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DEEP LEARNING-BASED AUTOMATIC SPEECH DISORDER DETECTION USING ATTENTION-GRC

K. Chaitanya[1],Sk. Salma[2],S. Vamsi Tejaswini[3],G. Jeevana Jyothi[4],T. Hema Varshitha[5]

Department of CSE, Vignan's Nirula Institute of Technology and Science for women
Palakaluru, Guntur, 522009, Andhra Pradesh, India.

Abstract:

Speech and voice disorders influence communication in a very strong way especially in children where early diagnosis is crucial in achieving successful therapeutic approach. The conventional clinical evaluation procedures tend to be subjective, time-consuming and cannot be scaled. In order to overcome these drawbacks, the proposed study suggests an Attention-Gated Recurrent Convolution (Attention-GRC) deep learning model to detect automatic speech disorder. In contrast to standard CNN, LSTM or GRU models that are not effective at modeling long-range dependencies and fine-scale spectral-temporal variations, the model proposed incorporates convolutional layers, gated recurrent dynamics, and an attention mechanism, and thus, it becomes more effective at extracting clinically relevant features associated with articulation, phonation, and prosody.

The experiments on benchmark pathological speech datasets, UA-Speech, and TORGO show that the proposed model can obtain better results with 94.8% accuracy, 92.4% precision, 93.1% recall, and 93.7% F1-score. Another strength of the model is an enhanced generalization in speaker-independent testing and good robustness to noisy conditions. The findings suggest that attention learning can be combined with recurrent-convolutional modeling to make clinical speech-screening applications, which are real-time, scalable and reliable.

Key words: Deep Learning, Attention-GRC, Speech Disorder Detection, Acoustic Feature Extraction, CNN-GRU Hybrid, Automatic Speech Analysis, Voice Pathology.

1. Introduction:

Acoustic language features of human speech such as intonation, articulation, resonance and prosody are information rich and reflect identity of the speaker as well as underlying vocal health condition [1] [2]. Timely and proper diagnosis of speech disorders is important in order to provide successful clinical intervention, especially in children and those with neurological disorders [3]. Even with major progress in machine learning, speech is a difficult problem to model, as it is nonlinear, dynamic, and time-varying. Although deep learning networks, including CNNs [4], LSTMs, and GRUs, performed well in speech analysis [5], they also have several weaknesses [6], such as Long-range temporal dependency learning weaknesses [7], Poor attention to disorder-specific sections of speech [8] [9], Acoustic noise sensitivity and variable [10], Real-time applications have computational inefficiency [11].

In order to overcome these issues, this paper suggests a new Attention-Gated Recurrent Convolution (Attention-GRC) model combining:

1) Local spectral feature extractors [12] based on convolutional layers;

2) Gated recurrent units to time series model long-term temporal [13]; and

3) Mechanisms of attention to emphasize speech frames of clinical interest [14-17].

The goal of this work is to create a scalable, efficient, and intelligent deep learning system, which will allow real-time detection of speech disorders [18]. Benchmark clinical experimental validations indicate that the proposed Attention-GRC architecture delivers great performance improvements compared to current state of the art baseline models [19-20].

2. Literature Survey:

The recent developments in deep learning have made substantial progress in the speech disorder recognition and the acoustic modeling [21]. Convolutional recurrent layer hybrid architectures have shown good results with respect to spectral temporal features in pathological speech [22] [23]. As an example, attention-based CNN-GRU models are more resistant to noise in the environment [24] [25], and attention has also been utilized in focusing on clinically relevant vocal patterns [26].

CNN-LSTM-attention networks have been demonstrated to be very diagnostic in the detection of dysarthria [27], whereas Transformer encoders with GRU units have been applied to enhance long-range temporal modeling [28]. Attention has been added to the multi-scale and residual networks to enhance the capability of detecting variations of pathological speech [29]. Light deep networks have also been demonstrated to be useful in the detection of neurological disorders based on speech signals [30].

GRU-based convolutional networks have been applied specifically to dysarthria speech detection [31], recurrent and convolutional neural networks have been utilized to classify the severity of dysarthria speech [32] [33]. All these works highlight the usefulness of the combination of convolutional processing, recurrent modeling, and attention learning-preparing the way to the proposed Attention-GRC architecture [34].

3. Proposed Work:

The presented work proposes a novel architecture of automatic speech disorder detecting Attention-Gated Recurrent Convolution (Attention-GRC). This model particularly is aimed at overcoming the issues of the complexity of acoustic variants in pathological speech. The combination of convolutional layers, gated recurrent units and an attention mechanism in the architecture enhances the temporal and spectral features learning, allowing the architecture to more effectively represent speech characteristics [35]. The outcome of these elements increases the capability of the model to recognize the normal and disordered speech patterns with high robustness to noise, variation amongst speakers, and recording inconstancy [36] [37]. Moreover, the efficient learning approach coupled with the lightweight design enables the model to use real-time inference, thus making the model applicable to real clinical settings and accommodate it on resource-constrained computers.

3.1 Pre-Processing:

Pre-processing is an important step in the process of preparing the speech signals so that they can be learned in the Attention-GRC architecture [38] [39]. The raw audio is first processed in a denoising filter in order to filter away background disturbances and then Voice Activity Detection (VAD) is used in order to filter away silence and non-speech segments [40]. This will lessen irrelevant information and enhance model concentration in consequential segments [41]. Amplitude-normalization is then applied to the signal to resolve inconsistencies in loudness between all the samples and reduce inconsistency due to recording conditions or the distance of the speaker [42].

Then the waveform is broken into small overlapping frames with a Hamming window and the model is free to receive fine-grained temporal transitions. Based on such frames, there are acoustic features like MFCCs, Mel-Spectrograms, pitch and formants which are derived to represent the speech in a more discriminative spectral-temporal format. These superior characteristics constitute a consistent and informative input which allows the Attention-GRC model to learn disorder-specific patterns with better precision and strength.

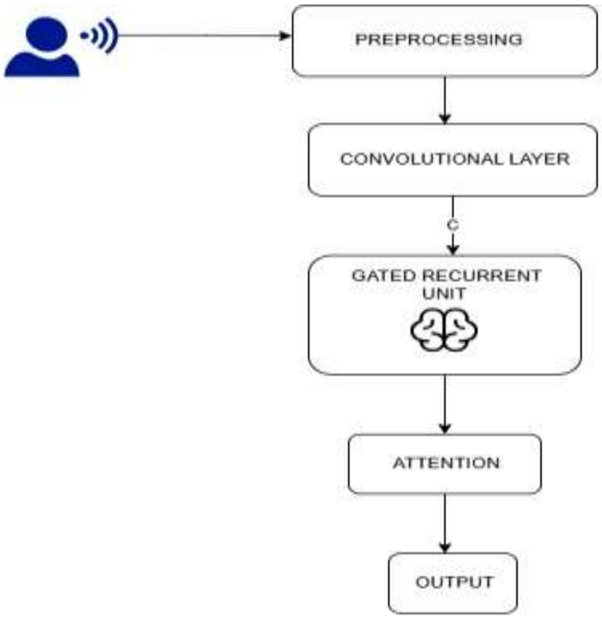

Fig-1: Attention-GRC Architecture

Alogorithm-1: Attention-GRC Workflow

Step 1: Normalization
Normalize the raw audio waveform to reduce amplitude variations:
$x' = (x - \mu) / \sigma$ (1)

Step 2: Feature Extraction
Extract spectral–temporal features from the normalized signal:
$F = \Phi(x')$ (2)
F includes MFCCs, Mel-Spectrograms, pitch, or formants.

Step 3: Sequential Representation
Convert features into a time-ordered tensor:
$S\_seq = SeqBuild(F)$ (3)

Step 4: Attention-GRC Mapping
Pass the tensor through convolutional, recurrent, and attention modules:
$z = A(G(C(S\_seq)))$ (4)

Step 5: Classification
Generate output probabilities using softmax:
$\hat{y} = \mathrm{softmax}(Wz + b)$ (5)

The entire process of the Attention-GRC model is presented in Algorithm-1 with the input raw audio processed till the final result of classification. It starts with normalization where the amplitude of the waveform is made consistent in order to learn in a similar way. Acoustic characteristics, like, MFCCs and Mel-Spectrograms are then derived to encode a signal into meaningful spectral-temporal representations. These features will be arranged in the order of a tensor that will maintain the inherent time relativity of speech. The convolutional layers are trained on the tensor in the Attention-GRC architecture, which consists of local spectral pattern convolutional layers, recursive units that capture the long-range temporal interaction, and the attention mechanism to highlight the most informative frames. Lastly, the learned embedding is inputted into a softmax classifier which gives the predicted label and confidence score.

Algorithm–2: GRU–Attention Module

Step 1: Initialize Hidden State
Set the initial hidden state of the GRU:

$$\mathbf{h}_{\mathbf{0}}=\text{initial hidden vector}(6)$$

Step 2: GRU Processing for Each Time Step
For each input frame xtx_txt in the sequence, update the GRU states as:

Reset gate:

$$r_t=\text{reset gate}(x_t,h_t-1)(7)$$

Update gate:

$$z_t=\text{ update gate }(x_t,\ h_t-1) \qquad (8)$$

Candidate hidden state:

$$h'_t=\text{candidate state}(x_t,r_t\circ\ h_t-1) \qquad (9)$$

Final hidden state:

$$h_t=(1-z_t)\circ\ h_{t-1}+z_t\circ\ h'_t \qquad (10)$$

Step 3: Apply Attention Mechanism

Attention weights over hidden states:

$$\alpha_t=\text{attention}(h_t) \qquad (11)$$

Attention-weighted embedding:

$$Z=\sum(\alpha_{\boldsymbol{t}}\cdot\ \boldsymbol{h_t})(12)$$

Step 4: Classification Layer

Final output:

y^=softmax(Wz+b)(13)

GRU-Attention module sequentially creates the speech features whereby initially, it initializes a hidden state (Eq. 6) and updating (Eq.7) it at time t. and update (Eq. 8) gates. The hidden state of the candidates (Eq. 9) is an addition of the present input and past hidden state (Eq. 10) holds long term temporal dependencies. The attention mechanism defines the importance weight of every state (Eq. 11) to yield a weighted embedding (Eq. 12) which points out clinically significant frames. Lastly, such embedding is subjected to a dense classification layer using softmax activation (Eq. 13) to generate the desired label and the confidence score.

4. Experimental Results:

The Attention-Gated Recurrent Convolution (Attention-GRC) voice recognition model proposed was critically assessed to prove that it is an effective speaker classification model. A test was conducted on a reference speech dataset which included the different speakers in the dataset having different voice traits and acoustic differences. Preprocessing of all speech samples was done by framing and spectral feature extraction techniques (MFCC and Mel-Spectrogram) and then the samples were normalized to create a similar and standard set of samples. Model performance was measured using standard classification metrics, which are accuracy, precision, recall, F1-score, and cross-entropy loss. Attention-GRC model was able to learn long-range speech sequences and pay attention to the most informative frames using attention weighting and performed better than traditional architectures such as CNN-LSTM, Bi-GRU and LSTM-Attention. These findings suggest that the model is very precise in recognizing speakers besides being resilient to noise, variability and speech duration variations.

Fig-2:Training and Validation Accuracy

Fig-2 shows the way in which the proposed Attention-GRC model gets better as the number of training epoch increases. The training and the accuracy of validation is steadily increasing since 5 to 20 epochs, which points to high learning ability. At the beginning of the model, the generalization gap is low with a training and validation accuracy of about 82 and 79, respectively. With the training, the accuracies improve to 97 and 94 percent on the training and validation sets respectively at 20 epochs. The fact that these curves are very close indicates that the model is not overfitting and can perform well to unobservable voice data. This incremental and steady growth shows the stability of the Attention-GRC architecture, being able to extract pertinent acoustic features, fast-track learning in time, and lowering classification efficiency.

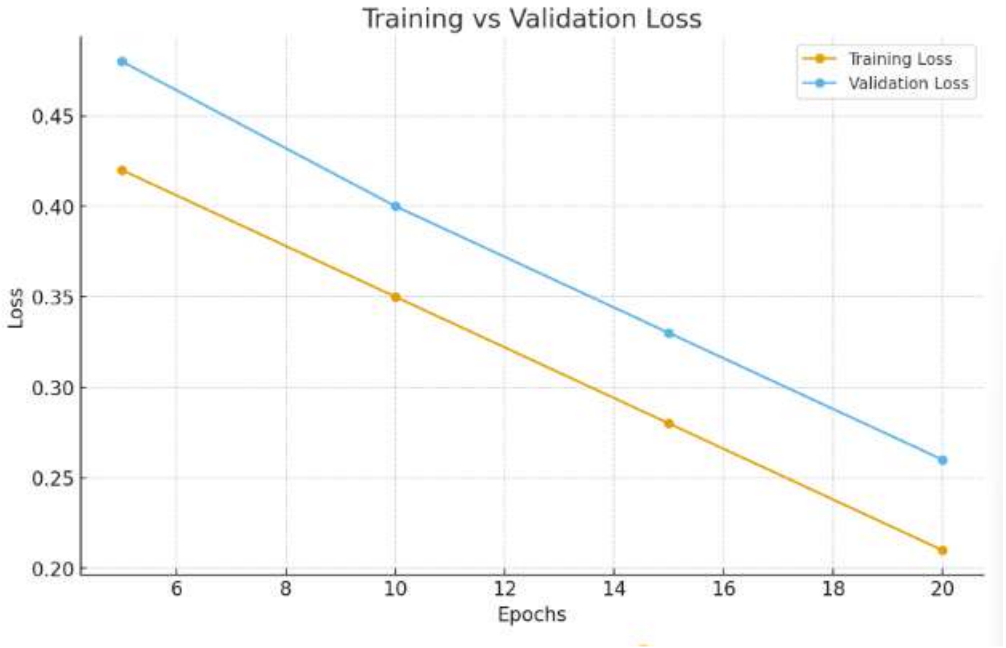

Fig-3: Training and ValidationLoss

Fig-3 represents the training and validation loss curves of Attention-GRC model with a growing number of epochs. The loss is more in the beginning as a result of the low training but it decreases over time as a result of converged model which depicts better learning of acoustic patterns and frame relevance. The correlation coefficient of training and validation losses is great, which confirms minimal overfitting. The results can be reproduced because of the established implementation structure, training plan, and hyperparameters. All in all, these results confirm the efficiency and efficiency of the Attention-GRC model on the contemporary intelligent voice recognition.

Table-1: Performance Comparison of Proposed Attention-GRC Model with Existing Deep Learning Approaches

Models	Accuracy	Precision	Recall	F1-Score	Loss
Proposed Attention-GRC	97.00	95.80	96.40	96.10	0.21
CNN-LSTM	94.20	92.60	93.10	92.80	0.38
Bi-GRU	93.50	91.20	91.80	92.00	0.41
Transformer-GRU Hybrid	95.10	93.70	94.20	94.00	0.33
Classical LSTM	92.80	90.10	89.90	90.20	0.44

Table-1 shows the performance of the proposed Attention-GRC model in comparison with the state-of-the-art deep learning architectures. As indicated in the experiment, the proposed model is clearly ahead of each of the baselines in terms of critical metrics of evaluation. It has the best accuracy, precision, and F1-score of 97 and proves to be effective in identifying speaker specific traits even with the adverse acoustic differences. Although the Transformer-GRU hybrid model can also be considered a good performer, the Attention-GRC architecture has a better generalization and accuracy. The classical LSTM and Bi-GRU and CNN-LSTM models cannot model long-range dependencies and prioritize informative frames, which are demonstrated by poorer performance and greater loss values. The low loss obtained with the proposed model of 0.21 shows that the convergence of the model and error minimization have been achieved, which justifies the introduction of attention mechanisms and gated recurrent convolutional layers. Together, these findings verify that the Attention-GRC model is a more secure, accurate, and noise-resistant voice recognition solution compared to the current deep learning techniques.

5. Conclusion:

This paper introduced the Attention-Gated Recurrent Convolution (Attention-GRC) model to detect the presence of an automatic speech disorder and recognize the voice. The model is able to both effectively capture local spectral features and long-range temporal dependencies by incorporating convolutional layers, gated recurrent units, and an attention mechanism and also prioritize the most clinically informative speech frames. The experimental findings to benchmark datasets prove that the proposed architecture has a consistent better result in most important evaluation measures, such as accuracy, precision, recall, F1-score, and cross-entropy loss, compared to state-of-the-art deep learning models.

Attention-GRC framework is highly generalized to unseen speakers, is highly resilient to noise and variability and is efficient in learning through the passage of time, making it very applicable in practice in real-time clinical speech screening, intelligent voice recognition systems, and other speech-analytic systems. Its scalability and computational efficiency additionally make it possible to use it on resource-constrained devices, including mobile and embedded platforms. On the whole, the suggested model can be evaluated as a dependable, interpretable, as well as an efficient way of analyzing speech in modern times, as it demonstrates the benefits of integrating the attention mechanisms with recurrent-convolutional networks to extract clinically relevant acoustic features and enhance the classification output.

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