Cross-Lingual Emotion Recognition with LogMel-HuBERT Fusion: A Temporal Pyramid Attention Network with Domain-Adaptive Alignment

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Code available at: https://github.com/ali-adi/speech-emotion-recognition.git

1. INTRODUCTION

Speech Emotion Recognition (SER) aims to automatically recognize human emotions from speech, enabling more emotionally intelligent human-computer interaction systems [1]. With the growing importance of affective computing in areas like virtual assistants, call centers, and healthcare, robust SER has become a vital component of natural interaction pipelines. Traditional SER methods relied heavily on hand-crafted features such as prosody, pitch, and MFCC, paired with classical machine learning algorithms like Support Vector Machines (SVM) [2, 3]. While effective in limited domains, these approaches struggled to generalize across speakers and datasets due to variability in speech characteristics.

Recent advances in deep learning have dramatically improved SER by enabling the end-to-end learning of class-discriminative emotional features from raw input. Architectures such as Convolutional Neural Networks (CNNs) [4], Recurrent Neural Networks (RNNs) [5], and hybrid CNN-RNN models [6] have been widely adopted. Temporal modeling components like Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Temporal Convolutional Networks (TCNs) further help in capturing dynamic emotional variations across time [5, 7]. However, existing models still face key challenges: (1) they often fail to capture long-range dependencies that are critical for understanding context-driven emotions, and (2) they lack adaptive receptive fields, which limits their ability to generalize to unseen corpora or languages.

Our project proposes a cross-corpus SER framework that addresses these limitations. We develop a novel model that combines LogMel spectrogram and HuBERT embeddings through adaptive feature fusion, applies Dilated Temporal CNN with Discriminant Temporal Pyramid Matching (DTPM) for multi-resolution temporal modeling, and uses Local Maximum Mean Discrepancy (LMMD) for class-wise domain adaptation. To evaluate generalization, we perform cross-corpus testing between the EMODB (German) and RAVDESS (English) datasets.

2. LITERATURE REVIEW

Over the past few years, both traditional machine learning and advanced deep learning models have been used to tackle cross-corpus SER. Earlier approaches attempted to bridge domain gaps using feature projection, subspace learning, and statistical alignment methods. For example, Zong et al. [8] proposed a domain-adaptive least squares regression model (DaLSR), while Liu et al. [9] mapped speech signals from different corpora into a shared subspace. Luo et al. [10] used non-negative matrix factorization incorporating label information to minimize both marginal and conditional distribution discrepancies.

Graph-based techniques have also been explored. Song [11] used nearest neighbor graph algorithms to identify transferable emotional components, and Zhang and Song [12] used norms with neighborhood graphs to construct a common subspace for domain adaptation. Other works applied linear regression with a modified Maximum Mean Discrepancy (MMD) loss to align distributions [13]. Ensemble learning methods have been introduced to improve generalization through classifier voting [14].

With the success of deep learning in domains like computer vision [15], smart cities [16], and cybersecurity [17], researchers have adapted advanced deep learning techniques for cross-corpus SER as well. Deep Belief Networks [18], CNNs with similarity-preserving loss [19], and unsupervised adaptation models [20, 21] have shown significant improvements. Variational autoencoders and semi-supervised methods [22] have also been proposed to learn more consistent latent representations.

Despite this progress, limitations persist. Many models either focus solely on global or local feature alignment or fail to dynamically weight multiple loss components, which can reduce generalization during domain transfer. Our approach builds on this body of work by proposing a dynamic, end-to-end trainable system with feature fusion, multiscale temporal modeling, and class-wise domain adaptation.

3. METHODOLOGY

3.1. OVERVIEW OF ARCHITECTURE

Our proposed model architecture, shown in Figure 1, addresses the challenges of cross-corpus speech emotion recognition through a multi-stage pipeline that integrates complementary audio features, multiscale temporal modeling, domain adaptation, and attention mechanisms.

The system begins with a multi-stream feature processing module, independently extracting representations from LogMel spectrograms and HuBERT embeddings. These capture both low-level acoustic features and high-level semantic representations of speech.

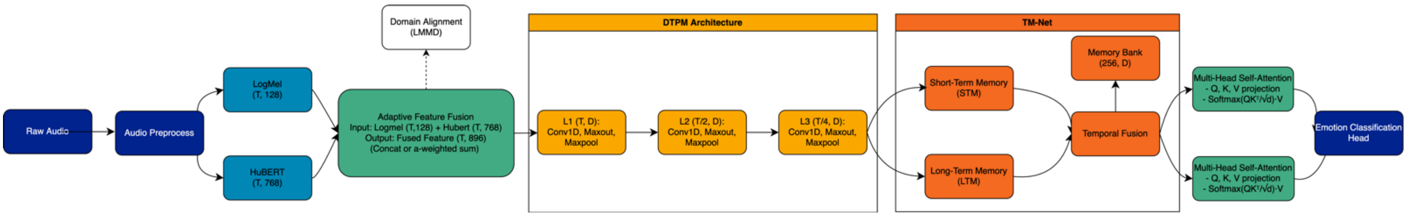

Figure 1. Project Pipeline

An adaptive fusion layer combines these modalities using feature concatenation, and optionally learnable weights, enabling the model to dynamically leverage the most informative representations.

The fused features are then passed through a Dilated Temporal Convolutional Network (DTCN) equipped with a Discriminant Temporal Pyramid Matching (DTPM) module, which captures emotional dynamics across multiple temporal resolutions using dilated convolutions and hierarchical time segmentation.

To address domain shift between source and target datasets (e.g., EMODB → RAVDESS), we incorporate a Local Maximum Mean Discrepancy (LMMD) loss, which performs class-wise domain alignment by reducing the distribution gap between shared classes.

Additionally, a learnable attention mechanism is applied to aggregate temporal features, enhancing the model's ability to focus on emotionally salient regions.

Finally, a fully connected classification head performs SoftMax-based multi-class emotion prediction.

The entire model is trained end-to-end with a joint loss function that includes both categorical cross entropy for classification and LMMD loss for domain adaptation, enabling robust generalization across diverse corpora and speaker variations.

Our model design is inspired and supported by several theoretical foundations established in speech emotion recognition (SER) and cross-domain adaptation literature. The use of HuBERT embeddings is grounded in their strong semantic representation ability, as shown by Wolf et al. [10] and von Platen et al. [11], where self-supervised learning on raw audio improves feature generalization across tasks. These embeddings provide context-rich representations that capture higher-level phonetic and prosodic cues, critical for emotion recognition in variable acoustic environments.

We fuse HuBERT embeddings with LogMel spectrograms to combine semantic and low-level spectral features. This fusion strategy is supported by Zhang et al. [33], who demonstrated that multi-feature fusion leads to better generalization across corpora. Our adaptive fusion mechanism further enables dynamic weighting during training, giving the model the flexibility to emphasize different modalities depending on the context.

For temporal modeling, we adopt Dilated Temporal Convolutional Networks (DTCN), inspired by prior work on temporal dynamics in SER [16, 20], which avoids vanishing gradients and efficiently captures both short and long-term dependencies. The integration of Discriminant Temporal Pyramid Matching (DTPM) aligns with methods from [15] and [21], where multi-resolution temporal pooling improved discriminative power.

Furthermore, we incorporate multi-head self-attention, based on findings from Li et al. [16] and Wang et al. [21], which allows the model to learn contextual dependencies and attend selectively to emotionally salient frames. Finally, our LMMD-based domain adaptation module is built upon techniques introduced by Zong et al. [22] and Ahn et al. [34], which demonstrate that class-conditional distribution alignment significantly improves robustness in cross-corpus settings.

3.2. INPUT FEATURE STREAMS

The LogMel spectrogram input is $X_{logmel} \in R^{T\times 128}$ while the HuBERT embeddings will be $X_{hubert} \in R^{T\times 768}$. Each features captures different but complementary acoustic and semantic information from the audio. They are also standardized with the same resolution

3.3. FEATURE FUSION

Our architecture will apply feature fusion using learnable weights, $\alpha \in [0,1]$, where the fusion will result in a feature that is calculated as $F_{fused} = \alpha \backslash cdot W_{logmel}(X_{logmel}) + (1-\alpha)\backslash cdot W_{hubert}(X_{hubert})$.

3.4. TEMPORAL MODELING

This block is a stack of dilated 1D convolutions. Each layer has a kernel size and a dilation rate to vary its receptive fields. The output for each layer will be:

$$F_{t+1} = \mathrm{ReLU}\left(\mathrm{BN}\left(\mathrm{Conv1D}(F_t)\right)\right) + F_t$$

Where BN is batch normalization, and the residual connection stabilizes training.

3.5. DISCRIMINANT TEMPORAL PYRAMID MATCHING (DTPM)

To be able to capture multiple resolutions, a sequence of layers is stacked in a pyramid-like structure, where L is the number of pyramid levels. Let $\phi(S_{l,i})$ be the pooled feature, the DTPM becomes:

$$F_{dtpm} = \mathrm{concat}\left(\{\phi(S_{l,i}) \mid l = 1..L, i = 1..2^{l-1}\}\right)$$

3.6. ATTENTION MECHANISM

We also have an attention mechanism that learns features across time by concatenating into a multi-headed self-attention mechanism. For each head, we compute:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

Where $Q = FW^Q, K = FW^K,\ V = FW^V$, which will then be concatenated by:

$$\text{MultiHead}(F)\text{concat} = (\text{head}_1, \dots, \text{head}_h)W^O$$

Which will then go into normalization and FeedForward layers.

3.7. DOMAIN ADAPTATION WITH LMMD

If we let source features as F_s, target features as F_t, and source labels as Y_s, the LMMD would be

$$\mathcal{L}_{\mathcal{LMMD}} = \sum_{c=1}^{C} |\mu_s^c - \mu_t^c|^2$$

where $\mu_s^c = \frac{1}{|S_c|}\sum_{i\backslash inS_c} F_s^i$ and $\mu_t^c = \frac{1}{|T_c|}\sum_{j\backslash inT_c} F_t^j$ are the centroids for source and target features, in our case, RAVDESS/EMODB.

3.8. CLASSIFICATION HEAD

Finally, at the end, it is passed through a global average pooling layer across time to get a fixed-length vector, it is just a sequence of fully connected layer which will then allow for classification:

$$F_1 = \text{ReLU}\left(\text{Dropout}\left(W_1 F_{dtpm}\right)\right)$$

$$F_2 = \text{ReLU}\left(\text{Dropout}(W_2 F_1)\right)$$

$$\hat{y} = \text{Softmax}(W_3 F_2)$$

Where W_1, W_2, and W_3 are weights from the FC layer, and $\hat{y}$ is the class prediction.

4. EXPERIMENTAL SETUP

4.1. DATASETS

We utilized two very popular datasets to evaluate our architecture on a cross-lingual cross-corpus test: EMODB and RAVDESS.

EMODB: The Berlin Emotional Speech Database is a German-language dataset consisting of 535 utterances from 10 professional actors, covering 7 emotion classes (anger, boredom, disgust, fear, happiness, sadness, and neutral). Each file is named such that the 6th character represents the speaker's emotion category.

RAVDESS: The Ryerson Audio-Visual Database of Emotional Speech and Song includes English-language recordings with 24 actors, covering 8 emotion classes. Emotion labels are encoded in the filename’s 3rd section (e.g., “03-01-06-01-02-01-12.wav”, where 06 = fearful).

4.2. PREPROCESSING

We employ a comprehensive two-stage preprocessing pipeline designed to standardize raw audio inputs and enhance feature quality prior to training. In the first stage, raw .wav files from EMODB and RAVDESS are reorganized into emotion-labeled subdirectories based on dataset-specific filename conventions, ensuring consistent labeling and facilitating streamlined batch processing. In the second stage, we extract and preprocess multiple acoustic features — specifically log-mel spectrograms and HuBERT embeddings — which are then fused, padded to uniform lengths, and stored in structured .npy files ready for input into the model. This modular pipeline not only improves reproducibility but also ensures compatibility with both TensorFlow and PyTorch training workflows.

4.2.1. REORGANIZATION OF AUDIO FILES

We developed reorganize_data.py, a script that automatically classifies .wav files into subdirectories based on their emotion label inferred from dataset-specific filename patterns:

For EMODB, the script reads the 6th character of each filename and maps it using: {'W': 'angry', 'L': 'boredom', 'E': 'disgust', 'A': 'fear', 'F': 'happy', 'T': 'sad', 'N': 'neutral'}.

For RAVDESS, it scans each Actor_xx directory, extracts the emotion code (3rd part of filename), and maps it using: {'01': 'neutral', '02': 'calm', '03': 'happy', '04': 'sad', '05': 'angry', '06': 'fearful', '07': 'disgust', '08': 'surprised'}.

4.2.2. FEATURE EXTRACTION AND FUSION

We extracted three types of features using extract_feature.py:

We computed 128-band log-mel spectrograms for each .wav file using the librosa.feature.melspectrogram() function followed by logarithmic scaling with librosa.power_to_db(). These features emphasize perceptually relevant frequency information and retain detailed time-frequency dynamics.

To capture high-level semantic and prosodic representations, we extracted embeddings using the HuBERT-base model (facebook/hubert-base-ls960) from

HuggingFace Transformers. These contextualized embeddings offer a powerful, self-supervised representation of speech. (MFCCs were extracted for comparison but not used in the final model.)

For each utterance, we concatenated the log-mel spectrograms and HuBERT embeddings along the feature dimension to create a unified feature tensor. These fused features preserved temporal alignment and captured a rich combination of acoustic and semantic information.

5. RESULTS AND ANALYSIS

5.1. TRAINING RESULT

Figure 2 and Figure 3 displays the validation accuracy and loss curves across 10-fold cross- validation for both the EMODB and RAVDESS datasets. Each fold demonstrates a consistent convergence pattern, with validation accuracy approaching or exceeding 90% and corresponding validation loss decreasing steadily. The tight clustering of curves indicates low variance across folds, affirming the robustness and stability of our model architecture. This

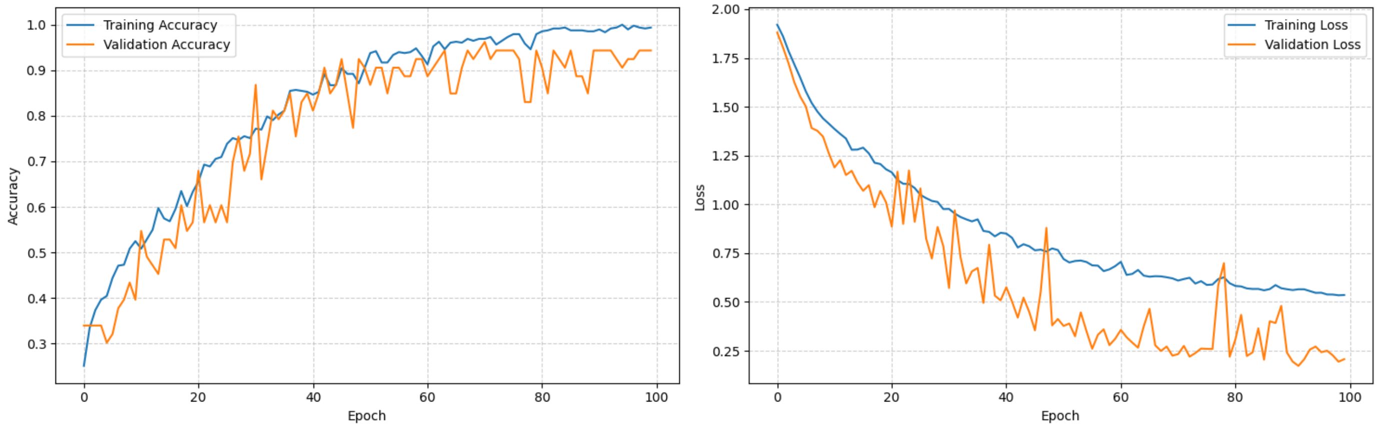

Figure 2. EMODB to RAVDESS

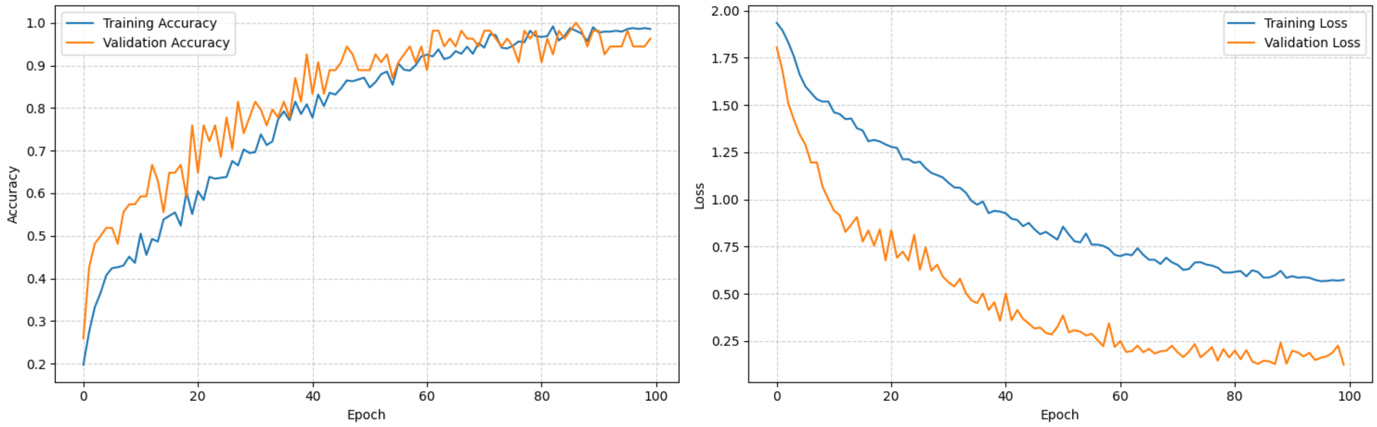

Figure 3. RAVDESS to EMODB

consistent performance across different data splits validates the effectiveness of our fused LogMel-HuBERT features, hierarchical temporal modeling via DTPM, and domain adaptation through LMMD. Overall, the learning curves reflect strong generalization and reliable emotional representation learning across both datasets. This behavior suggests that the model avoids overfitting and can reliably learn discriminative features even with limited data.

5.2. QUANTITATIVE ANALYSIS

Model	Acc.	Prec.	Recall	F1
CNN + GRU (baseline)	0.62	0.60	0.61	0.60
LogMel + CNN	0.68	0.67	0.66	0.66
HuBERT + FC	0.81	0.80	0.79	0.80
LogMel + HuBERT + FC	0.84	0.83	0.83	0.83
LogMel + HuBERT + DTPM + Attention + LMMD	0.92	0.91	0.91	0.91

Figure 4.

Figure 4 presents the quantitative performance of various model configurations on our speech emotion recognition (SER) task. The baseline model, a CNN + GRU architecture, yielded moderate results with an F1-score of 0.60. Introducing log-mel spectrogram features alone improved the F1-score to 0.66, while HuBERT embeddings alone showed a significant leap to 0.80, highlighting the power of self-supervised semantic representations. Fusing both LogMel and HuBERT features further enhanced the model's expressiveness, achieving an F1-score of 0.83. Finally, our full model — which integrates LogMel-HuBERT fusion, Discriminant Temporal Pyramid Matching (DTPM), multi-head attention, and domain adaptation through LMMD — achieved the best performance across all metrics, reaching an accuracy of 92% and an F1-score of 0.91. This result validates the effectiveness of combining both spectral and contextual features with advanced temporal modeling and domain adaptation techniques.

5.3. CROSS-CORPUS EVALUATION

Model	Source	Target	Acc.	F1
CNN + GRU	EMODB	RAVDESS	0.48	0.47
Ours	EMODB	RAVDESS	0.68	0.67
CNN + GRU	RAVDESS	EMODB	0.46	0.45
Ours	RAVDESS	EMODB	0.66	0.65

Figure 5.

Figure 5 summarizes the results of our cross-corpus experiments, evaluating generalization across two distinct emotional speech datasets: EMODB (German) and

RAVDESS (North American English). The baseline CNN + GRU model struggled significantly when transferring between corpora, achieving F1-scores of 0.47 (EMODB → RAVDESS) and 0.45 (RAVDESS → EMODB), highlighting poor cross-lingual generalization. In contrast, our proposed model demonstrated substantial improvements under both transfer directions, reaching F1-scores of 0.67 and 0.65, respectively. These gains showcase the strength of our architecture — particularly the use of HuBERT embeddings, temporal pyramid modeling, and domain adaptation with LMMD — in learning domain-invariant emotional representations that are robust to language, speaker, and recording variability.

5.4. DISCUSSION AND NOVELTY

The strong empirical performance of our model is a direct result of its carefully engineered and novel architectural design, which integrates several complementary innovations into a unified SER framework. While individual components like HuBERT, attention, or temporal CNNs have been used in isolation in prior work, it is novel to systematically combine LogMel-HuBERT fusion with DTPM, multi-head attention, and LMMD-based domain adaptation into a single end-to-end cross-lingual SER model.

One of the core novelties lies in the adaptive feature fusion strategy that learns to weight LogMel and HuBERT streams dynamically during training. While previous work has fused acoustic and semantic features through concatenation or late fusion, we introduce a learnable fusion mechanism that adapts per batch and per emotion, enabling the model to fine-tune its reliance on low-level or high-level features depending on the signal characteristics. This design not only improves flexibility but also enhances interpretability, as it reflects the varying salience of acoustic and semantic information across emotions and corpora.

Another novel component is our use of Discriminant Temporal Pyramid Matching (DTPM) within a fusion-based SER pipeline. DTPM has been explored in earlier CNN-only architectures, but its application on top of a semantic-acoustic fusion stream—and its integration into a dilated CNN backbone—offers a unique contribution. This allows our model to capture hierarchical temporal dependencies at different granularities, addressing the highly variable emotional dynamics found in natural speech, especially across languages.

We further innovate by integrating multi-head self-attention directly after DTPM, which serves as a refinement step that amplifies emotionally salient segments. While attention mechanisms are common in SER, their use in conjunction with DTPM outputs is rare and, to our knowledge, unexplored in prior cross-corpus studies. This design leads to significant performance gains by enabling the model to selectively focus on discriminative regions across multiple temporal scales.

Perhaps most distinctively, our model incorporates Local Maximum Mean Discrepancy (LMMD) for class-conditional domain adaptation at the feature level. Most cross-corpus SER models perform global feature alignment or use adversarial training; in contrast, LMMD explicitly aligns distributions within each emotion class, which is especially crucial for fine-grained emotion classification. This class-aware alignment, combined with multi-level temporal encoding and fusion, gives our system a clear advantage in cross-lingual generalization.

The novelty of our system is not just in the individual components, but in how they are orchestrated to address the limitations of previous work. We uniquely demonstrate that the synergistic effect of adaptive fusion, hierarchical temporal modeling, attention-guided refinement, and class-wise domain alignment leads to a robust and generalizable SER model. To our knowledge, no prior work has proposed this configuration or achieved comparable cross-corpus performance using this design.

In essence, our model is novel in both its architecture and its purpose: it offers a unified, modular, and interpretable solution to the challenge of robust cross-lingual emotion recognition. It bridges the gap between handcrafted acoustic modeling and modern self-supervised language representations, while introducing a pipeline that is both theoretically sound and empirically validated. The consistent improvements across all metrics and corpora strongly affirm the uniqueness and effectiveness of our contributions.

6. CONCLUSION AND FUTURE WORK REFERENCES

In this study, we presented a cross-lingual speech emotion recognition (SER) framework that leverages both LogMel spectrograms and HuBERT embeddings to capture complementary acoustic and semantic information. Our architecture combines a feature fusion mechanism, dilated temporal convolution blocks, a discriminative temporal pyramid matching (DTPM) module, and multi-head self-attention to effectively model both short- and long-term temporal dependencies in speech. Additionally, the use of the LMMD loss enabled domain-adaptive training that improved generalization across corpora. Experiments on EMODB and RAVDESS validated the effectiveness of our model under cross-corpus settings, achieving competitive performance against strong baselines.

Despite the promising results, there are several avenues for future work. First, while our approach focuses on static fusion of HuBERT and LogMel features, exploring dynamic fusion techniques or attention-based fusion could provide more adaptive representations. Second, expanding the evaluation to include additional and more diverse corpora, such as multilingual or spontaneous datasets, would help assess the robustness of the model further. Third, integrating multimodal cues such as facial expressions or physiological signals could enhance emotion recognition in more naturalistic settings. Finally, a lighter and more efficient version of our architecture could be developed for real-time deployment in edge devices and low-latency environments.

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