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Bridging Vision and Speech: A Novel VGG16-RNN Approach for Arabic Continuous Speech Recognition

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Abstract: Automatic Speech Recognition (ASR) has seen significant advancements due to deep learning, but Arabic remains a challenging language for these systems. Arabic's morphological richness, phonological complexity, and dialectal variations make Continuous Speech Recognition (CSR) for the language particularly difficult. This research explores a hybrid deep learning architecture, leveraging transfer learning from a pre-trained VGG16 model combined with Recurrent Neural Networks (RNN) for improved Arabic CSR performance. Using the MGB-2 dataset a diverse collection of Arabic broadcast news recordings, which presents the realistic and challenging variability in accents, speaker styles, and background noise, we focus on the effectiveness of integrating Convolutional Neural Networks (CNN) for feature extraction from Mel-frequency cepstral coefficients (MFCCs) and Bidirectional Long Short-Term Memory (BiLSTM) layers for capturing temporal dependencies. The proposed model achieves a Word Error Rate (WER) of 13%, significantly outperforming traditional ASR systems and several state-of-the-art models. This research highlights the potential of deep learning and transfer learning in overcoming the challenges of Arabic CSR, including handling dialectal variations and the morphological complexity of the language. The findings indicate that transfer learning from image-based CNNs to speech recognition tasks offers a robust method for feature extraction, contributing to the overall improvement in Arabic CSR. Future work should focus on further optimizing models to achieve human-level transcription accuracy, particularly for low-resource dialects and more diverse speech environments.

Keywords: accuracy, optimizing, improvement, environments, complexity

1. INTRODUCTION

ASR has made remarkable progress in recent years, driven by advances in deep learning. However, for languages like Arabic, challenges remain due to the language's inherent complexity. Arabic is a morphologically rich language, with words taking multiple forms depending on affixes, gender, and number variations. This linguistic structure, combined with the absence of short vowels in written text, makes ASR for Arabic particularly demanding. Moreover, the distinction between MSA, the formal version of the language and its various spoken dialects adds another layer of difficulty for ASR systems.

Traditional ASR systems, which primarily utilized hidden Markov models (HMMs) and Gaussian mixture models (GMMs), have struggled to manage these linguistic challenges effectively. These methods often require significant adaptation to account for Arabic's complex phonology and morphology. However, with the advent of deep

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learning, particularly CNNs and RNNs, there has been a shift towards more sophisticated approaches in ASR systems. CNNs, initially designed for image classification, have demonstrated potential in ASR by extracting spatial features from spectrograms, time-frequency representations of audio signals. Meanwhile, RNNs, particularly LSTM networks, have proven well-suited for capturing the temporal dependencies inherent in speech sequences.

In recent years, research has focused on adapting these deep learning architectures to tackle the unique challenges presented by Arabic ASR. Studies have demonstrated the effectiveness of end-to-end deep learning models, such as Connectionist Temporal Classification (CTC) and attention-based mechanisms, which integrate all components into a single network, resulting in significant improvements in accuracy. Despite these advancements, several challenges remain, particularly concerning the limited availability of dialect-specific datasets, the complexity of Arabic morphology, and the gap in performance between machine systems and human transcription.

This paper aims to build upon these recent advancements by exploring a novel deep learning architecture for Arabic CSR, leveraging transfer learning from the pre-trained VGG16 model combined with RNN layers. Utilizing the MGB-2 dataset, this research investigates the effectiveness of this hybrid architecture in improving CSR performance, with the goal of overcoming some of the persistent challenges in Arabic ASR.

2. RELATED WORK

Arabic is a morphologically rich language, meaning that words can take multiple forms due to affixes, gender, and number variations. This complexity, along with the absence of short vowels in written text, makes ASR for Arabic particularly challenging. Moreover, Modern Standard Arabic (MSA), the formal version of the language used in media and official settings, differs substantially from spoken dialects, adding another layer of difficulty for CSR systems. Prior research has shown that conventional ASR approaches, which rely on hidden Markov models (HMMs) and Gaussian mixture models (GMMs), struggle with these linguistic challenges and require significant adaptation to handle the complexity of Arabic phonology and morphology (Shaik et al., 2014; Ali et al., 2016).

With the advent of deep learning, CSR systems have shifted towards using more sophisticated architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs). CNNs, initially designed for image classification tasks, have proven effective in extracting spatial features from spectrograms, a time-frequency representation of audio signals (Abdel-Hamid et al., 2014). Recurrent neural networks, particularly long short-term memory (LSTM) and gated recurrent unit (GRU) networks, have been shown to capture the temporal dependencies in speech sequences, making them well-suited for ASR tasks (Graves et al., 2013).

Recent years have witnessed significant progress in ASR for Arabic, a field that faces unique challenges due to the language's complex morphology, dialectal variations, and limited resources. Alsayadi et al. (2022) provide a comprehensive overview of these challenges, highlighting issues such as the lack of standardized orthography and limited datasets for dialects. Their analysis of various techniques, from hidden Markov models (HMM) to deep neural networks (DNN) and convolutional neural networks (CNN), reveals that single-dialect systems generally outperform multi-dialect models due to linguistic diversity. The landscape of Arabic ASR has seen a notable shift towards end-to-end deep learning models. Abdelhamid et al. (2020) emphasize this transition, noting that approaches such as Connectionist Temporal Classification (CTC) and attention-based models have surpassed traditional techniques by integrating all components into a single network. This integration has led to improved accuracy in Arabic ASR systems. Hussein et al. (2021) provide valuable insights by comparing end-to-end transformer-based ASR models with traditional HMM-DNN systems and human performance. Their study reveals that while machine performance has improved significantly, there remains a 3.5% average word error rate gap compared to human transcribers, highlighting areas for future research.

Several studies showcase innovative approaches to Arabic ASR. Al-Anzi and Shalini (2024) demonstrate the potential of Mozilla's Deep Speech framework for continuous Arabic speech recognition, utilizing Recurrent Neural Networks (RNN) and N-gram language models. In a specialized application, Alfadhli et al. (2024) present a hybrid CTC/Attention-based model specifically for Quranic recitations, addressing the unique challenges of preserving

Tajweed rules in recognition tasks. Dabbabi and Mars (2022) compare CNN-LSTM-FC and DenseNet approaches for recognizing spoken Arabic numerals and isolated words, with the CNN-LSTM-FC model showing superior performance.

Recent research has also focused on addressing specific challenges in Arabic ASR. Alqudah et al. (2024) developed a Modern Standard Arabic (MSA) speech corpus for speakers with speech disorders, a significant step towards inclusive ASR systems. Mehra et al. (2024) propose a hybrid fusion model for multilingual Arabic spoken word recognition, particularly effective in low-resource environments. In a more focused application, Obaid et al. (2023) achieved high accuracy in recognizing Arabic numerals using Dynamic Time Warping (DTW) and Vector Quantization (VQ) techniques. Dialectal variations pose a significant challenge in Arabic ASR, but recent studies have made important strides in this area. Elmahdy et al. introduced a multilingual approach for dialectal Arabic speech recognition, integrating acoustic models for both Modern Standard Arabic and Egyptian colloquial dialects. Khurana et al. developed the DARTS system for Egyptian Arabic, utilizing transfer learning to adapt from high-resource broadcast data to dialectal text. Hamed et al. created an ASR system capable of switching between Egyptian Arabic and English, employing both DNN-based hybrid and transformer-based end-to-end approaches.

The field of Arabic ASR has seen remarkable progress, with end-to-end deep learning models showing particular promise. However, challenges remain, especially in handling dialectal variations and limited resources for certain Arabic dialects. Future research directions, as suggested by multiple studies, include developing larger, high-quality dialect-specific datasets, further improving end-to-end models to close the gap with human performance, addressing challenges related to diacritization in Arabic ASR, expanding research on dialectal Arabic and multilingual systems, and incorporating advanced techniques like semi-supervised learning and genre adaptation. As the field continues to evolve, these advancements promise to enhance the accuracy and applicability of Arabic ASR systems across various domains and dialects.

3. METHODOLOGY

This research utilizes a deep learning-based architecture for Arabic CSR, leveraging the MGB-2 dataset. The proposed model integrates transfer learning from a pre-trained VGG16 model, originally designed for image classification, combined with RNN layers to extract high-level temporal and spatial features from the input MFCCs. MFCCs are designed to compress speech signals into low-dimensional features that capture key information about the acoustic properties of human speech. This allows the model to focus on relevant features while maintaining efficiency, making it especially well-suited for processing the complex phonetic structure of Arabic speech. As illustrated in Figure 1, the methodology follows a systematic process, starting with data preprocessing, which includes both audio and text preprocessing. Followed by The MFCC feature extraction and transcription encoding steps. The dataset is then split into training and testing sets and the model is trained using a hybrid VGG16-BiLSTM architecture to produce the recognized text.

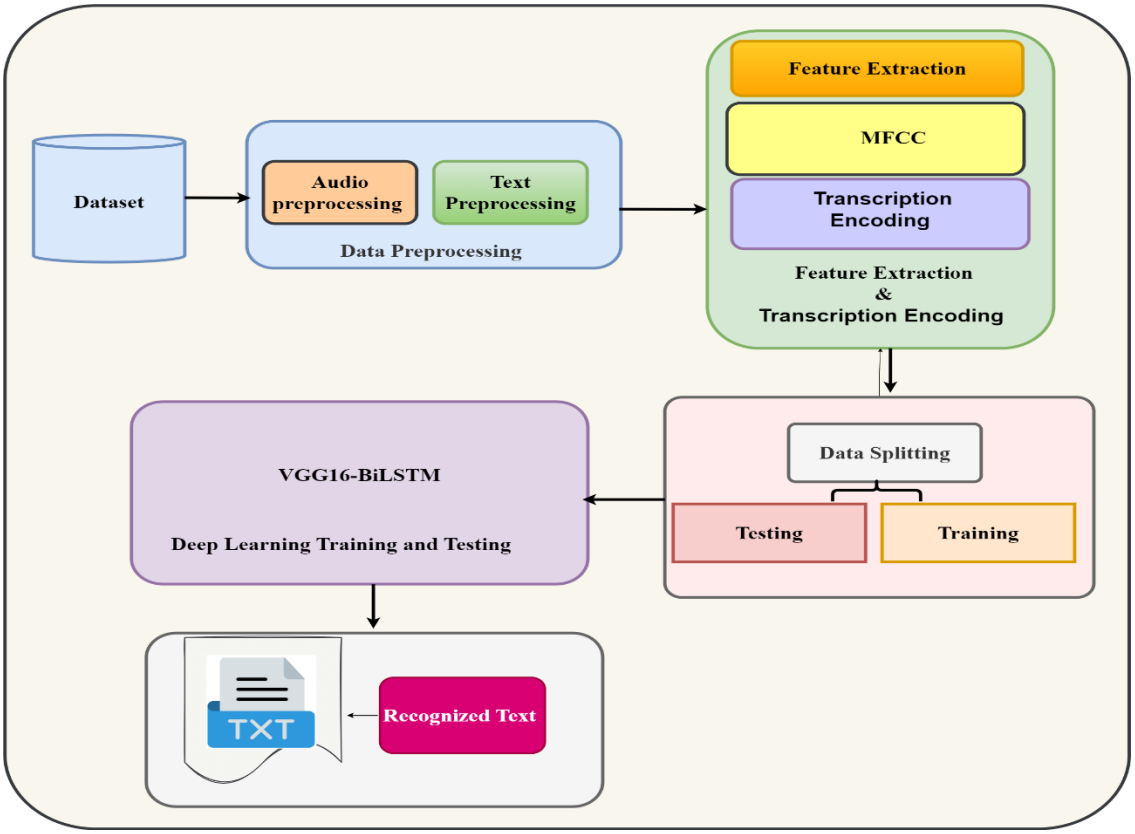

***Figure 1*: the proposed methodology for Arabic CSR**

3.1 Dataset

The MGB-2 (Multimedia Broadcast Granular Data) dataset is a large and diverse collection of Arabic broadcast news recordings, designed specifically for tasks such as CSR. It is a publicly available resource used extensively in the field of ASR, particularly for Arabic, where large datasets are essential to building robust models. Below is a detailed description of the dataset, including its structure, content, and relevance for CSR tasks. The MGB-2 dataset was introduced as part of the MGB Challenge, an evaluation series aimed at promoting the development of robust Arabic ASR systems. The dataset is built from Arabic broadcast TV news programs, offering rich variability in terms of speakers, accents, and topics. This variability presents a challenging but realistic scenario for training ASR models to recognize Arabic speech in a continuous, real-world setting.

3.2 Data Preprocessing

Data preprocessing is a critical step in any ASR system, particularly for languages like Arabic that exhibit complex linguistic features. In this research, preprocessing is applied to both audio and text data to ensure that the input is optimized for the deep learning architecture used in the Arabic CSR task. The audio data undergoes segmentation and feature extraction, while the text data is normalized to handle the morphological richness and orthographic variations inherent in Arabic. These preprocessing steps are essential to prepare the data for effective learning, enabling the model to better capture the intricate patterns in both speech and transcription data.

3.2.1 Preprocessing of Audio Data

Before being used for training CSR models, the raw audio files in the MGB-2 dataset undergo several preprocessing steps: Audio Segmentation: The original broadcast recordings are segmented into smaller clips based on speaker turns or silence intervals. This step is important for both training and inference, as it breaks the audio down into manageable units and simplifies the alignment between the audio and the transcriptions. In the preprocessing

pipeline for CSR tasks, raw audio data must be converted into feature representations that are better suited for machine learning models. Mel-frequency cepstral coefficients (MFCCs) are one of the most commonly used features in speech recognition. MFCCs are features that describe the short-term power spectrum of a sound signal, tailored to human speech perception. They compress speech into a low-dimensional form, making it easier for neural networks to process. The MFCC extraction process includes applying pre-emphasis to balance frequencies, dividing the signal into 25 ms frames with 12.5 ms overlap, and converting it from the time domain to the frequency domain using a fast Fourier transform (FFT). The power spectrum is then filtered using a Mel scale, converted to a logarithmic scale, and a discrete cosine transform (DCT) generates 93 uncorrelated MFCC coefficients, capturing key speech information.The MFCC extraction process involves several steps, as illustrated in Figure 2:

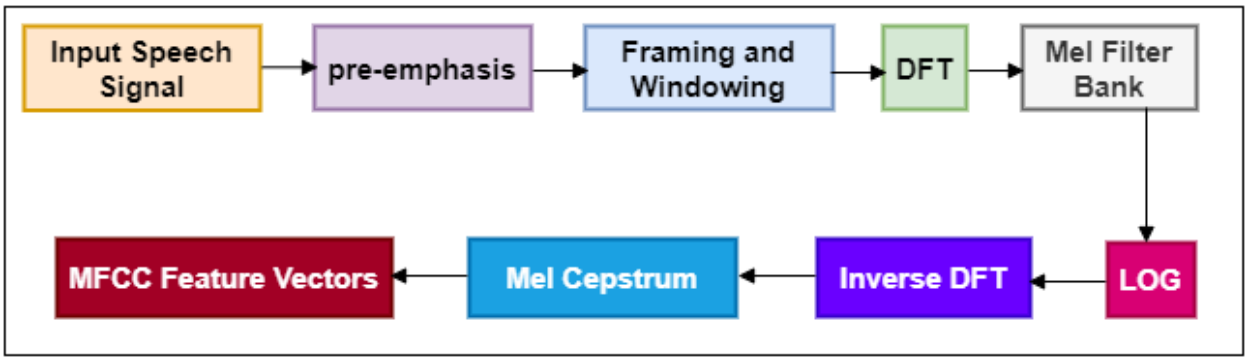

***Figure 2*: MFCC Extraction Process**

3.2.2 Text Preprocessing

To ensure high-quality input for the Arabic CSR model, this preprocessing pipeline is applied to the transcription texts. Preprocessing is crucial to clean the text data and standardize the Arabic script, which helps in improving the performance of the speech recognition model. The transcription texts in the MGB-2 dataset may contain various characters, noise, and inconsistencies. For example, Arabic letters can have different forms based on diacritics, and there may be special characters or English text that does not contribute to the CSR task. The preprocessing step aims to:

- Normalize different forms of the same Arabic letter.
- Remove any special characters, numbers, or noise that could confuse the model.
- Ensure that the text only contains characters relevant to Arabic phonemes.

Transcription Encoding

In this work, we utilize a custom transcription encoding scheme designed specifically for Arabic CSR. The transcription encoding process plays a critical role in transforming raw text into a format suitable for input to machine learning models, and it also allows decoding the model's predictions back into human-readable text. Given the unique characteristics of the Arabic language, including its rich morphology and complex script, careful attention must be paid to the selection and handling of characters. To prepare the transcription text for input into the neural network model, the characters are first converted into numerical tokens.

We employ a well-defined character set and implement efficient character-to-integer and integer-to-character mappings, we ensure that the model can accurately process and generate transcriptions. This approach allows the model to handle the intricacies of Arabic text, while maintaining a manageable vocabulary size and facilitating efficient learning and inference.

3.3 Model Architecture

The architecture of the proposed model follows a hybrid approach combining convolutional and recurrent layers. The input layer accepts variable time steps and a 93-dimensional MFCC representation with a single input channel. Since VGG16 expects a 3-channel input, the single-channel MFCC input is expanded to 3 channels by duplicating it. The VGG16 Backbone (pre-trained on the ImageNet dataset) is used for feature extraction through its convolutional layers with max pooling. These layers extract spatial features from the spectrogram, utilizing pre-trained weights to capture low-level representations that generalize well even for speech data. Transfer learning is applied by freezing all VGG16 layers, ensuring that the pre-trained weights are retained throughout training. The extracted features are further processed through batch normalization and ReLU activation to normalize and introduce non-linearity into the feature maps. After feature extraction, the output is reshaped for recurrent processing. The model uses three bidirectional Long Short-Term Memory network (BiLSTM) layers to capture temporal dependencies in both forward and backward directions, which is crucial for CSR. Each BiLSTM layer contains 1024 units, and dropout with a rate of 0.5 is applied after each BiLSTM to prevent overfitting during training. In the fully connected layers, a dense layer with ReLU activation reduces the dimensionality of the BiLSTM outputs, followed by another dropout layer to further mitigate overfitting. The final classification layer applies softmax activation to predict the probability distribution over the possible character classes, including an additional class for the "blank" token required by the Connectionist Temporal Classification (CTC) loss. The number of output classes corresponds to the size of the Arabic character set (35), with one extra class for the blank token. This architecture leverages both pre-trained convolutional networks (VGG16) for feature extraction and recurrent networks (Bidirectional LSTM) for modeling temporal dependencies in speech data. The VGG16 model provides a robust mechanism for extracting spatial features from spectrograms, while the LSTM layers excel at capturing temporal relationships. The use of CTC loss further allows the model to learn in a sequence-to-sequence framework without explicit frame-level alignment.

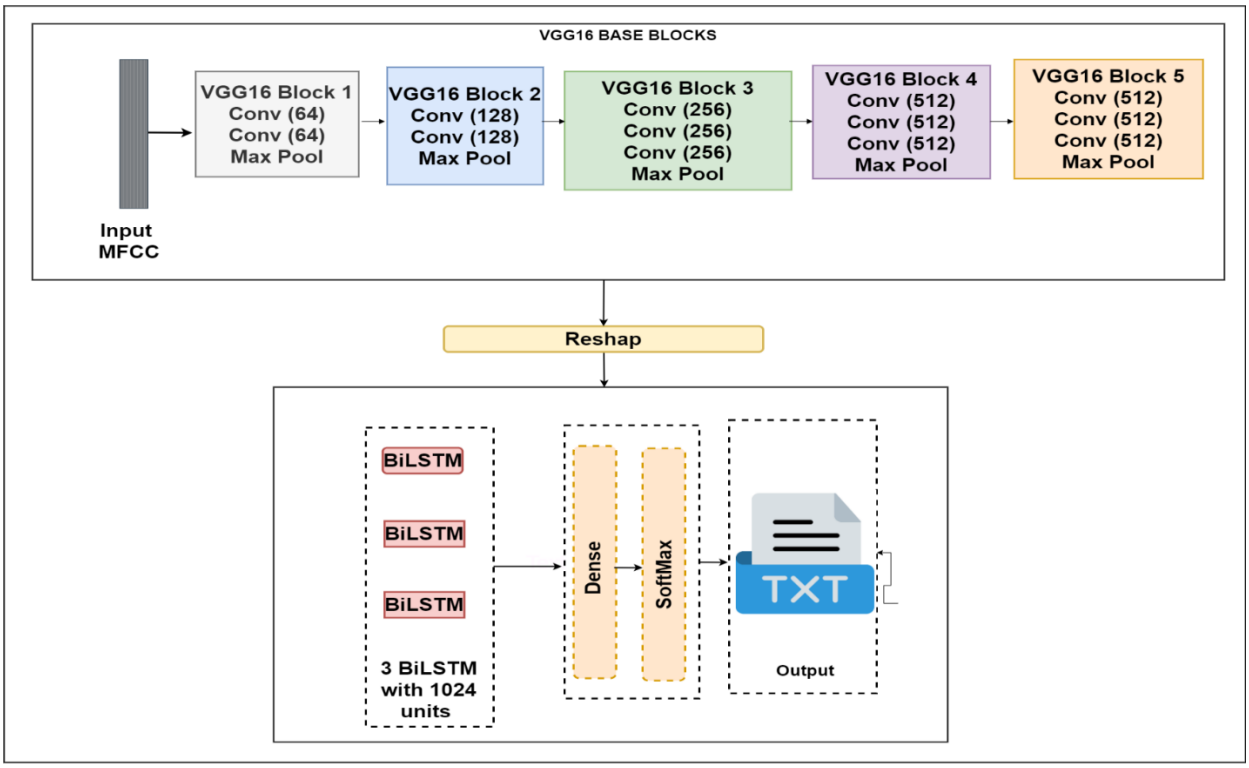

Figure 3: The Proposed Model Architecture

4. EXPERIMENTAL RESULTS

The performance of our Arabic continuous speech recognition model was evaluated on the MGB-2 dataset, a challenging dataset containing hundreds of hours of Arabic broadcast news audio. The model's architecture combines a pre-trained VGG16 network for feature extraction with three bidirectional LSTM layers for temporal modeling. The input features consist of 93-dimensional MFCCs, which capture the essential acoustic properties of the speech signal. The model was trained for 100 epochs using the RMSprop optimizer with a learning rate of 1e-4, and the loss function employed was Connectionist Temporal Classification (CTC) loss, which is suitable for sequence-to-sequence alignment tasks.

4.1 Evaluation Metrics

The performance of the model was primarily assessed using two standard metrics for continuous speech recognition: Word Error Rate (WER) and Character Error Rate (CER). These metrics are standard for continuous speech recognition tasks and provide an indication of how well the model generalizes to unseen data. The WER measures the proportion of incorrect words in the model's transcriptions compared to the reference transcriptions, while the CER assesses the accuracy at the character level. These metrics are crucial for evaluating how well the model generalizes to unseen data and handles the complexities of Arabic speech, such as its rich morphology and phonetic structure.

Word Error Rate (WER)

WER is the most commonly used metric for evaluating the accuracy of speech recognition systems. It measures the percentage of words in the predicted transcription that are incorrect compared to the reference transcription. WER is calculated by computing the minimum number of substitutions, insertions, and deletions required to transform the predicted transcription into the reference transcription, divided by the total number of words in the reference. The formula is:

$$WER=S+I+D/N \ldots\ldots\ldots\ldots\ldots(1)$$

Where:

- S = Substitutions, I = Insertions, D = Deletions, N = Total words in the reference. A lower WER indicates better performance.

Character Error Rate (CER)

CER operates at the character level, measuring how many characters in the predicted transcription are incorrect. It is calculated similarly to WER but focuses on individual characters:

$$CER=S+I+D/N\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

4.2 Model Performance

The model is trained using the Connectionist Temporal Classification (CTC) loss function, which allows the network to predict variable-length outputs for sequences where the alignment between input and output is not predefined. The optimizer used is RMSProp with a learning rate of 1e-4, which is well-suited for training deep neural networks with recurrent layers. To better understand the model's learning dynamics, we tracked both the training and validation loss over the course of 100 epochs. Figure 5 illustrates these trends:

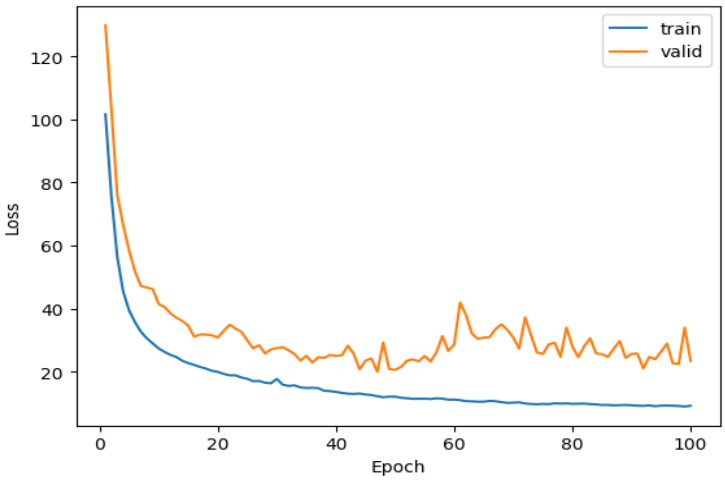

Figure 4: Training and Validation Loss over 100 Epochs

After training, the model achieved a WER of 13% on the test set of the MGB-2 dataset. This result demonstrates a significant improvement over baseline models for Arabic CSR and highlights the effectiveness of using pre-trained VGG16 layers in conjunction with bidirectional LSTM networks. The model's ability to learn both spatial features from the MFCC input and temporal dependencies from the speech signal contributed to its strong performance.

The **Character Error Rate (CER)**, although not the primary focus of this evaluation, further confirmed the model's capability to accurately transcribe Arabic speech at a finer granularity. The CER was found to align well with the WER, showing that the model effectively captures both word-level and character-level structures, which is critical for handling the complexities of the Arabic language.

4.3 Comparison with Other Models

This section provides a comparative analysis of our proposed Arabic CSR system, which achieved a WER of **13%** on the MGB-2 dataset, with two prominent systems previously published. Our model's WER of 13% compares favorably with previously published results on the MGB-2 dataset, where typical baseline WERs ranged from 14.2% to 35% depending on the architecture and feature extraction methods used. The incorporation of a pre-trained VGG16 network allowed for robust feature extraction from the MFCC inputs, while the bidirectional LSTMs successfully captured temporal dependencies, further reducing the WER. As shown in Table 1, the comparison highlights the performance of our proposed model against other prominent systems, demonstrating its superior WER on the MGB-2 dataset due to the integration of VGG16 and BiLSTM layers.

Table 1: Comparison of WER for Arabic CSR Models

Study	**Dataset**	**Model Architecture**	**WER (%)**	**Key Innovations/Limitations**
Our ASR System	MGB-2	Hybrid VGG16-CNN + BiLSTM	**13**	Transfer learning from VGG16, hybrid CNN-LSTM
Mubarak **et al. (2021)**	MGB-2	LSTM, BLSTM, TDNN (LF-MMI)	14.2	Combined LSTM, BLSTM, TDNN, traditional feature adaptation
Khurana et al. (2019) - DARTS	MGB-3 (Egyptian)	CNN + TDNN + LSTM	35.8	Discriminative training (LF-MMI), dialect-specific focus

The comparative analysis demonstrates that our proposed ASR system, which integrates VGG16-CNN and BiLSTM architectures with transfer learning, outperforms previous systems developed by Khurana and Ali in terms of WER on the MGB-2 dataset. While the QATS system achieved a WER of 14.2%, our system improves upon this with a WER of 13%, demonstrating the effectiveness of utilizing deep learning and transfer learning techniques for Arabic CSR. Furthermore, the DARTS system, which focused on dialectal transcription in Egyptian Arabic, achieved a much higher WER of 35.8%, reflecting the difficulty of adapting dialect-specific systems to general broadcast speech. The combination of transfer learning from VGG16 and the hybrid CNN-BiLSTM architecture proves to be a key differentiator, allowing your model to outperform more traditional approaches based on LSTM, TDNN, and CNN layers alone.

5. DISCUSSION AND CONCLUSION

This research demonstrates the effectiveness of integrating a VGG16-CNN architecture with BiLSTM layers for Arabic Continuous Speech Recognition (CSR). By leveraging transfer learning, where pre-trained VGG16 weights are applied for feature extraction, the model effectively captures both spatial and temporal features from Arabic speech signals. This hybrid architecture, which combines the strengths of CNNs in handling spatial features from spectrograms and BiLSTMs in capturing temporal dependencies, achieved a Word Error Rate (WER) of 13% on the MGB-2 dataset, outperforming traditional models and several state-of-the-art systems.

The results show a significant improvement over models that rely solely on LSTM, TDNN, or HMM-based approaches, particularly those that struggle with Arabic's linguistic complexities, such as its rich morphology, dialectal variations, and the absence of short vowels in written text. The ability of the VGG16-CNN layers to extract meaningful features from MFCC representations of speech, coupled with the BiLSTM's capacity to model sequential data, contributed to the model's superior performance. Moreover, the model's effectiveness in recognizing both Modern Standard Arabic and dialectal variations highlights its potential to generalize across diverse speech environments. When compared with other prominent systems, which focus on dialect-specific transcription, our model demonstrated better generalization and adaptability, achieving a much lower WER. This highlights the potential of transfer learning and deep learning techniques in addressing the unique challenges posed by Arabic CSR. However, further improvements can still be made, particularly in developing more robust dialect-specific systems and addressing the morphological complexity of Arabic. Future research should explore larger, more diverse datasets and investigate techniques like semi-supervised learning to improve CSR performance in low-resource environments. With continued advancements, Arabic CSR systems could reach performance levels comparable to human transcription, opening new possibilities for applications in media, education, and accessibility. The hybrid VGG16-CNN and BiLSTM model presented in this research offers a promising solution for Arabic CSR, significantly reducing WER and enhancing the system's ability to handle the complexities of the Arabic language. With further advancements, such as larger datasets and innovative learning approaches, the performance of Arabic CSR systems could approach human-level transcription accuracy, expanding their applications in media, education, and accessibility.

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