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# Hybrid 3DCvT-BiGRU Model for Lip Reading Recognition

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**Abstract.** Lip reading — the process of understanding spoken language by visually interpreting lip movements — has gained significant importance in scenarios where audio is unclear, noisy, or unavailable. Despite considerable progress in deep-learning-based visual speech recognition, existing systems continue to suffer from inadequate fine-grained spatial detail, weak temporal modelling, limited generalisation across speakers, and prohibitive computational demands in real-time deployment settings. This paper presents a novel automatic lip-reading system that converts silent video into readable text through a hybrid deep-learning pipeline. The proposed architecture integrates a 3D Convolutional Vision Transformer (3DCvT) — which captures rich spatiotemporal features across both local motion patterns and global spatial context — with a Bidirectional Gated Recurrent Unit (BiGRU) network that models sequential lip-movement dependencies in both the forward and backward temporal directions. Connectionist Temporal Classification (CTC) is employed for label-sequence alignment during training and inference. Experimental evaluation on lip-movement video data demonstrates that the proposed model achieves 96% word-level recognition accuracy with low inference latency, outperforming a standalone 3D CNN baseline (87%) and a pure Transformer model (92%). The system is designed for deployment in real-world accessibility applications, including assistive communication tools for hearing-impaired individuals, speech recognition in acoustically challenging environments, and silent-video analysis for surveillance and security contexts. The paper further provides a detailed critical analysis of limitations in current models and outlines directions for future research including speaker adaptation, audio-visual fusion, and multilingual dataset construction.

**Keywords:** Lip Reading · Visual Speech Recognition · 3D Convolutional Vision Transformer (3DCvT) · Bidirectional GRU · Deep Learning · Spatiotemporal Feature Extraction · Connectionist Temporal Classification · Silent Video Translation · Sequence Modelling · Accessibility Technology.

## 1 INTRODUCTION

### *1.1 Background and Motivation*

Lip reading, also referred to as Visual Speech Recognition (VSR), is the process of understanding spoken words by observing the movements of a speaker's lips and facial musculature rather than relying on acoustic signals. The ability to interpret speech from visual cues alone has long been considered a uniquely human skill, yet recent advances in computer vision and deep learning have made it increasingly tractable for automated systems. Lip reading is especially valuable in situations where audio is unavailable, severely degraded by environmental noise, or must remain confidential for privacy or security reasons.

Traditional speech recognition systems — including the most sophisticated contemporary models — depend overwhelmingly on high-quality acoustic input. When the signal-to-noise ratio is low, as occurs in factory floors, crowded public spaces, or noisy transportation environments, their performance deteriorates substantially. For individuals with hearing impairments, systems capable of interpreting visual speech can serve as a critical communication bridge. In surveillance and forensic applications, lip reading from silent video footage can provide actionable intelligence when audio recording is technically or legally prohibited.

The past decade has witnessed remarkable progress in visual speech recognition driven by deep learning. Three-dimensional convolutional neural networks (3D CNNs) have demonstrated an ability to capture spatiotemporal motion patterns that flat 2D convolutions cannot. More recently, transformer architectures have introduced attention mechanisms capable of modelling long-range spatial and temporal dependencies far beyond the reach of convolutional receptive fields. Nevertheless, each paradigm carries its own limitations, and the challenge of building a system that is simultaneously accurate, efficient, and robust to natural real-world variation remains open.

### *1.2 Problem Statement*

Despite significant advances in deep-learning-based lip reading, several fundamental challenges continue to impede

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practical deployment of these systems. First, many architectures fail to capture fine-grained lip motion details, particularly when video quality is reduced by compression, low frame rate, or motion blur [9]. Second, models that are primarily designed for spatial feature extraction often treat each video frame as an isolated observation, neglecting the temporal progression that is essential for distinguishing visually similar phonemes [2,7]. Third, recognition accuracy degrades considerably when models trained on curated laboratory datasets encounter the diversity of real-world speakers — individuals differ markedly in facial structure, lip shape, skin tone, the presence of facial hair, speaking rate, and regional accent [8]. Finally, the high computational cost of transformer-based architectures makes them impractical for real-time or mobile deployment, limiting their applicability outside well-equipped research settings [1,4].

A comprehensive solution must therefore address all four of these dimensions simultaneously: it must extract rich spatial detail from individual frames, model temporal continuity across frames, generalise to diverse speakers and environments, and do so within a computational budget compatible with real-time operation.

### *1.3 Research Objectives*

The objectives of this research are as follows. First, to design and implement a hybrid architecture — combining a 3D Convolutional Vision Transformer (3DCvT) and a Bidirectional Gated Recurrent Unit (BiGRU) — that jointly optimises spatiotemporal feature extraction and sequence modelling for visual speech recognition. Second, to train and evaluate the proposed model on standard lip-movement video datasets using Connectionist Temporal Classification (CTC) for sequence alignment [10]. Third, to conduct a rigorous quantitative comparison between the proposed model and representative baseline architectures in terms of recognition accuracy, loss, precision, and inference latency. Fourth, to analyse the limitations of the proposed approach and identify concrete directions for future research.

### *1.4 Paper Organisation*

The remainder of this paper is organised as follows. Section 2 reviews existing lip-reading systems and situates the proposed work within the broader literature. Section 3 describes the system architecture and design rationale. Section 4 presents the complete methodology, covering preprocessing, feature extraction, sequence modelling, and prediction. Section 5 provides a detailed critical gap analysis identifying key shortcomings in the state of the art. Section 6 reports the experimental evaluation and discusses the results. Section 7 concludes the paper and outlines directions for future research.

## 2 RELATED WORK

### *2.1 Convolutional Neural Network-Based Systems*

The introduction of deep convolutional neural networks (CNNs) to visual speech recognition brought substantial improvements by enabling end-to-end learning of visual features directly from pixel data. LipNet [7], proposed in 2016, was among the first end-to-end models for sentence-level lip reading. It employed a sequence of 3D convolutional layers to capture short-range spatiotemporal motion patterns, followed by Gated Recurrent Units (GRUs) for sequence decoding. Trained with CTC loss, LipNet achieved 95% character-level accuracy on the GRID corpus, a significant benchmark result. However, the model was evaluated under constrained recording conditions with a single speaker population and consistent lighting, and its generalisation to real-world data was limited.

The CTC-LipReader [10], published in 2022, similarly combined a 3D CNN backbone with CTC-based sequence decoding. Although architecturally similar to LipNet, the CTC-LipReader achieved lower accuracy (87%) on more diverse datasets, highlighting the difficulty of generalising 3D CNN-based features beyond the training distribution. The AVSR-Hybrid system (2023) paired a conventional CNN for frame-level feature extraction with an LSTM for temporal modelling, reaching 90% recognition accuracy with moderate inference latency. The LSTM's unidirectional processing of temporal context, however, precluded it from exploiting future context that can be important for resolving phonemic ambiguity.

### *2.2 Transformer-Based Systems*

The introduction of self-attention mechanisms via the Transformer architecture [Vaswani et al., 2017] opened new possibilities for modelling long-range contextual dependencies in lip-reading sequences. The TM-Transformer (2021) applied a dedicated Vision Transformer (ViT) backbone to lip-movement video, achieving state-of-the-art contextual modelling quality. However, the quadratic computational complexity of the self-attention mechanism with respect to sequence length imposes severe constraints on deployment: the model requires substantial GPU memory and exhibits high inference latency, making it unsuitable for real-time applications or resource-constrained devices [1,4]. Furthermore, transformer-only architectures benefit less from the inductive biases of convolution — such as translation equivariance and local feature hierarchy — which are directly relevant to lip motion modelling.

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### *2.3 Hybrid Architectures*

The limitations of both purely convolutional and purely attention-based models have motivated research into hybrid architectures. Systems combining CNN feature extractors with RNN sequence decoders represent an early form of hybridisation, and have consistently outperformed both components in isolation. More recent work has explored direct integration of convolutional and transformer layers within a single feature extraction backbone [1,4]. The Mini-3DCvT architecture [1] introduced a lightweight 3D Convolutional Vision Transformer that achieved strong spatiotemporal representation quality at a fraction of the parameter count of full-scale transformers, demonstrating that the complementary strengths of convolutional inductive biases and global attention can be combined efficiently. The proposed model builds upon this line of work by pairing the 3DCvT backbone with a BiGRU decoder, achieving further gains in recognition accuracy and a significant reduction in inference latency compared with transformer-only systems.

**Table 1. Comparative analysis of representative lip-reading models.**

| System | Year | Approach | Temporal Modelling | Accuracy | Latency |
|---|---|---|---|---|---|
| LipNet [7] | 2016 | 3D CNN + GRU | Moderate | 95% | Moderate |
| TM-Transformer | 2021 | Vision Transformer | High | — | High |
| CTC-LipReader [10] | 2022 | 3D CNN + CTC | Low | 87% | Moderate |
| AVSR-Hybrid | 2023 | CNN + LSTM | Moderate | 90% | Moderate |
| **Proposed Model** | **2025** | **3DCvT + BiGRU** | **High** | **96%** | **Low** |

## 3 SYSTEM DESIGN

### *3.1 Overall Architecture*

The proposed system is structured as a sequential processing pipeline comprising four major stages: video preprocessing and lip-region extraction, spatiotemporal feature extraction via the 3DCvT backbone, temporal sequence modelling via the BiGRU decoder, and final word-level classification. The entire pipeline is trained end-to-end using CTC loss, which permits the model to learn directly from video-label pairs without requiring frame-level phoneme annotations. Figure 1 provides a high-level overview of the system.

### *3.2 Frontend: 3DCvT Module*

The 3DCvT module constitutes the spatial-temporal frontend of the architecture. It accepts a fixed-length sequence of lip-region video frames as input and produces a compact sequence of high-level spatiotemporal feature vectors. The module consists of alternating 3D convolutional blocks and transformer encoder layers. The convolutional blocks apply learnable 3D filters across both spatial dimensions and the temporal dimension simultaneously, enabling the detection of motion patterns — such as the opening and closing of the mouth, or the protrusion and retraction of the lips — at multiple spatial scales. The transformer encoder layers that follow apply multi-head self-attention to the resulting feature maps, allowing the model to relate distant spatial positions within each frame and to model dependencies between non-adjacent frames in the temporal sequence.

This hybrid convolutional-attention design directly addresses the central trade-off in deep spatiotemporal modelling. Pure 3D CNNs are computationally efficient and respect the local structure of visual motion, but their receptive fields grow only linearly with network depth, limiting their ability to capture global spatial context. Pure attention mechanisms offer unrestricted global receptive fields but discard the spatial inductive biases that are advantageous for visual data and incur quadratic computational cost in sequence length. By composing both, the 3DCvT achieves rich global context with the efficiency and inductive bias of convolution.

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### *3.3 Backend: BiGRU Sequence Decoder*

The sequence of spatiotemporal feature vectors produced by the 3DCvT frontend is passed to a Bidirectional Gated Recurrent Unit (BiGRU) network. Each BiGRU layer processes the input sequence twice: once in the chronological (forward) direction and once in reverse (backward). The gating mechanisms of the GRU — specifically the update gate and the reset gate — enable the network to selectively retain or discard information as it propagates through the sequence, addressing the vanishing gradient problem that afflicts vanilla RNNs on long sequences.

The bidirectional design is particularly beneficial for lip reading because the correct interpretation of an ambiguous lip position often depends on both preceding and subsequent articulatory context. For example, the distinction between the bilabial consonants /p/, /b/, and /m/ is visually identical in isolation; their disambiguation requires contextual information drawn from the phonemes that precede and follow them in the utterance. By simultaneously maintaining forward and backward hidden states, the BiGRU is able to integrate this bilateral context in a computationally efficient manner.

### *3.4 Classification and Sequence Decoding*

The concatenated forward and backward hidden states produced by the final BiGRU layer are passed through a fully connected (dense) classification layer with a softmax activation, producing a probability distribution over the vocabulary at each time step. Since the length of the output sequence from the BiGRU does not in general align with the length of the target label sequence, Connectionist Temporal Classification (CTC) [10] is employed for both training and decoding. CTC marginalises over all possible alignments between the output sequence and the target label sequence, enabling the model to be trained from video-transcript pairs without any temporal labelling of phoneme boundaries. At inference time, greedy CTC decoding or beam-search decoding is applied to obtain the final word prediction.

## 4 METHODOLOGY

### *4.1 Preprocessing and Lip-Region Extraction*

Raw input video is first decoded into individual frames at the original frame rate. Each frame is resized to a fixed spatial resolution to ensure consistent input dimensions across the dataset. Face detection is then applied to each frame using a fast detector, and the detected face region is passed to a facial landmark localisation algorithm based on an ensemble of regression trees [11]. This algorithm localises 68 facial landmarks in under one millisecond per frame, providing precise coordinates for the lip corners, upper lip boundary, lower lip boundary, and surrounding regions. Using these coordinates, the lip region is cropped from each frame and aligned to a canonical reference configuration by estimating and applying an affine transformation. The aligned lip crops are stacked into a three-dimensional tensor of shape ($T \times H \times W \times C$), where T is the number of frames, H and W are the spatial dimensions of the crop, and C is the number of colour channels.

Prior to being fed into the model, pixel values are normalised to the range [0, 1] and standardised per-channel using mean and standard deviation statistics computed over the training set. Data augmentation techniques — including random horizontal flipping, small random rotations, brightness and contrast jitter, and temporal jittering of frame selection — are applied during training to improve generalisation and reduce overfitting.

### *4.2 Feature Extraction with 3DCvT*

The preprocessed lip-region tensor is passed through the 3DCvT module. In the first stage, a sequence of 3D convolutional layers — each followed by batch normalisation and a non-linear activation function — extracts hierarchical local motion features. The filters in these layers span three spatial dimensions: vertical, horizontal, and temporal, allowing the network to detect motion patterns such as lip opening velocity, lateral spread, and protrusion. Max-pooling layers are applied along the temporal dimension at regular intervals to reduce the effective sequence length and thereby reduce the computational cost of the subsequent transformer layers.

In the second stage, the resulting feature map is flattened along the spatial dimensions to produce a sequence of feature vectors — one per remaining temporal position — which is fed into the transformer encoder. Learnable positional encodings are added to the feature vectors to preserve temporal order information, since the self-attention mechanism is permutation-invariant by design. The transformer encoder consists of multiple layers, each comprising multi-head self-attention followed by a position-wise feed-forward network, with residual connections and layer normalisation applied around each sub-layer. The output is a refined sequence of contextualised spatiotemporal feature vectors that captures both fine-grained local motion detail and long-range temporal context.

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### *4.3 Temporal Modelling with BiGRU*

The spatiotemporal feature sequence from the 3DCvT module is fed into a stacked BiGRU network. At each time step, the forward GRU processes the current feature vector together with its forward hidden state from the previous time step, while the backward GRU processes the current vector together with its backward hidden state from the next time step. The update gate controls how much of the previous hidden state is carried forward, and the reset gate controls how much of the previous hidden state influences the computation of the candidate hidden state. These gates are learned through end-to-end backpropagation and adapt to the temporal statistics of the training data.

Multiple BiGRU layers are stacked to increase the depth of temporal abstraction. Dropout is applied between layers during training to regularise the network and prevent co-adaptation of hidden units. The final BiGRU layer outputs a hidden state at each time step that integrates information from the entire sequence in both temporal directions, providing a rich and context-aware representation of the lip-movement sequence at each frame.

### *4.4 Training Procedure and Loss Function*

The entire model — encompassing the 3DCvT frontend, the BiGRU decoder, and the final classification layer — is trained end-to-end using the Adam optimiser with an initial learning rate of $1 \times 10^{-4}$ and gradient clipping to prevent exploding gradients. The CTC loss function computes the negative log-likelihood of the target label sequence summed over all valid CTC alignments, providing a differentiable training signal without requiring frame-level annotation. A learning rate scheduler reduces the learning rate by a factor of 0.5 whenever the validation loss plateaus, encouraging the optimiser to converge to a sharper minimum. Training is conducted on a GPU-accelerated workstation for a fixed number of epochs, with early stopping based on validation word error rate to prevent overfitting.

## 5 CRITICAL GAP ANALYSIS

### *5.1 Weak Temporal Continuity Modelling*

Lip reading is inherently a spatiotemporal task: the interpretation of a lip position is meaningful only in the context of the trajectory through which it was reached and toward which it is heading. Systems that treat each frame independently, or that model temporal dependencies only within a short sliding window, fail to exploit the long-range sequential structure of spoken language [7]. This manifests in practice as unstable or inconsistent predictions: the same physical lip configuration may be classified as different words depending on arbitrary variations in processing order or context window boundary. Without a robust temporal backbone, models also struggle to handle natural speech phenomena such as coarticulation — the physical blending of adjacent phonemes — which smears the boundaries between discrete articulatory gestures [2]. The BiGRU decoder in the proposed architecture directly addresses this limitation by maintaining hidden states that accumulate evidence across the entire sequence in both temporal directions, enabling stable and context-dependent predictions.

### *5.2 Computational Resource Demands*

The computational demands of deep lip-reading models — particularly transformer-based architectures — represent a significant barrier to practical deployment. Full-scale vision transformers require large GPU memory footprints during both training and inference due to the storage of attention matrices, which scale quadratically with sequence length [1,4]. Training such models from scratch is feasible only on high-end hardware clusters, limiting accessibility for research groups with modest resources. At inference time, the high latency of transformer-only models makes real-time lip reading impractical on standard consumer hardware, let alone on low-power mobile or embedded devices [7].

The hybrid 3DCvT+BiGRU design addresses this gap through a principled decomposition of responsibilities: the 3DCvT handles the computationally intensive spatial modelling through a lightweight implementation of transformers that reduces attention complexity, while the BiGRU handles sequential modelling at substantially lower cost than a full transformer decoder. The result is a model that achieves competitive accuracy with a significantly lower latency profile, as validated by the experimental results.

### *5.3 Dataset Scarcity and Lack of Diversity*

Publicly available lip-reading datasets remain limited in scale and diversity relative to the breadth of real-world application contexts [5]. Most benchmark datasets
— including GRID, LRW (Lip Reading in the Wild), and LRS3 — were collected from native English speakers in relatively controlled acoustic and visual environments. These datasets do not adequately represent the diversity of accents, languages, recording conditions, age groups, and facial characteristics encountered in global deployment. Training on such narrow distributions tends to overfit to dataset-specific artefacts and results in models that fail silently

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when deployed in genuinely unconstrained settings. The construction of large-scale, multilingual, multi-speaker datasets with naturalistic recording conditions is therefore a critical priority for advancing the field.

## 6 EVALUATION AND DISCUSSION

### *6.1 Experimental Setup*

The proposed model was evaluated on lip-movement video data collected from publicly available benchmark sources. Each video sample was preprocessed according to the procedure described in Section 4.1. The dataset was partitioned into training, validation, and test sets following standard splits. The model was trained for a maximum of 100 epochs with early stopping, and the checkpoint achieving the best validation word error rate was selected for final evaluation. All experiments were conducted on a GPU-equipped workstation. Three architectures were compared: a 3D CNN baseline, a standalone Transformer model, and the proposed 3DCvT+BiGRU system. All models were trained under identical data conditions to ensure a fair comparison.

### *6.2 Quantitative Results*

Table 2 presents the quantitative performance metrics for all three architectures. The proposed model achieves 96% word-level recognition accuracy, representing an improvement of 9 percentage points over the 3D CNN baseline and 4 percentage points over the Transformer. The proposed model matches the Transformer in terms of loss and precision while achieving substantially lower inference latency — comparable to the 3D CNN, which makes no use of attention mechanisms. This result validates the central hypothesis of the paper: that the complementary strengths of convolutional spatiotemporal feature extraction and bidirectional sequential modelling can be integrated without incurring the latency penalty of a full transformer decoder.

**Table 2. Quantitative performance comparison of evaluated architectures.**

| Model | Accuracy | Loss | Precision | Latency | Remarks |
|---|---|---|---|---|---|
| 3D CNN | 87% | Moderate | Average | Moderate | No global attention |
| Transformer | 92% | Low | High | High | High compute cost |
| **Proposed (3DCvT + BiGRU)** | **96%** | **Low** | **High** | **Low** | **Best overall balance** |

### *6.3 Latency Analysis*

Inference latency is a critical metric for real-time lip-reading applications. The Transformer model, despite achieving 92% accuracy, exhibits high latency due to the quadratic complexity of its self-attention mechanism relative to the input sequence length. As video sequences grow longer, this latency increases non-linearly, quickly rendering the Transformer impractical for continuous lip reading in real-time settings. The proposed 3DCvT+BiGRU model achieves low latency comparable to the 3D CNN baseline. This is attributable to two design choices: first, the 3DCvT employs a lightweight transformer configuration with reduced attention head count and feature dimensionality relative to a full-scale vision transformer; second, the BiGRU decoder processes the feature sequence in linear time with respect to sequence length, providing constant-time complexity per token. Together, these choices yield a model that is both highly accurate and deployable in time-constrained applications.

### *6.4 Qualitative Analysis*

Beyond the aggregate metrics, the behaviour of the proposed model on specific error categories reveals important qualitative characteristics. The model demonstrates substantially improved performance on phoneme pairs that are visually similar but acoustically distinct — such as the pairs (p, b, m) and (f, v) — relative to the 3D CNN baseline. This improvement is attributed to the global attention mechanism in the 3DCvT, which allows the model to relate the current lip configuration to those observed earlier and later in the utterance, providing the bilateral context necessary for disambiguation. The BiGRU decoder further improves robustness to variable speech rates by modulating the temporal resolution of its hidden state transitions according to the cadence of the input sequence.

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The model also shows improved robustness to minor variations in head pose and partial lip occlusion compared with the Transformer baseline, likely due to the stronger local inductive biases inherited from the 3D convolutional layers. When evaluated on samples with challenging lighting conditions — including backlit and shadow-affected faces — the accuracy reduction is less severe than for the 3D CNN baseline, suggesting that the attention mechanism in the 3DCvT is partially able to compensate for degraded local feature quality by aggregating evidence from less-affected spatial regions.

### *6.5 Limitations of the Proposed System*

Notwithstanding the positive results, several limitations of the proposed system warrant acknowledgement. First, the model requires significant GPU resources for training, which may restrict accessibility for research groups without access to high-end computing infrastructure [1,4]. Second, recognition accuracy degrades on low-resolution or motion-blurred video that falls below the quality threshold assumed during preprocessing [8]. Third, the model is sensitive to significant changes in lighting conditions that were not represented in the training data, and its performance on heavily occluded faces — for example, those wearing face masks or large beards — has not been systematically evaluated. Finally, the training and evaluation datasets employed in this work lack diversity in terms of speaker demographics, languages, and recording environments [5,9], which may limit the generalisability of the reported accuracy figures to real-world deployment contexts.

## 7 CONCLUSION AND FUTURE WORK

### *7.1 Conclusion*

This paper has presented a hybrid deep-learning architecture for visual speech recognition that integrates a 3D Convolutional Vision Transformer (3DCvT) with a Bidirectional Gated Recurrent Unit (BiGRU) network. The 3DCvT component extracts rich spatiotemporal features from sequences of lip-region video frames, combining the local inductive biases and computational efficiency of 3D convolutions with the global receptive field of transformer self-attention. The BiGRU decoder models the temporal progression of these features in both the forward and backward directions, producing stable and context-aware predictions that integrate bilateral sequential context across the full utterance. The complete pipeline is trained end-to-end using Connectionist Temporal Classification, enabling direct optimisation from video-transcript pairs.

Experimental evaluation demonstrates that the proposed model achieves 96% word-level recognition accuracy with low inference latency, outperforming standalone 3D CNN (87%) and Transformer (92%) baselines by margins of 9 and 4 percentage points, respectively. Crucially, the proposed model achieves this accuracy improvement without the high latency that makes the Transformer unsuitable for real-time deployment. These results validate the design principle that spatiotemporal feature richness and efficient temporal sequence modelling are complementary properties that, when combined in a carefully designed hybrid architecture, yield performance superior to either component in isolation.

The system demonstrates strong potential for deployment in real-world accessibility applications, including assistive communication tools for hearing-impaired individuals, speech recognition in acoustically challenging environments such as industrial settings and crowded public spaces, and silent-video analysis for surveillance and forensic applications. The critical gap analysis presented in Section 5 provides a detailed characterisation of the challenges that remain to be addressed before such deployment can be achieved at scale, and motivates the directions for future work described below.

### *7.2 Future Work*

Several promising directions for future research are identified on the basis of the limitations and analysis presented in this paper. First, speaker-adaptive and personalised lip-reading mechanisms will be investigated to improve robustness across diverse individuals [3]. Meta-learning approaches — such as Model-Agnostic Meta-Learning (MAML) and its variants — offer a promising framework for enabling rapid adaptation to new speakers from small numbers of labelled examples without full retraining. Second, the integration of audio and visual modalities into a unified Audio-Visual Speech Recognition (AVSR) system represents a natural extension of the current work [7]. A well-designed AVSR system can exploit the complementarity of the two modalities, using visual features to improve robustness in acoustically noisy conditions and audio features to disambiguate visually similar phonemes.

Third, the construction and curation of larger, multilingual lip-reading datasets with broader speaker diversity, language coverage, and recording environment variation is a critical community-level priority [5,9]. The availability of such datasets will enable more rigorous evaluation of generalisation and will support the development of models that can operate reliably in genuinely global deployment contexts. Fourth, advanced transformer variants — including

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hierarchical architectures such as Swin Transformer and Video Swin Transformer, which apply local window attention to reduce computational complexity — will be evaluated as alternative backends for the spatiotemporal feature extraction stage [1,4]. These architectures may offer further improvements in the accuracy-latency trade-off relative to the current 3DCvT implementation. Finally, knowledge distillation techniques will be explored as a means of compressing the trained model for deployment on mobile and edge devices, bringing the benefits of the system to resource-constrained deployment contexts.

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