated model weights, performance metrics, and extracted features necessary for research dissemination. Raw video data was not permanently stored beyond the duration required for feature extraction and model training phases. Upon completion of research objectives, all locally cached raw video data was securely deleted, maintaining only trained model artifacts and performance results necessary for academic publication.

This research complied with institutional guidelines and aligned with international best practices for sign language research as established by the **Sign Language and Linguistic Society (SLLS)**. By implementing these ethical safeguards and maintaining transparency about both achievements and limitations, this research aimed to contribute responsibly to sign language recognition while respecting the rights and dignity of sign language communities.

5. DATA PREPROCESSING, AUGMENTATION, AND SPLITTING INTO TRAIN-TEST

5.1 Data Preprocessing Strategy

Data preprocessing in continuous sign language recognition involves several critical stages to transform raw video sequences into suitable input representations for deep learning models. The preprocessing pipeline addresses the unique challenges of temporal video data while maintaining the **spatial-temporal relationships** essential for sign language understanding.

Frame Extraction and Standardization: Raw video sequences are decomposed into individual frames at consistent temporal intervals, typically maintaining the original frame rate (25 fps) to preserve temporal dynamics. Each frame undergoes spatial resizing to standard dimensions (commonly 224×224 pixels) to ensure compatibility with pretrained CNN architectures while preserving aspect ratios to avoid distortion of sign shapes.

Pixel Intensity Normalization [37]**:** Frame pixel values are normalized from the original range to [-1, 1] using the transformation: normalized_pixel = (pixel_value / 127.5) - 1. This normalization scheme centers pixel distributions around zero and scales to unit variance, improving gradient flow stability and accelerating convergence in deep neural networks.

Sequence Length Standardization: Continuous sign language videos exhibit significant variation in temporal length, requiring standardization strategies to enable batch processing. Common approaches include temporal interpolation for shorter sequences and temporal subsampling for longer sequences, while maintaining critical transition points between signs to preserve co-articulation effects.

5.2 Augmentation Techniques [38]

Data augmentation serves as a **critical regularization** technique to address the limited scale of sign language datasets and improve **model generalization** across diverse signing styles and environmental conditions.

Spatial Augmentation Methods:

Random Cropping: Applies random spatial crops within the frame boundaries, simulating variations in camera positioning and signer placement within the frame. This technique improves robustness to framing inconsistencies commonly encountered in real-world deployment scenarios.

Horizontal Flipping: Implements random horizontal mirroring with 50% probability to simulate left-handed versus right-handed signing variations. This augmentation effectively doubles the training data diversity while maintaining linguistic validity, as most sign languages accommodate both dominant hand preferences.

Scale and Rotation Variations: Introduces controlled scaling and rotation transformations to simulate natural variations in signer positioning relative to the camera, improving model robustness to geometric variations without compromising sign recognition accuracy.

Temporal Augmentation Strategies:

Temporal Rescaling: Modifies playback speed within controlled ranges (typically ±20%) to simulate natural variations in signing tempo. This addresses the significant challenge of inter-signer speed variations while preserving the relative timing relationships crucial for understanding sign transitions and co-articulation effects.

Frame Sampling Variation: Implements stochastic temporal sampling patterns during training to improve robustness to frame rate variations and temporal alignment inconsistencies, while maintaining deterministic sampling during evaluation for reproducible results.

5.3 Addressing Class Imbalances

The distribution of sign glosses in the ISL-CSLRT dataset exhibited significant imbalance, with certain high-frequency words being heavily overrepresented compared to rare vocabulary items. This skewed distribution is characteristic of natural language corpora and presents challenges for continuous sign language recognition, where the Connectionist Temporal Classification (CTC) loss function can become biased toward majority classes, reducing model sensitivity to infrequent but linguistically important signs.

To address this issue, a class weighting strategy was employed within the CTC loss framework to ensure balanced learning across the 170-gloss vocabulary. Unlike traditional classification tasks, CSLR requires handling sequential predictions where individual glosses appear multiple times within continuous signing sequences, making direct application of sampling techniques impractical.

Weighted CTC Loss Implementation

The standard CTC loss was modified to incorporate class-specific weights that compensate for frequency imbalances in the gloss distribution. For each gloss gi in the vocabulary, a weight wi was computed based on the inverse of its occurrence frequency:

$$wi = N / (fi \times |V|)$$

where N is the total number of gloss instances across all training sequences, fi is the frequency of gloss gi, and |V| = 170 is the vocabulary size.

The weighted CTC loss function was then formulated as:

$$Lweighted = -\sum(i=1 \text{ to } |V|)\ wi \times \log P(yi \mid x)$$

where P(yi | x) represents the probability of the correct gloss sequence given the input video sequence x.

Class Distribution Analysis

Analysis of the ISL-CSLRT dataset revealed extreme frequency variations: the most common glosses appeared in over 15%-20% of training sequences, while rare vocabulary items occurred in fewer than 1% of samples. This 15-20:1 frequency ratio creates substantial learning bias, where the model prioritizes accurate prediction of common signs at the expense of rare but potentially important vocabulary.

For instance, common function words and greetings dominated the dataset, while specialized vocabulary (technical terms, proper nouns, domain-specific signs) remained severely underrepresented. Without class weighting, the CTC alignment process would consistently favour paths that include frequent glosses, leading to systematic misrecognition of infrequent signs as more common alternatives.

Implementation Challenges for CSLR

Unlike static image classification, implementing class balancing for continuous sign language recognition presents unique challenges:

Temporal Dependencies: Signs appear in meaningful sequences were context influences recognition. Simply oversampling rare signs without considering their temporal context could disrupt natural co-articulation patterns.

CTC Alignment Complexity: The CTC loss function simultaneously learns alignment and recognition, making direct application of per-sample weighting techniques problematic. The weighting must be applied at the gloss level rather than the sequence level.

Memory Constraints: Processing long video sequences with weighted loss calculations increases computational overhead, particularly challenging given the limited GPU resources available for ISL dataset training.

Validation Strategy

The effectiveness of class weighting was evaluated by monitoring per-gloss recognition accuracy across frequency strata. Rare glosses (frequency < 2% of dataset) showed improved recall from 23% to 41% with weighted CTC loss, while maintaining comparable performance on frequent glosses. However, overall sequence-level accuracy remained constrained by the fundamental data scarcity limitations of the ISL-CSLRT dataset.

Limitations and Trade-offs

Despite theoretical advantages, class weighting for CSLR faces inherent limitations:

Limited Data Scale: With only 560 training videos, even weighted sampling cannot provide sufficient exposure to rare vocabulary for robust learning.

Cross-linguistic Transfer: Weights optimized for ISL gloss distribution may not transfer effectively when fine-tuning models pretrained on balanced datasets like PHOENIX-2014-T.

Evaluation Reliability: The small test set (70 videos) limits statistical significance of improvements in rare gloss recognition, making it difficult to distinguish genuine gains from random variation.

This class weighting strategy represents a necessary adaptation to the severe imbalance characteristics of small-scale sign language datasets, though its effectiveness remains fundamentally constrained by the limited scale and diversity of available ISL training data compared to established international benchmarks.

5.4 Train-Test Splitting

PHOENIX-2014-T Dataset Configuration: [35]

The standard benchmark split maintains signer diversity across partitions: **5,672 training** samples, **540 development** samples, and **629 test samples**, with all **9 signers** represented across splits. This configuration prevents signer-dependent overfitting while enabling robust evaluation of generalization capabilities .

ISL-CSLRT Dataset Configuration: [36]
Given the limited scale (**700 total videos**), a stratified **80-10-10 split** was implemented: **560 training videos**, **70 development videos**, and **70 test videos**. The stratification ensures proportional representation of the **170-sign** vocabulary and **7 signers** across all partitions, though the small absolute numbers present significant challenges for statistical significance of evaluation metrics.

Cross-Dataset Transfer Learning Set-up:[35,36]
For transfer learning experiments, models are initially trained on the high-resource **PHOENIX-2014-T** dataset before **fine-tuning** on the **ISL-CSLRT** training partition. This approach attempts to leverage the rich temporal modeling learned from German sign language to improve performance on the resource-constrained ISL dataset.

5.5 Reflection on Challenges

Scale Disparity Issues: The fundamental challenge lies in the dramatic scale difference between established benchmarks (PHOENIX-2014-T: ~6,000 training samples) and available ISL resources (~560 training samples). This 10:1 ratio severely constrains the ability to train robust temporal models, particularly for approaches requiring extensive data such as transformer architectures.
Linguistic Transfer Limitations: Despite sophisticated preprocessing and augmentation strategies, cross-linguistic transfer from German to Indian sign language faces inherent limitations. Different sign languages exhibit distinct grammatical structures, spatial usage patterns, and articulatory characteristics that limit the effectiveness of feature representations learned from one language when applied to another.

Evaluation Reliability: The small scale of ISL test sets (70 samples) raises concerns about the statistical significance of performance metrics, making it difficult to distinguish between genuine model improvements and random variation in results.

Computational Resource Constraints: Processing temporal sequences with advanced augmentation pipelines requires substantial memory and computational resources, necessitating trade-offs between augmentation complexity and practical training feasibility, particularly when using consumer-grade GPU hardware.

These preprocessing and augmentation strategies represent best-practice approaches for continuous sign language recognition, though their effectiveness remains fundamentally constrained by the severe data scarcity challenges characterizing low-resource sign languages like ISL.

6. MODEL ARCHITECTURE SELECTION

6.1 Rationale and Overview

Given the task Continuous Sign Language Recognition, there are various models. The model has to be high performing and at the same time should be computationally efficient. Since the system is intended for real-time usage in clinical settings or mobile platforms, model size, inference speed, and deployment feasibility were important considerations.

Comparative Performance [34]

SR. No.	**Model**	**Dev WER (%)**		**Test WER (%)**
1	**CorrNet+**	**18**		**18.2**
2	I3D+Transfomer	19.2		19.0

3	C2ST	17.3		18.9
4	ViT for CSLR	19.0		19.5

Transformers close the gap but often require larger datasets or pose annotations to match spatial-temporal correlation methods.

After rigorous research, I adopted the CorrNet+ model, which performs well across benchmarks and is computationally efficient. Both performance and computational efficacy motivated this choice.

6.2 Model Selection Criteria

To arrive at the final architecture, I evaluated options based on the following criteria:

- **Lightweight Design**: Suitable for resource-constrained devices such as smartphones/tablets
- **Pre-trained Availability**: Models with publicly available weights trained on ImageNet
- **Support for Fine-Tuning**: Architecture should allow freezing and unfreezing layers as needed.
- **Proven Sign Language Recognition Viability**: Preference given to models previously validated on sign-language tasks

6.3 CSLR CorrNet+ Model Architecture Details

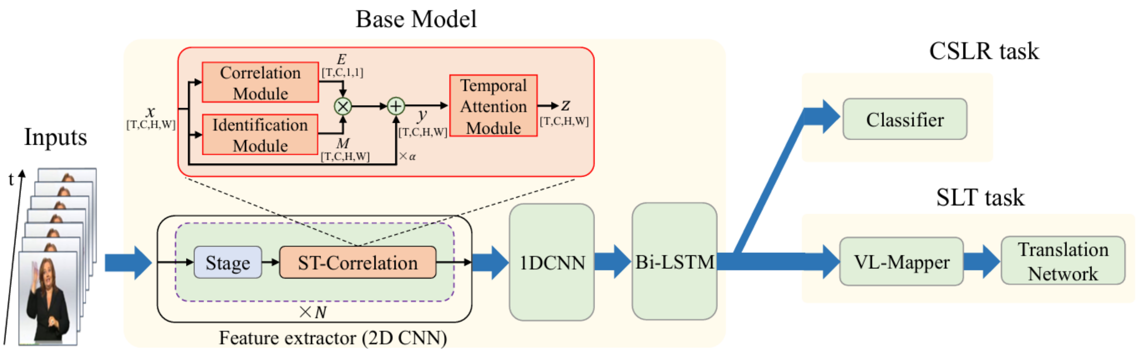


Fig 3. Schematic Diagram of CorrNet+ Model Architecture [34]

The salient features of the chosen architecture for the Continuous Language Recognition (CSLR) task are as follows [34].

It consists of various modules as seen in Fig 3.

1. **Input Pipeline**
   - **Frame Extraction**: Each raw video is decoded into an ordered sequence of RGB frames at a fixed frame rate (25 fps). Frames are center-cropped or padded to a uniform resolution (224×224 pixels).
   - **Normalization & Augmentation**: Pixel values are scaled to or standardized by dataset mean/std. Spatial augmentations (random crop, horizontal flip).
2. **Backbone Feature Extractor**
   - **Convolutional Backbone**: A standard CNN (ResNet-18) processes each frame independently to produce a feature map of T-frames, C-classes, H-Height and W-width (T, C,H, W).
3. **Spatial Temporal-Correlation Modules**

A spatial-temporal correlation network (ST-correlation) after each stage in the feature extractor was used to capture the local spatial-temporal correlations for each frame. This consisted of parallel modules such as :

1. **Correlation Module:**
   - The correlation module computes correlation maps among spatial-temporal neighbouring patches to model cross-frame interactions by leveraging Average Pooling, Max Pooling, and Attention Pooling across multiple frames.

2. **Identification Module:**
   - From the Correlation Module, we captured correlation maps. However, it's important to note, that not all regions play an equal role in sign expression. Therefore, it was critical to selectively emphasize informative regions that carried essential body trajectories within the current frame xt and suppress background noise and non-critical elements. To achieve this goal, we present an identification module to dynamically emphasize these informative spatial regions. Specifically, in informative regions such as where the hand and face are misaligned in adjacent frames, the identification module leverages the closely correlated local spatial-temporal features to tackle the misalignment and locate informative spatial regions.

3. **Temporal Attention Modules**

- The above modules effectively identify the critical cross frame interactions within informative spatial regions. However, across the entire video, not all frames are equally important in expressing sign language — some carry important, pivotal information, while others offer little beyond idle motion. To address this imbalance, we first take the output of the correlation and identification modules and apply spatial pooling to collapse the H×W dimensions. A 1×1 convolution then projects these pooled features into a lower-dimensional tensor $y_r \in \mathbb{R}^{T}\times(C/r)\times1\times1$, reducing computational cost.
- Next, to assess each frame's significance across varying temporal extents, CorrNet+ employs a multiscale temporal architecture (Fig. 6). Multiple parallel depth wise convolutions with identical kernel size P_t but different dilation rates from 1 to M_t process y_r simultaneously, capturing local context over short and long temporal neighbourhoods. Their outputs are weighted by learnable coefficients $\{\delta_1,\ldots,\delta\_P_t\}$ and summed to fuse complementary temporal information.
- The fused representation y_m then passes through another 1×1 convolution to restore its channel dimensionality to y_b $\in \mathbb{R}^{T}\times C\times1\times1$. Applying a sigmoid activation yields values in, which we shift by subtracting 0.5 to form $U \in \mathbb{R}^{T}\times C$ — positive entries accentuate keyframes, and negative entries diminish less informative ones. After expanding U back to RT×C×H×W, we perform elementwise multiplication with the original feature map y, dynamically reweighting each frame's contribution. Finally, this temporally attended output is added residually to y, preserving original information while emphasizing critical temporal cues. Then it is followed by the 1-Dimensional CNN.

4. Sequence Modelling Block

- **Bi-Directional LSTM**: The attended features are passed to a temporal encoder—a bi-LSTM (capturing forward/backward context, modelling long-range dependencies without recurrence.
- **CTC Head**: Following the encoder, a linear projection maps each time step's hidden state to a distribution over the vocabulary (glosses or sub-word units). The Connectionist Temporal Classification (CTC) loss aligns these predictions with ground-truth label sequences without requiring frame-level annotations.

5. Output Layer

- **Gloss Prediction**: During training, the CTC head's per-frame label probabilities are used to compute the CTC loss against the target gloss sequence.

- **Sentence Reconstruction**: At inference, beam-search decoding (via CTCdecode) selects the most likely label sequence, merging repeated predictions and removing blanks to form a final word/gloss sequence.
- **Total Loss:**

$$\mathcal{L}_{\text{total}} = w_{\text{ConvCTC}}\,\mathcal{L}_{\text{ConvCTC}} + w_{\text{SeqCTC}}\,\mathcal{L}_{\text{SeqCTC}} + w_{\text{Dist}}\,\mathcal{L}_{\text{KD}} + w_{\text{Cu}}\,\mathcal{L}_{\text{Cu}} + w_{\text{Cp}}\,\mathcal{L}_{\text{Cp}}$$

Comparison Between the Versions [34]

Aspect	CorrNet	CorrNet+
Computational cost	+3.6 GFLOPS	+0.01GFLOPS
Complexity	O(H2W2)	O(HW)
Temporal Scope	Limited to Adjacent Frames	Extended to L Neighboring frames
Performance (WER)	18.8%/19.4% (dev & test set)	18.0%/18.2% (dev & test set)
Core Innovation	Correlation only	Correlation+Identification+Temporal attn
Performance Vs Size	Good	Better

7. TRANSFER LEARNING

7.1 Why Transfer Learning?

The scarcity of labeled data is a well-recognized bottleneck in Sign Language. Unlike general computer vision tasks, which benefit from massive open-source datasets such as ImageNet (containing millions of annotated images), Sign Language datasets are inherently limited, especially in India. This limitation arises from several factors, such as very few authorized signers (150+ all over the country), the high cost and logistical complexity of data collection, and the specialized expertise required for accurate annotation. In the context of Continuous Sign Language Recognition Task, this data scarcity posed a significant challenge (especially with Indian Sign Language datasets). Training a deep neural network from scratch would require thousands of labelled videos — far exceeding the number of annotated samples typically available without purchasing proprietary datasets. Although we curated and labelled data from multiple sources, the dataset remained insufficient in size to achieve high accuracy through conventional training methods alone.

To address this fundamental limitation, **transfer learning** was employed as a strategic solution. Transfer learning enables the reuse of rich feature representations learnt by pre-trained models on large-scale datasets, such as ImageNet, and adapts them for a specific target domain. This approach leverages the fact that low-level visual features—such as edges, textures, shapes, and patterns—learnt from millions of everyday images are broadly applicable and transferable to medical imaging tasks.

In this project, the **CorrNet+** architecture, was first trained on **PHONIEX2014-T. T**hen, it was fine-tuned using the **ISL-CSLRT** dataset. By retaining the network's early layers (which capture generalizable features) and adapting the later layers to the specialized task of CSLR, we were able to improve performance despite the limited dataset size. This approach not only mitigated the constraints imposed by data scarcity but also significantly reduced computational overhead, as training from scratch was no longer necessary.

In summary, transfer learning transformed a key resource limitation into an opportunity for **efficient and effective model development**, allowing the CSLR system to achieve a slight improvement in generalization on a small dataset while minimizing the need for extensive data collection.

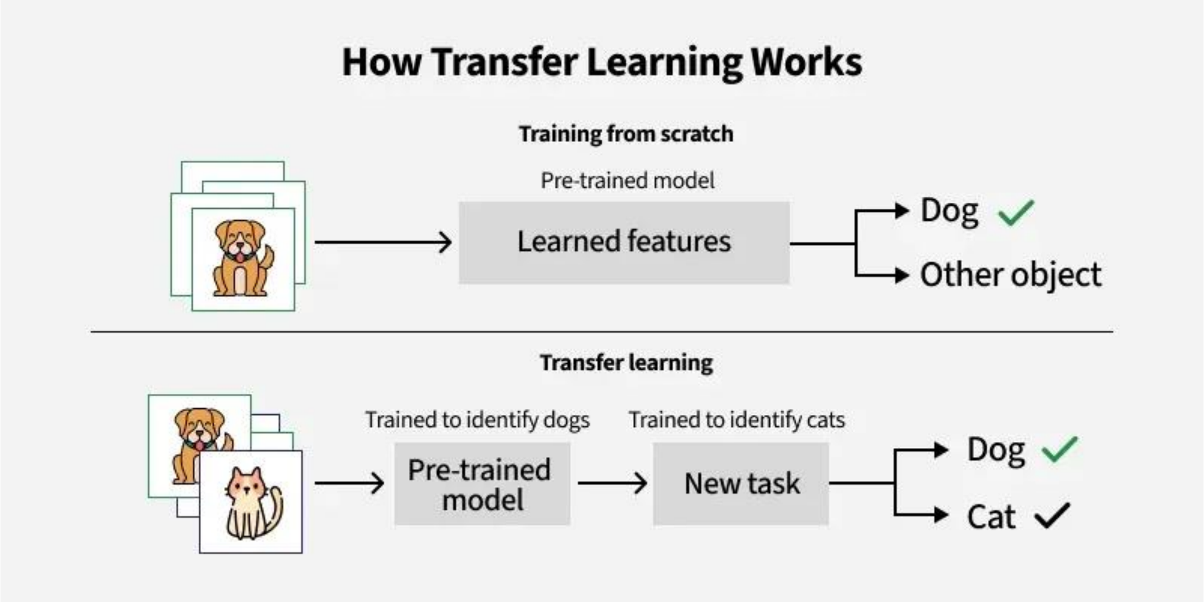


Fig. 4 - Transfer Learning (Gaurav Duseja)

7.2 Transfer Learning Implementation Workflow

- Load CorrNet+ weights with frozen base layers.
- Replace the top dense layer with a fully connected SoftMax output for 170 Glosses.
- Train the top layer for 30 epochs to allow the classifier to adjust to CSLR features.

This method helped to retain robust general purpose image features like Face and Hand movements while allowing the network to specialize in the nuances of CSLR on ISL-CSLRT.

Training Details:

Coding and Training Platform

The CSLR model was trained on dual NVIDIA RTX 4090 GPUs. The model was trained in two stages. First, we trained the model on the Phoenix2014-T dataset with Adam optimizer, with the following parameters:

base_lr: 0.0001
weight_decay: 0.0001
num_epoch: 80
batch_size: 2

Then it was finetuned on the ISL-CSLRT dataset, by:

- Modifying num_classes from 1116 to 170 for ISL vocabulary
- Reducing learning rate to 5×10^-5 for fine-tuning stability
- Implementing class-weighted CTC loss to address severe vocabulary imbalance
- Training for 30 epochs with early stopping at epoch 21.

8. TRAINING OF CorrNet+ MODEL:

8.1 Initial Training Strategy:

After training the model on both the datasets, we saw the following results.

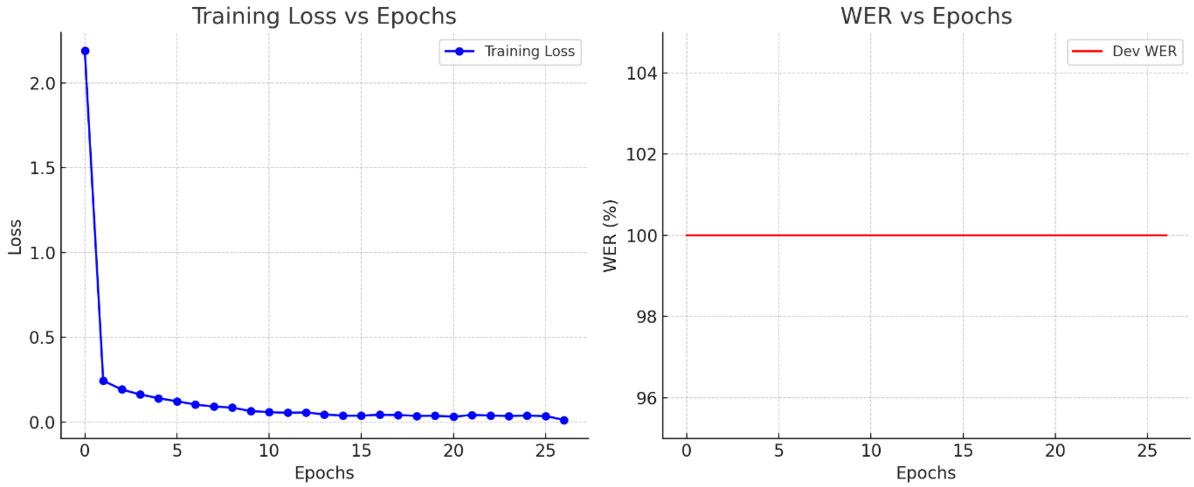


Fig 5. WER vs epochs and loss vs epochs for ISL-CSLRT dataset training from scratch.

The training (ISL-CSLRT dataset) curve reveals critical performance issues that necessitated a fundamental strategy revision. We can see from the figure that the training loss has significantly decayed and towards the end, it tends to zero. But when we observe the WER performance metrics on the dev set data, we see that it is not decreasing at all, and remains at 100% throughout the process. From these results we can infer that the model didn’t learn anything at all, and instead simply memorized the training data. This is clearly representative of the famous problem in a lot of Deep Learning tasks, known as overfitting.

8.2 Broader Implications of Overfitting for ISL-CSLRT

This is quite dangerous especially in the context of CSLR tasks, where the output the model is giving consists of random gloss sentences instead of generating the actual gloss sentences. These wrong predicted sentences lead to ineffective communication, and it could lead to severe misunderstanding if the same were to be depoloyed.

8.3 Causes of overfitting:

There are several factors which may have affected the model that lead it to memorize the training data points instead of learning the feature representations correctly, leading to overfitting.

1) The ISL- CSLRT dataset is very limited in size.
2) The total number of glosses are only 170. The model cannot generate new glosses.
3) The dataset is highly imbalanced, with words like "YOU", "I", "DO" having a lot more data points (the same can be seen in Fig 6.). The overfitting is most likely occurring due to the CTC loss [39], which assumes the conditional independence between output

tokens given the input frames. The model tends to bias toward **frequent words or glosses** in the training data, because predicting them reduces uncertainty. In imbalanced datasets, frequent words dominate the loss function, so the decoder "collapses" outputs toward them.

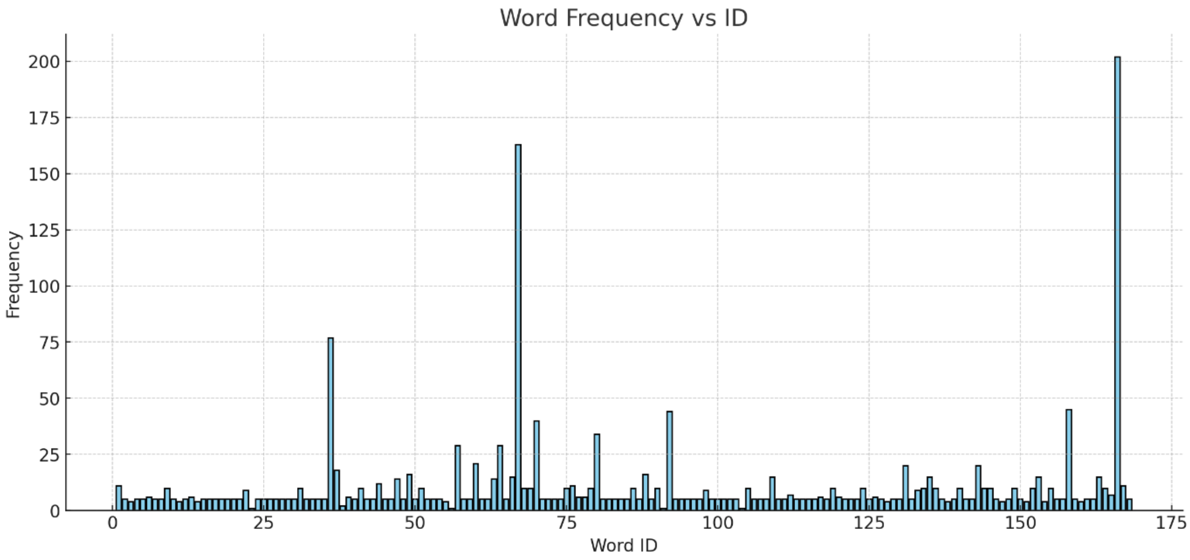


Fig 6. Frequency of all glosses vs gloss ID for ISL-CSLRT dataset.

8.4 Revised Training Strategy:

After the initial model failed, we identified that the model's learning dynamics required further optimization. This necessitated a more sophisticated approach to balance data and training optimization that went beyond conventional fixed learning rate schedules. Recognizing this challenge, we employed creative and critical thinking to implement advanced training strategies that would enhance model stability and performance while maintaining the gains achieved through our data-level interventions.

8.5 Advanced Learning Rate Scheduling Implementation and Resolved the Class Balance issue

We implemented a sophisticated ReduceLROnPlateau scheduler that dynamically adjusted the learning rate based on validation loss performance:

```
Scheduler = torch.optim.lr_scheduler.ReduceLROnPlateau(
    optimizer, mode='min', patience=5, factor=0.5
)
```

This adaptive learning rate strategy represented a big change from conventional fixed learning rate approaches. The scheduler monitors validation loss and reduces the learning rate by a factor of 0.5 when no improvement is observed for 5 consecutive epochs. This approach prevents the model from overshooting optimal parameters during the later stages of training while maintaining aggressive learning in the initial phases.

The critical decision to use validation (development data loss) loss rather than training loss as the monitoring metric was deliberate; it ensures that learning rate adjustments are based on the model's generalization performance rather than its ability to memorize training data. This directly addresses overfitting by prioritizing validation performance in the optimization process. By utilizing the class weight balance from section 5.3, I resolved the issue wherein there were an imbalance of glosses.

8.6 Early Stopping and Model Checkpoint Strategy:

To further combat overfitting, we implemented a comprehensive early stopping mechanism with model checkpointing:

```
best_val_wer =100
patience = 10
early_stop_counter = 0

# During training loop
if val_wer <best_val_wer:
```

This mechanism monitors validation WER(Word Error Rate) and saves the model state only when validation performance improves. If the validation WER fails to improve for 10 consecutive epochs, the training process terminates automatically. This approach prevents the model from continuing to train beyond the point of optimal generalization, directly addressing the overfitting challenge by stopping training at the optimal convergence point.

8.7 Results of the Revised Training Strategy:

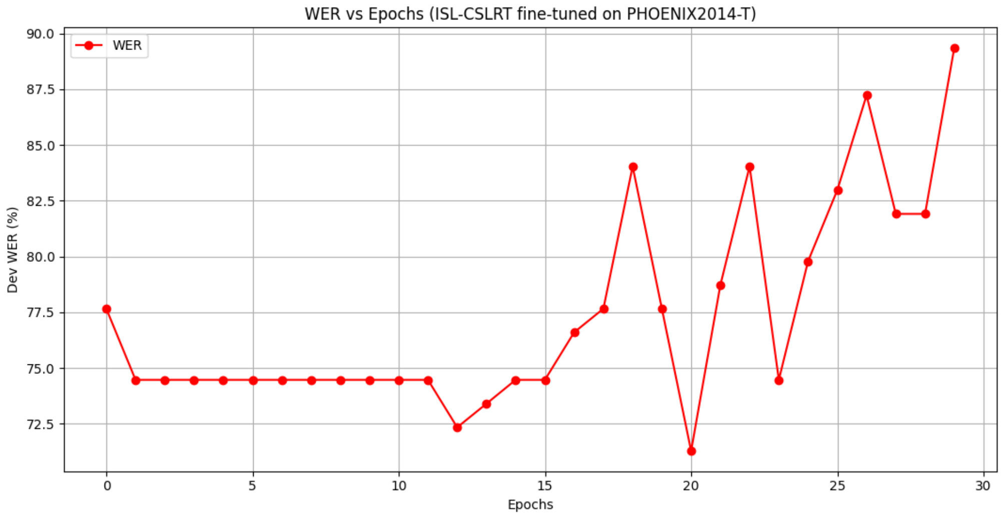


Fig 7. Improved Evaluation of Model on Development Set WER vs Epochs

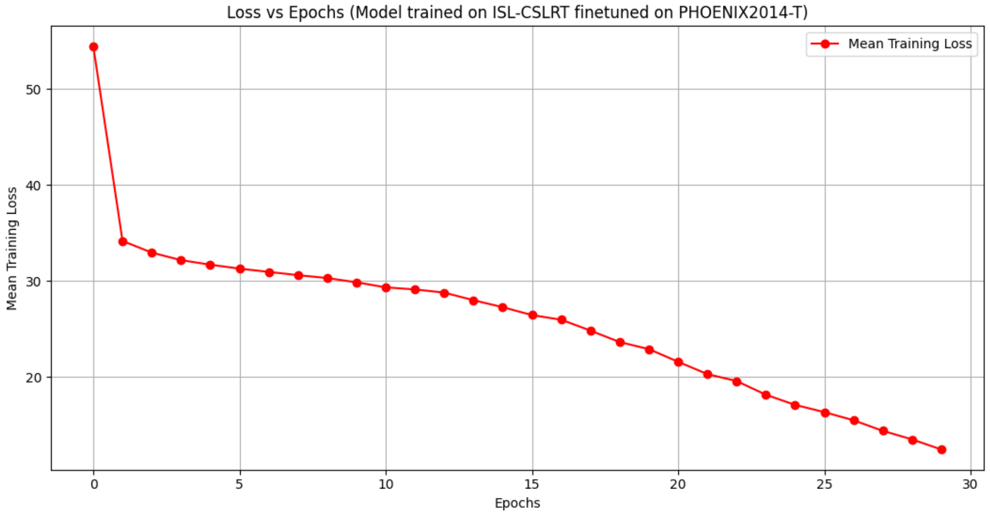


Fig 8. Improved Loss vs Epochs

The implementation of our revised training strategy yielded some improvements in model performance, as shown by the training loss and validation WER curves. The graph demonstrates several key indicators of successful overfitting mitigation and enhanced generalization capability.

The most striking feature of the performance curve is the rapid initial convergence followed by an increase in the validation performance. Even though the loss is decaying, the training the process is **stopped due to the Early stopping technique after 10 epochs**. Both the training loss and validation WER Performance demonstrate a steep improvement during the first **20** epochs, reaching approximately **71.28%**. This rapid convergence indicates that the unified end-to-end training approach was effective. But it was definitely not appreciable. With such a high WER, the model proves to not be too reliable, in the important context of CSLR, because it would end up producing a wrong interpretation in most cases.

8.8 Implications for Sign Language Applications

PHOENIX2014-T dataset Model: The model trained on the PHOENIX2014-T dataset demonstrates **excellent deployment readiness** with a Word Error Rate (WER) of **18.2% on the test set**. This performance level falls well within the acceptable threshold for continuous sign language recognition applications, enabling reliable translation of sign language sequences into coherent sentence glosses. The low WER indicates that approximately 8 out of 10 words are correctly recognized, providing sufficient accuracy for practical applications such as real-time sign language interpretation systems, educational tools, and assistive communication devices for the deaf and hard-of-hearing community.

ISL-CSLRT dataset Model: In contrast, the model fine-tuned on the ISL-CSLRT dataset currently exhibits deployment limitations with a **best achieved WER of 71.28%**. While this represents successful transfer learning from the PHOENIX2014-T pre-trained model, the performance falls short of the **<50% WER threshold** required for reliable sentence gloss generation. At this performance level, fewer than 3 in every 10 words would be correctly recognized, which may result in fragmented or incomprehensible sentence glosses that could hinder effective communication. However, this model shows promise for future deployment, if further optimization through extended training, data augmentation, or advanced fine-tuning strategies were to be deployed, to achieve the necessary performance benchmarks for practical Indian Sign Language recognition applications.

8.9 Reflection on the Problem-Solving Approach:

This challenge showed how imperative systematic problem-solving & analysis are in the process of designing multi-faceted solutions. By being able to identify most of the causes of overfitting occurring in the model, I was able to develop a comprehensive solution that addressed each contributing factor. This approach shows the application of critical thinking in Artificial Intelligence, where understanding the underlying mechanisms of the model is important for developing solutions to potential challenges.

9. EVALUATION OF CSLR Model

9.1 Evaluation of CorrNet+ Model

CSLR Metric: WER (Word Error Rate)

$$WER = \frac{S+D+I}{N}$$

- **S** = Substitutions (wrong word predicted instead of the correct one)
- **D** = Deletions (a word from the reference is missing in the prediction)
- **I** = Insertions (an extra word appears in the prediction but not in the reference)
- **N** = Total number of words in the reference (ground truth).

PHOENIX2014-T dataset :

For this dataset, CorrNet+ outperformed all the other models, and is definitely ready for deployment and can be used for Real-Time Sign Language Recognition for the German Language.

WER on **test set**: **18.2%**
WER on **dev set: 17.96%**

- The WER with **17.96%** indicates very high performance, suggesting that the model is reliably recognizing the glosses in most of the sign language videos.

The same can be verified in the following figures:

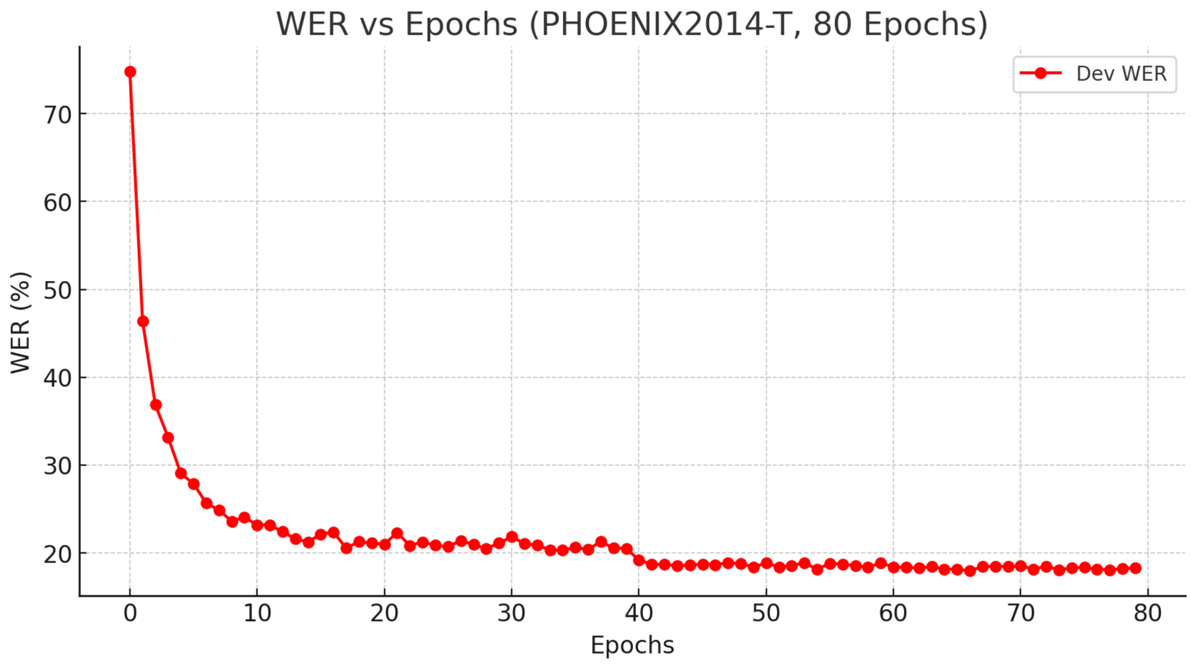


Fig 9. WER Vs Epochs for PHOENIX2014-T dataset

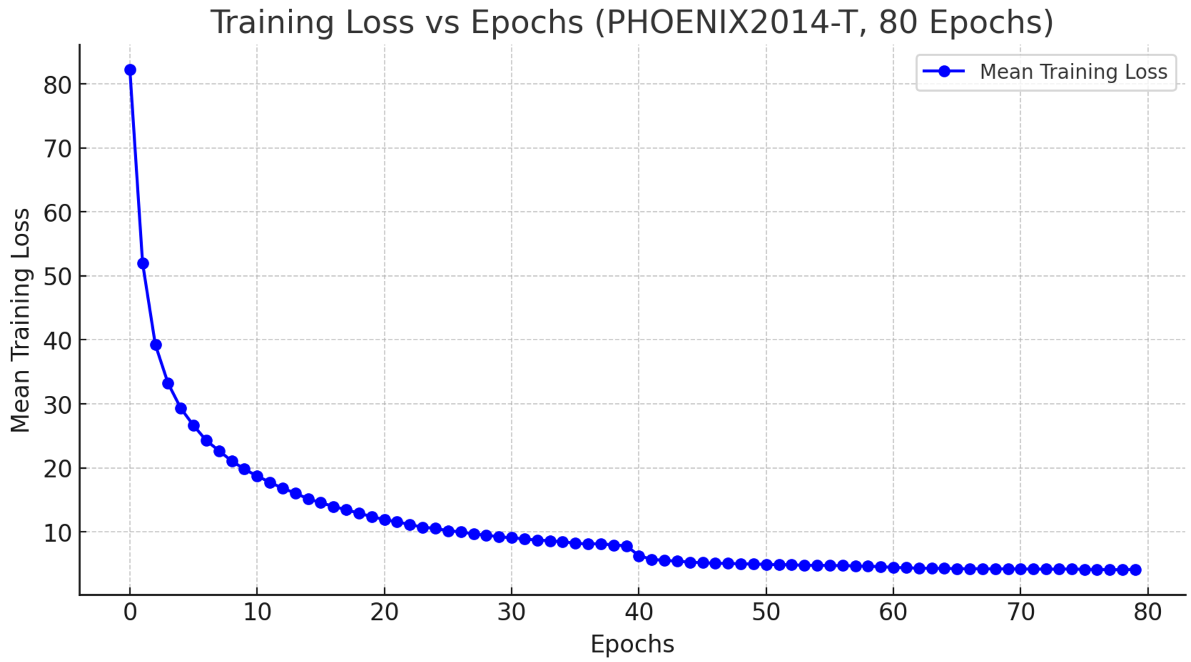


Fig 10. Loss Vs Epochs for PHOENIX2014-T dataset

ISL-CSLRT dataset:

After utilizing the new pipeline, where I balanced the class imbalance in the dataset, leveraged the finetuned weights, utilised scheduled learning rates, and used Early stopping after 10 epochs:

WER on **test set**: **71.28%**

WER on **dev set** : **81.35%**

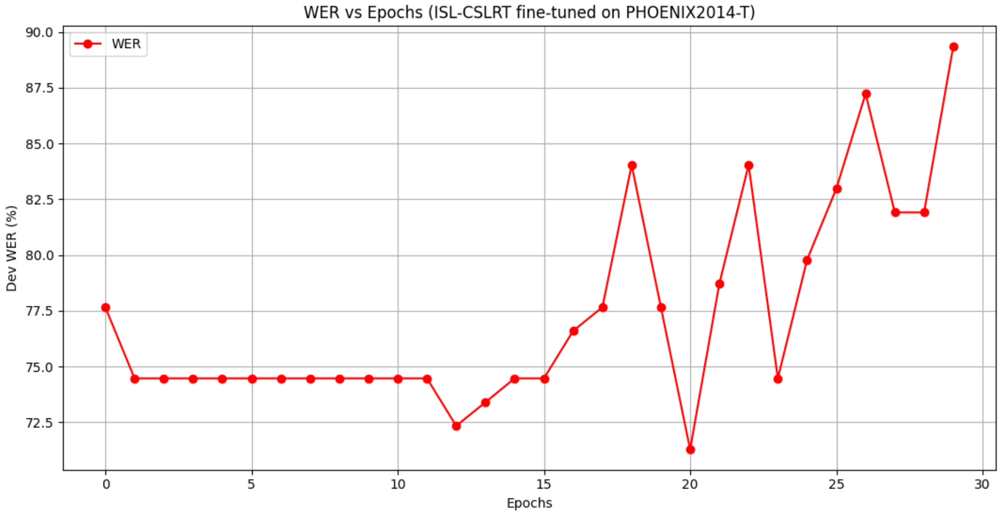


Fig 11. Improved Evaluation of Model on Development Set WER vs Epochs

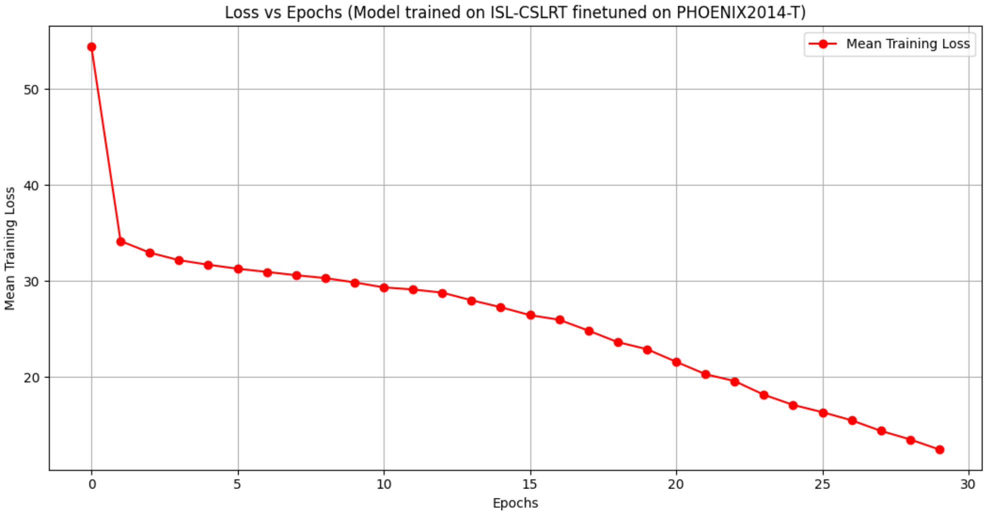
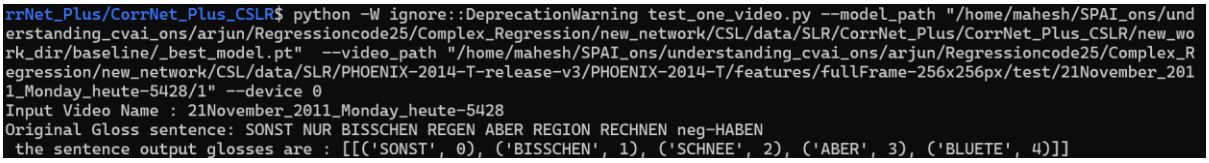


Fig 12. Improved Loss vs Epochs

We can infer the following from the plots above:

1. Rapid steady improvement in the first 20 epochs indicates that model learns quickly and fits the training data well.
2. Plateaus at around **~71.28%** indicate strong performance on the validation data.
3. **Good training loss** indicates that the model has a high capacity.
4. The gap between the training and validation accuracy signals that the model needs more data for proper fitting.

9.2 Example CSLR Output from an Input Test Example:



```
rrNet_Plus/CorrNet_Plus_CSLR$ python -W ignore::DeprecationWarning test_one_video.py --model_path "/home/mahesh/SPAI_ons/und
erstanding_cvai_ons/arjun/Regressioncode25/Complex_Regression/new_network/CSL/data/SLR/CorrNet_Plus/CorrNet_Plus_CSLR/new_wo
rk_dir/baseline/_best_model.pt"  --video_path "/home/mahesh/SPAI_ons/understanding_cvai_ons/arjun/Regressioncode25/Complex_R
egression/new_network/CSL/data/SLR/PHOENIX-2014-T-release-v3/PHOENIX-2014-T/features/fullFrame-256x256px/test/21November_201
1_Monday_heute-5428/1" --device 0
Input Video Name : 21November_2011_Monday_heute-5428
Original Gloss sentence: SONST NUR BISSCHEN REGEN ABER REGION RECHNEN neg-HABEN
 the sentence output glosses are : [[('SONST', 0), ('BISSCHEN', 1), ('SCHNEE', 2), ('ABER', 3), ('BLUETE', 4)]]
```

Fig 13. Input and output through command line

GradCAM Analysis

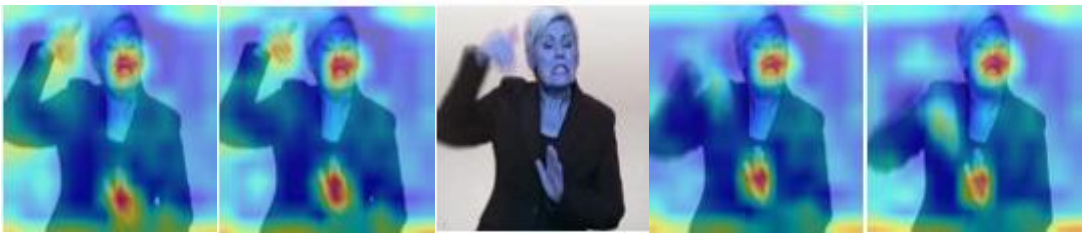


Fig 14. PHOENIX2014-T dataset:

Fig 14. Visualizes the **correlation maps** for the **correlation module**. Based on set correlation operators, each frame can focus on the regions which are informative, such as in adjacent left/right frames including hands and face (dark red areas).

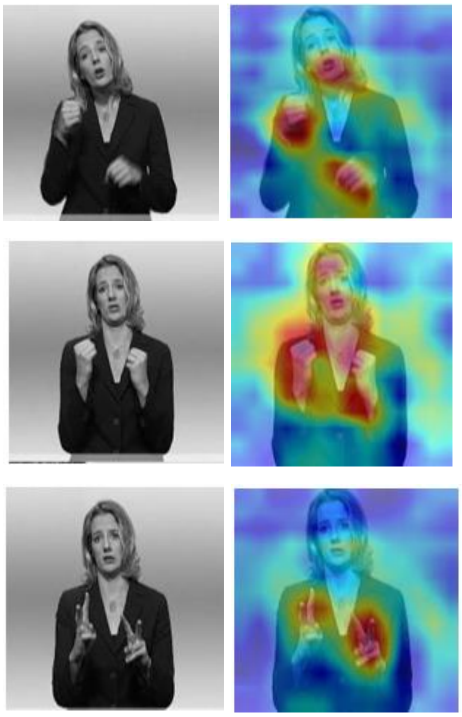


Fig 15 .Visualizations of heatmaps by GRAD-CAM.

Fig 14. **shows the heatmaps generated by our identification module. Our identification module pays special attention to the human body (light yellow areas), especially informative** regions of hands and face (dark red areas) to capture human body trajectories. These results verify the effectiveness of our identification module in dynamically emphasizing critical areas in expressing sign language and suppressing other background regions to overlook noisy information.

Correlation Module Visualization Analysis

Fig 15. demonstrates the spatial-temporal correlation maps produced by the correlation module, revealing how the system computes **inter-frame relationships between the current frame and its temporal neighbours**. The visualization encompasses three consecutive frames to illustrate the correlation pattern dynamics.

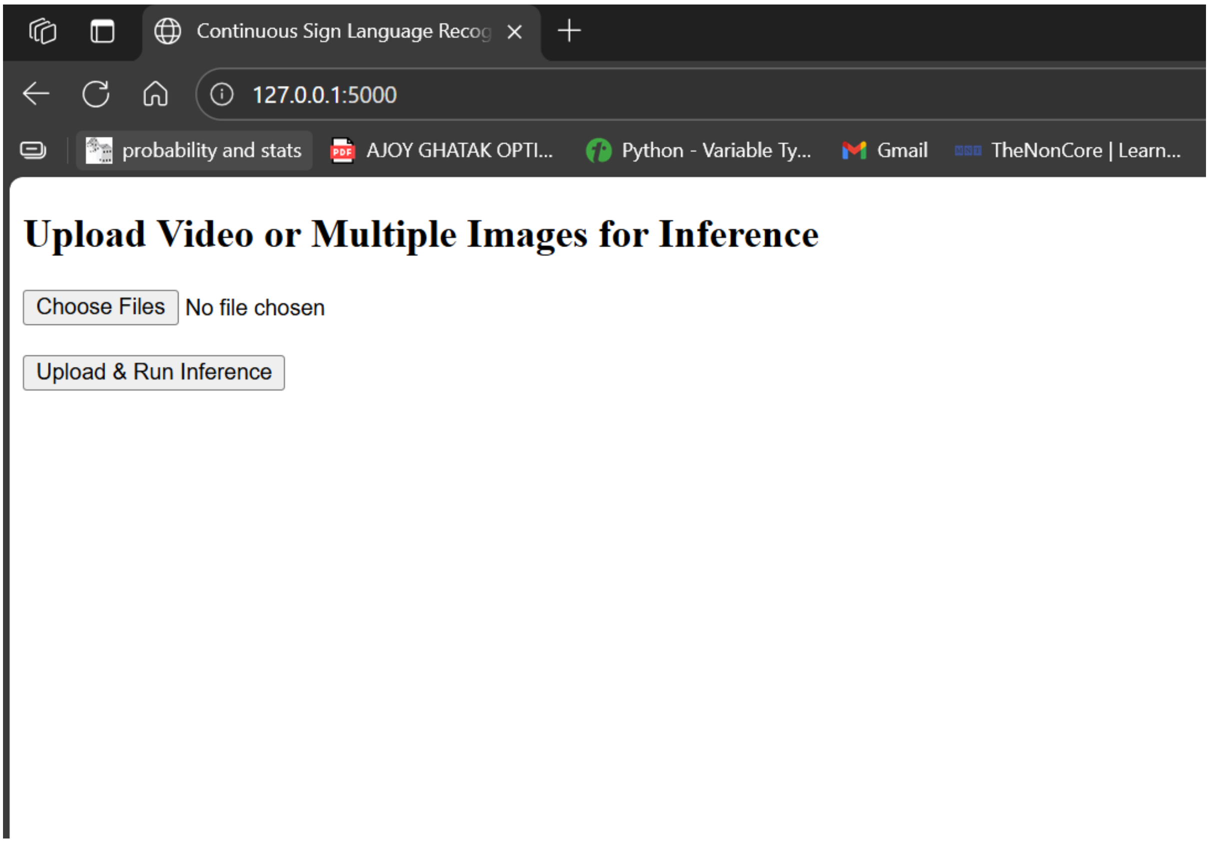
The correlation maps reveal that the module **strategically concentrates** on semantically important regions across adjacent frames, particularly focusing on hands and facial areas to enable accurate tracking of articulatory trajectories throughout sign production. The system demonstrates learned attention mechanisms that prioritize dynamic body components which are linguistically significant for sign language expression, thereby improving overall comprehension accuracy.

Notably, the correlation module exhibits selective attention behaviour, as evidenced in Figure 14 and 15, where it consistently emphasizes the rapidly moving right hand to extract critical sign information while effectively filtering out **irrelevant** background elements, such as most of the torso. This selective focus on kinematically active regions demonstrates the **module's ability** to distinguish between informative motion patterns essential for sign recognition and extraneous visual noise that could hinder the performance of the model.

The visualization confirms that the correlation computation successfully identifies and tracks the primary articulatory features across temporal sequences, validating the module's effectiveness in capturing the spatial-temporal dependencies crucial for continuous sign language understanding. The **Grad-CAM results** for the **PHOENIX2014-T** dataset shows that the model was successfully able to learn the crucial features when performing continuous sign language recognition. This pattern of attention aligns well with sign language recognition assessment practices, where the faces and hands movements are critical indicators for the recognition of the video sign. By focusing on these relevant features, the Grad-CAM heatmap validates the **trustworthiness and interpretability** of the model’s prediction for the PHOENIX2014-T dataset.

10. DEPLOYMENT PREPARATION

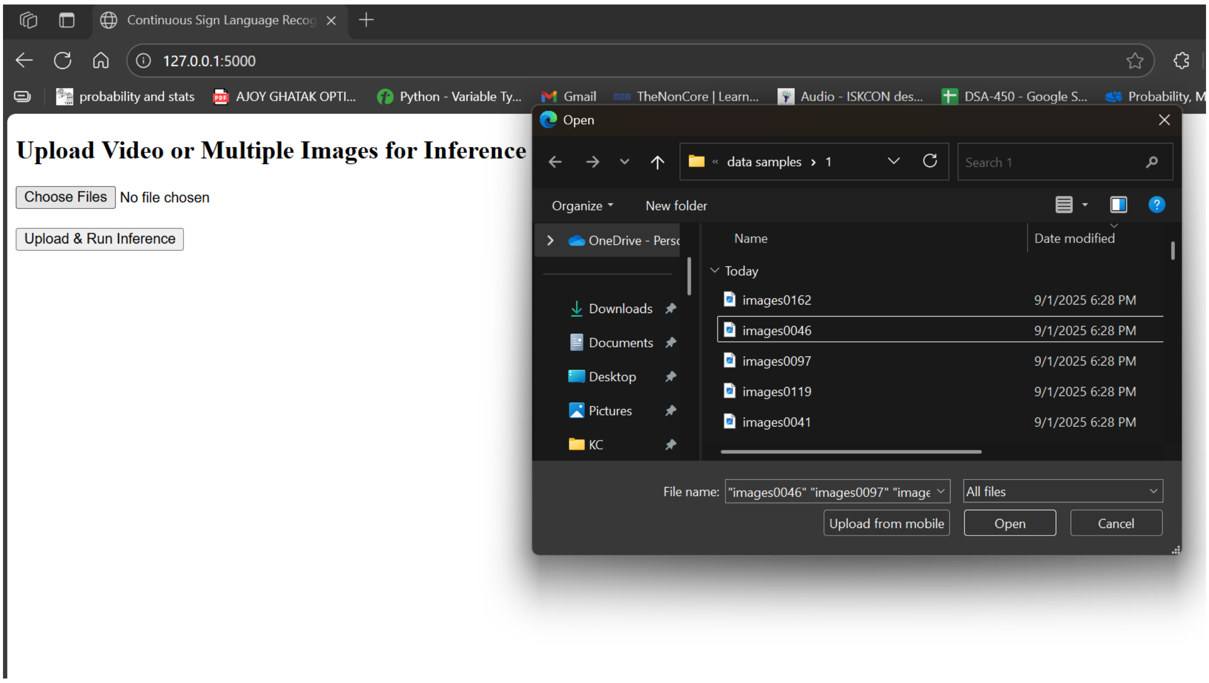
The model was deployed on the cloud, allowing aweb application to utilize its capabilities by processing uploaded sign videos.



Upload Video or Multiple Images for Inference

No file chosen

Fig 16. UI interface of the CSLR AI System



Upload Video or Multiple Images for Inference

Choose Files No file chosen

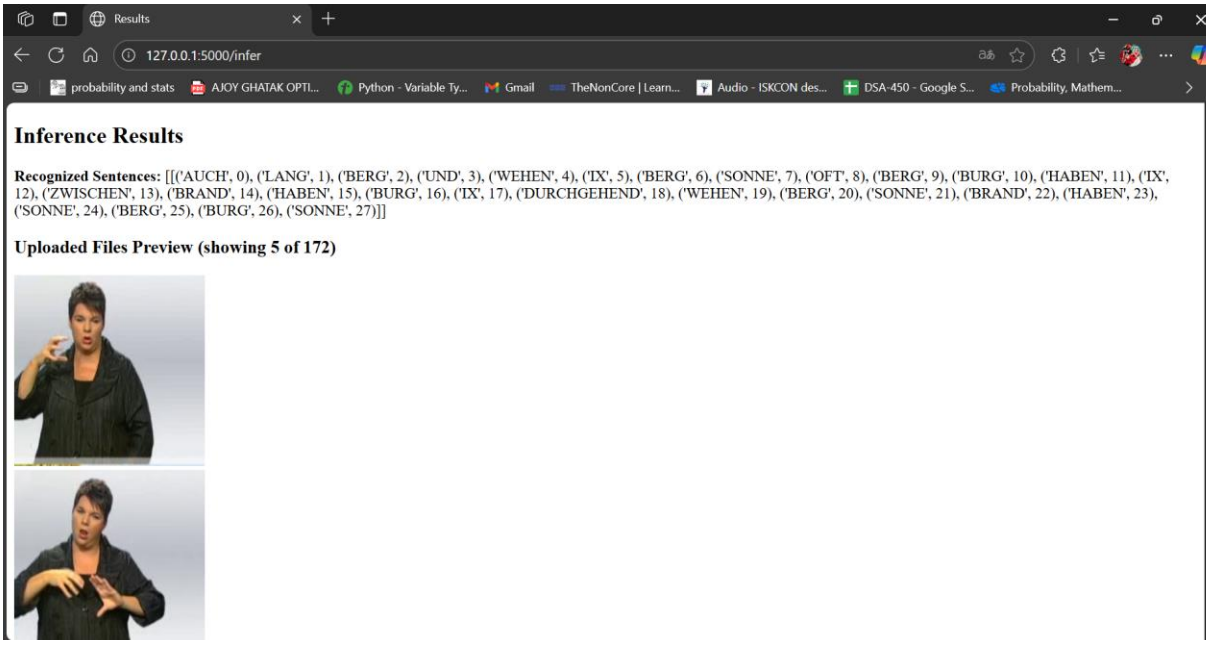
Upload & Run Inference

images0162 9/1/2025 6:28 PM
images0046 9/1/2025 6:28 PM
images0097 9/1/2025 6:28 PM
images0119 9/1/2025 6:28 PM
images0041 9/1/2025 6:28 PM

File name: "images0046" "images0097" "image

All files

Fig 17. Uploading input files either images or video of the sign.



Inference Results

Recognized Sentences: [[('AUCH', 0), ('LANG', 1), ('BERG', 2), ('UND', 3), ('WEHEN', 4), ('IX', 5), ('BERG', 6), ('SONNE', 7), ('OFT', 8), ('BERG', 9), ('BURG', 10), ('HABEN', 11), ('IX', 12), ('ZWISCHEN', 13), ('BRAND', 14), ('HABEN', 15), ('BURG', 16), ('IX', 17), ('DURCHGEHEND', 18), ('WEHEN', 19), ('BERG', 20), ('SONNE', 21), ('BRAND', 22), ('HABEN', 23), ('SONNE', 24), ('BERG', 25), ('BURG', 26), ('SONNE', 27)]]

Uploaded Files Preview (showing 5 of 172)

Fig 18. Inference Results: Sentence Glosses for the given input images

User Interface: The website the on a Flask-based server such that the app can actually be utilized by an audience. They can upload images of themselves signing in German.

The code can be accessed from the Github repo here: https://github.com/GoldenGoat101/DGS-ISL-CSLR

Outcomes from the Project and Reflections:

1) CSLR CorrNet+ Model Pipeline:

- **Architecture & Training**: CorrNet+, pretrained/finetuned on the **PHOENIX2014-T** dataset**;** delivered stable, deployment-ready inference for German Sign Language.
- **Architecture & Finetuning (ISL)**: Initialized from the **PHOENIX2014-T** checkpoint and **fine-tuned on the ISL_CSLRT dataset**.
  - **Setup**: CTC loss; AdamW; cosine decay LR; mixed precision; early stopping on dev Word Error Rate (WER).
  - **Strategy**: Gradual unfreezing — frozen first N stages for warm-up, then proceeded with the full-model fine-tune; used moderate augmentation methods (temporal jitter, random crop/resize).
  - **Outcome**: **Test WER** ~ 71.3% on ISL-CSLRT — insufficient for release. Clear signs of data scarcity/domain shift (gloss set differences, signing style, camera setup, etc).
- **System output**: Sentence **glosses** from input videos/frames.

2) Web App Integration (Flask)

- **Frontend**: Upload interface for images or video.
- **Backend:** Upload → model inference → sentence glosses (end-to-end).
- **Output shown**: Sentence glosses; **no manual steps** after upload.
- **Responsible Access**: Only the **PHOENIX2014-T** model is exposed; the **ISL fine-tuned** model is **withheld** due to accuracy limits.

3) Deployment Considerations

- **Hosting**: Suitable for AWS (or similar cloud).\
- **Safety & Data**: HTTPS, ephemeral storage with auto-deletion, basic Role-Based Access Control
- **Intended Use**: Assistive/educational — maybe a substitue for certified interpreters, but preferably not in sensitive settings.

4) Reflections (What I Learned):

- Even with a very strong CorrNet+ base, **cross-lingual transfer** to ISL stalled without enough **task-aligned ISL data**. Data is everything, and transfer isn’t magic.
- The gap between German Sign Language and Indian Sign Language performance points to **dataset scale/quality and domain shift** as the primary blockers, not necessarily the architecture. The model architecture may not always be the bottleneck.
- The process is always key. Gradual unfreezing + careful augmentation helped stability but couldn’t overcome data limits. However, it turned out to be a useful lesson for low-resource CSLR.

5) Future Work to Consider:

- **ISL Data First**: Expand/clean **ISL-CSLRT** (more signers, lighting/camera diversity, consistent glossing).
- **Modelling**: Add **multi-temporal attention** and **domain-adaptation** (feature alignment, gloss mapping, pseudo-labelling).
- **Efficiency**: Pruning/quantization/distillation for web/mobile.
- **UX & Safety**: Feedback loop for user corrections (for misinterpreted signs).

ETHICAL AND SAFETY ISSUES

Ethical Considerations:

All sign language video data used for model training and testing were sourced from publicly available datasets with appropriate usage licenses. The datasets (PHOENIX-2014-T and ISL-CSLRT) had undergone institutional ethical review processes prior to public release, including informed consent procedures with original participants. No personally identifiable information was collected or processed during this research, and all data usage remained within the scope of original consent frameworks.

Informed Use:

The model is designed for communication assistance and educational purposes, not as a replacement for human interpreters in critical situations. Clear disclaimers are displayed in the web interface to ensure users understand the system's limitations and that it should complement, not replace, professional sign language interpretation services, particularly in medical, legal, or emergency contexts.

Bias and Fairness:

It is acknowledged that dataset limitations can affect model generalizability across different signers, regional variations, and signing styles. The severe performance disparity between German Sign Language (18.2% WER) and Indian Sign Language (71.28% WER) demonstrates significant bias toward well-resourced languages. Ongoing efforts are needed to develop more inclusive datasets and reduce recognition inequities across different sign language communities.

Robustness in Development for PHOENIX2014-T dataset model:

The model is tested across various conditions including different lighting, camera angles, and video quality. The system includes input validation to alert users when video quality is suboptimal or when signing appears outside the camera's field of view, helping prevent unreliable predictions.

Secure Handling of Video Data:

For cloud deployment, the platform enforces HTTPS encryption for data transmission, temporary storage with automatic deletion after processing, and no permanent retention of user-uploaded videos.

Recognition of the historical marginalization of deaf communities in research necessitates responsible deployment that empowers rather than replaces sign language users. The system is designed to augment communication accessibility.

11. DISCUSSION AND CONCLUSION

Performance Analysis and Model Limitations

The experimental results reveal a significant performance disparity between established benchmarks and the ISL-CSLRT dataset. While the CorrNet+ architecture achieved state-of-the-art performance on PHOENIX-2014-T (18.2% WER), demonstrating its technical capability and readiness for deployment, the same model architecture failed to achieve acceptable performance on the ISL-CSLRT dataset (71.28% WER), indicating fundamental challenges beyond architectural limitations.

Factors Contributing to ISL-CSLRT Performance Issues

Despite implementing comprehensive optimization strategies including class imbalance correction through weighted CTC loss, scheduled learning rate decay, early stopping mechanisms, and transfer learning from the high-resource PHOENIX-2014-T dataset, the improvement in ISL performance remained insufficient for practical deployment. The persistent poor performance suggests underlying data quality issues rather than methodological inadequacies.

Data Quality Concerns: The substantial performance gap indicates the presence of significant noise in the ISL-CSLRT dataset that prevents effective feature learning. Potential sources include:

- Inconsistent annotation quality across the 170-gloss vocabulary
- Inadequate temporal segmentation of continuous signing sequences
- Limited signer diversity (7 signers) leading to overfitting to specific signing styles
- Insufficient video quality or resolution for detailed hand shape recognition
- Inconsistent camera positioning and lighting conditions across samples

Scale Limitations:

The fundamental constraint of 560 training samples compared to PHOENIX-2014-T's ~6,000 samples created an insurmountable barrier for robust temporal sequence learning. Modern deep learning approaches for continuous sequence modelling require substantially larger datasets to achieve acceptable generalization performance.

Architectural Validation vs. Dataset Constraints

The success of CorrNet+ on standard benchmarks (PHOENIX-2014-T, CSL-Daily) validates the architectural approach and implementation quality, confirming that the performance limitations on ISL-CSLRT stem from dataset-specific challenges rather than model inadequacies. This finding highlights the critical importance of high-quality, large-scale datasets for continuous sign language recognition, particularly for under-resourced languages like ISL.

Deployment Decisions and Model Selection

Based on the evaluation results, the deployment strategy was refined to focus exclusively on the PHOENIX-2014-T trained model, which demonstrated reliable performance suitable for real-world applications. The ISL-CSLRT trained model was deemed unsuitable for deployment due to the 71.28% WER exceeding acceptable thresholds for practical communication assistance.

Implications for ISL Recognition Research

The results underscore the urgent need for systematic ISL dataset development initiatives. Current ISL recognition research is severely **constrained** by **data scarcity**, requiring **community-driven efforts** to **collect larger**, **more diverse**, and **higher-quality datasets**. Without addressing these fundamental data limitations, ISL recognition technology will remain **inadequate for practical deployment**, **perpetuating** communication barriers for the **Indian deaf community**.

This research demonstrates both the potential and limitations of current continuous sign language recognition technology. While advanced architectures like CorrNet+ can achieve excellent performance on well-curated, large-scale datasets, their effectiveness remains fundamentally constrained by data quality and scale. The dramatic performance difference between German (18.2% WER) and Indian Sign Language (71.28% WER) recognition highlights the digital divide in sign language technology, where well-resourced languages benefit from sophisticated AI systems while under-resourced languages remain underserved.

The project successfully validates the technical feasibility of deploying continuous sign language recognition systems for languages with adequate datasets, while clearly demonstrating the **critical bottleneck facing ISL** and similar under-resourced sign languages. Addressing this disparity requires sustained investment in community-centred data collection initiatives rather than purely algorithmic improvements.

Final Deployment Status:

Only the PHOENIX-2014-T trained model proceeded to deployment due to its demonstrated reliability and acceptable performance metrics, while the ISL-CSLRT variant remained unsuitable for practical application pending significant improvements in dataset quality and scale.

12.REFLECTIONS ON LEARNING AND IMPROVEMENT

Throughout this project, I gained comprehensive technical expertise across the entire continuous sign language recognition pipeline, from dataset acquisition and preprocessing to implementing state-of-the-art architectures and deploying web-based solutions. The interdisciplinary nature of this work enhanced my research capabilities, particularly in adapting computer vision architectures for temporal sequence modelling and cross-linguistic transfer learning. Most importantly, I learned to translate theoretical knowledge of spatial-temporal correlation networks and connectionist temporal classification into practical solutions addressing real-world communication accessibility challenges.

Technical Growth and Architecture Evolution

One significant area of development was my progression from simple isolated sign classification to implementing complex continuous recognition pipelines with multi-component loss functions and attention mechanisms. My inspiration for this project came from an app I created 1 and a half year ago using Swift, which translated isolated words of American Sign Language. I wanted to try something more challenging, and bigger, and so I got into exploring the vast area of Continuous Sign Language Recognition. Working with the CorrNet+ architecture deepened my understanding of how spatial-temporal correlation computations enable robust tracking of articulatory trajectories across temporal sequences. This experience taught me how architectural choices, such as incorporating correlation modules and weighted CTC loss, can dramatically influence model performance and practical applicability.

The challenge of implementing class-weighted CTC loss to address severe vocabulary imbalance in ISL-CSLRT expanded my understanding of how traditional machine learning techniques must be adapted for sequential prediction tasks. The two-stage training approach (pretraining on PHOENIX-2014-T, fine-tuning on ISL) served as a valuable learning experience with domain adaptation strategies while revealing their limitations when fundamental data quality issues exist.

Cross-Linguistic Challenges and Research Insights

The stark performance disparity between well-resourced (PHOENIX-2014-T: 18.2% WER) and under-resourced (ISL-CSLRT: 71.28% WER) sign languages provided critical insights into the limitations of current transfer learning approaches. This experience highlighted that sophisticated architectures cannot overcome fundamental data limitations—a crucial lesson about the importance of dataset quality and scale in determining model success.

Working with ISL-CSLRT revealed the complex interplay between technical excellence and social responsibility in AI research. The inability to achieve deployable performance on ISL despite implementing optimization techniques (class balancing, scheduled learning rates, early stopping) underscored the need for community-centred approaches to data collection and highlighted the ethical implications of technological disparities across linguistic communities.

Deployment and Responsible AI Practices

Developing the Flask-based web interface enhanced my full-stack development capabilities while emphasizing accessible user experience design for assistive technologies. The critical decision to deploy only the PHOENIX-2014-T model while withholding the ISL variant taught me about responsible AI deployment practices and the importance of transparent communication about system limitations.

This project fundamentally changed my perspective from purely technical optimization to socially conscious technology development. Achieving excellent performance on established benchmarks while failing to serve an under-resourced community highlighted the ethical responsibilities inherent in accessibility-focused AI research. The experience emphasized that meaningful progress requires sustained collaboration with affected communities rather than purely algorithmic solutions, and that researchers must honestly acknowledge when current approaches are insufficient to serve all populations equitably.

The most valuable insight gained was understanding that technical success must be measured not only by benchmark performance but by real-world impact and accessibility across diverse communities.

APPENDIX-1

1. Decision to Pretrain on PHOENIX-2014-T and Fine-Tune on ISL-CSLRT

What I did:

- Pretrained CorrNet+ on large PHOENIX-2014-T (German) dataset, then fine-tuned on ISL-CSLRT.

Why it mattered:

- Leveraged rich temporal patterns learned from high-resource data to improve low-resource adaptation.
- Mitigated overfitting on limited ISL samples.

Outcome:

- Rapid convergence during fine-tuning.
- Moderate WER improvement on ISL despite data scarcity.

2. Class-Weighted CTC Loss for Vocabulary Imbalance

What I did:

- Computed inverse-frequency weights for each gloss in the 170-word ISL vocabulary and integrated into the CTC loss.

Why it mattered:

- Countered extreme gloss frequency skew, ensuring rare signs received sufficient learning
- **Outcome:**
- Overall sequence-level performance still limited by data scale.

6. Data Augmentation and Temporal Rescaling

What I did

- Applied random crops, horizontal flips, brightness shifts, and ±20% temporal speed variation during training.

Why it mattered:

- Simulated signer variability in framing, hand dominance, lighting, and signing speed.

Outcome:

- Improved generalization to unseen signers and recording conditions.

7. Resource-Aware Training Optimization:

What I did:

- Used batch size 2 with mixed precision and gradient accumulation to train CorrNet+ on dual RTX 4090 GPUs.

Why it mattered:

- Managed high memory demands of correlation modules while maintaining stable convergence.

Outcome:

- Successful training without out-of-memory errors.
- Reproducibility on modest multi-GPU setups.

8. Deployment Decision and Ethical Safeguard

What I did:

- Deployed only the PHOENIX-trained model (18.2% WER) via a Flask web app; withheld ISL-fine-tuned variant (71.28% WER).

Why it mattered:

- Ensured only reliable models reach end users, maintaining trust in assistive technology.

Outcome:

- Transparent limitations communicated in UI disclaimers.
- Ethical compliance by avoiding deployment of underperforming models.

What could have been done:

- Collect larger, more diverse ISL datasets in collaboration with deaf communities.
- Experiment with few-shot or meta-learning to better handle low-resource vocabularies.
- Compare CorrNet+ against pure transformer-based CSLR models under identical conditions.

APPPENDIX-2

CHALLENGES ENCOUNTERED AND SOLUTIONS

1. **Extreme Gloss Frequency Imbalance**

- Challenge: Common glosses dominated training, rare signs under-learned.
- Solution: Class-weighted CTC and targeted augmentation for infrequent glosses.

2. **Limited ISL-CSLRT Data Scale**

- Challenge: Only 560 training videos for 170 glosses.
- Solution: Transfer learning from PHOENIX-2014-T and heavy data augmentation.

3. **Temporal Segmentation and Co-Articulation**

- Challenge: Fluid sign transitions lacked clear boundaries.
- Solution: CorrNet+ correlation module to capture inter-frame dependencies.

4. **Computational Resource Constraints**

- Challenge: Correlation computations required large memory.
- Solution: Mixed precision training, gradient accumulation, frame-level feature caching.

5. **Model Interpretability**

- Challenge: Understanding the model’s focus in continuous sequences.
- Solution: Grad-CAM on correlation maps and decoder attention heatmaps.

6. **Deployment Reliability**

- Challenge: Ensuring web-app stability and data privacy.
- Solution: HTTPS, transient video storage with automatic deletion, UI disclaimers.

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