Investigating the effect of domain selection on automatic speech recognition performance: a case study on Bangladeshi Bangla

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The performance of data-driven natural language processing systems is contingent upon the quality of corpora. However, principal corpus design criteria are often not identified and examined adequately, particularly in the speech processing discipline. Speech corpora development requires additional attention with regard to clean/noisy, read/spontaneous, multi-talker speech, accents/dialects, etc. Domain selection is also a crucial decision point in speech corpus development. In this study, we demonstrate the significance of domain selection by assessing a state-of-the-art Bangla automatic speech recognition (ASR) model on a novel multi-domain Bangladeshi Bangla ASR evaluation benchmark — BanSpeech, which contains 7.2 hours of speech and 9802 utterances from 19 distinct domains. The ASR model has been trained with deep convolutional neural network (CNN), layer normalization technique, and Connectionist Temporal Classification (CTC) loss criterion on SUBAK.KO, a mostly read speech corpus for the low-resource and morphologically rich language Bangla. Experimental evaluation reveals the ASR model on SUBAK.KO faces difficulty recognizing speech from domains with mostly spontaneous speech and has a high number of out-of-vocabulary (OOV) words. The same ASR model, on the other hand, performs better in read speech domains and contains fewer OOV words. In addition, we report the outcomes of our experiments with layer normalization, input feature extraction, number of convolutional layers, etc., and set a baseline on SUBAK.KO. The BanSpeech will be publicly available to meet the need for a challenging evaluation benchmark for Bangla ASR.

Additional Keywords and Phrases: Automatic speech recognition, Domain selection, Spontaneous speech, Read Speech, Corpus design, Bangla

1 INTRODUCTION

Neural Network (NN) based Automatic Speech Recognition (ASR) requires vast quantities of transcribed speech data. Speech datasets can be broadly categorised into two types on the basis of data collection sources: 1) Read speech dataset in which the data is compiled by prompting the speakers to read texts from newspapers, books, etc. 2) Broadcast speech dataset in which the data is obtained from public domains such as television programs, YouTube videos, movies, and parliamentary speeches, among others. Although it is possible to extract clean read speech from broadcast sources, broadcast speech consists primarily of spontaneous speech in noisy and multi-talker environments. Moreover, due to inadequate bandwidth, the quality of read speech collected from broadcast sources often degrades. While compiling a speech dataset, domain selection is a crucial step whose impact on ASR performance might be substantial. Kibria et al. have developed SUBAK.KO, an annotated speech corpus for speech recognition research comprising 241 hours of Bangladeshi Bangla speech data, to address the dearth of annotated speech datasets in Bangla [1]. SUBAK.KO contains 229 hours of clean read speech and 12 hours of broadcast speech utterances. The recording scripts are collected from 40 text-domains, including conversations, sports, news, poetry, letters, etc., following the reception and production criteria for the text domains to build the corpus [2]. According to a cross-dataset evaluation, SUBAK.KO is a more balanced corpus with respect to regional accents and other types of speaker variability compared to another large-scale Bangladeshi Bangla speech corpus, LB-ASRTD, when evaluated on clean read speech test sets [1][3]. However, it is yet uncertain how well an ASR model based on SUBAK.KO performs in a range of domains, particularly those that include the majority of spontaneous speech. Human verbal communication consists primarily of spontaneous speech with some background noise, and past research indicates significant acoustical and linguistic variations between read speech and spontaneous speech [4].

This paper focuses on the following research question: do the 40 text domains considered while developing SUBAK.KO meet all of the reception and production criteria for developing an ASR corpus that can ultimately lead to improved performance in challenging real-world conditions, such as noisy, spontaneous, and multi-talker environments? Through a comprehensive evaluation of an ASR model trained on SUBAK.KO, we aim to shed light on the significance of domain selection for the development of a speech dataset. In order to study this, we present BanSpeech, a novel multi-domain Bangladeshi Bangla ASR evaluation benchmark consisting of 7.2 hours of speech data and 9802 utterances from 19 domains collected from YouTube and manually transcribed by human annotators. This speech dataset consists primarily of spontaneous speech from all domains, with the exception of audiobooks and biography domains, which comprise read speech. In this work, BanSpeech has been used to extensively evaluate the Bangla ASR trained on SUBAK.KO as well as the Google cloud Bangla Speech-to-Text system [5]. For training our ASR model, we use the 241-hour long Bangladeshi Bangla speech corpus SUBAK.KO, and similar to our previous study on LB-ASRTD [6], we train a deep Convolutional Neural Network (CNN) model while improving several aspects of the previously used architecture, such as experimenting with the number of convolutional layers, applying several normalization
techniques, and trying out some input feature extraction methods from audio signals and observing the effect of the number of Mel Frequency Cepstral Coefficients (MFCCs). The results of the enhanced ASR model are also reported in this paper. The rest of the paper is structured as follows: relevant literature review is done in section 2. In section 3, the preparation of the BanSpeech is described. We discuss the input feature extraction methodology as well as the architecture of our Bangla ASR model in section 4. Section 5 presents the speech and text corpus details used for acoustic modeling and language modeling, respectively. Results are shown and discussed in section 6. Section 7 concludes the paper and provides the future direction.

2 RELATED WORK

While prior to 2019, Bangla ASR research was limited to only isolated words and digit recognition using small datasets, some work has been done on Bangla large vocabulary continuous speech recognition (LVCSR) recently. Amin et al. examined DNN-HMM and GMM-HMM based techniques on a relatively small and speaker-independent Shruti corpus (21.64 hours) [7]. According to their findings, a larger data set is necessary for the DNN-HMM method to outperform the GMM-HMM method. Sumit et al. implemented the RNN-based Deep Speech 2 architecture on the non-public 300-hour-long "Sociam" Bangla telephone conversation-based dataset [8]. In addition to Sociam, they also added 50 hours from the Bangla Babel corpus. Developed in 2016, Bangla Babel is likewise a telephone conversation-based speech corpus, comprising 215 hours of speech [9]. However, Babel has West Bengal accented speech that is distinct from the Bangladeshi Bangla accent. Ahmed et al. prepared 960 hours of broadcast Bangla speech corpus by transcribing speech data in an automated way with pre-trained ASR models [10]. The corpus is not publicly accessible, and the authors focused on developing an algorithm to iteratively construct speech corpora in their work. However, the objective of our work is to empirically evaluate an ASR model on diverse domains to find out whether performance can vary across different domains. Samin et al. evaluated the quality of a large-scale publicly available LB-ASRTD corpus (229 hours) using deep learning-based approaches by conducting character-wise error analysis [6]. They also found a deep CNN-based acoustic model and a 5-gram Markov Language Model (LM) to be capable of achieving a lower word error rate (WER) on LB-ASRTD. In this study, we also use a deep CNN-based model and a 5-gram LM while utilizing a higher number of MFCCs during the input feature extraction and introducing layer normalization in each convolution layer. Based on an acoustic study on a regional accented speech and the character-wise error analysis on LB-ASRTD, the requirement of a new corpus with more speaker variability and character-wise well-balancedness was recommended [11][6]. Therefore, Kibria et al. developed the 241-hour long publicly available Bangladeshi Bangla SUBAK.KO corpus with the aim of addressing the above-mentioned issues of LB-ASRTD [1]. The Bengali Common Voice Speech dataset with over 400 hours of crowdsourced data has been made available on the Mozilla Common Voice Platform, and the campaign to address the scarcity of Bangla speech datasets is ongoing [12]. Although there are some annotated ASR corpora for Bangla, there is no comprehensive ASR evaluation benchmark in this language that can categorically investigate a model on a variety of domains, dialects, and speech types from multiple speakers.

3. BanSpeech DATASET

We collect speech data from the open-source platform YouTube. We consider 19 domains, namely television news, parliament speech, audio books, drama, class lecture, political talk show, interview, documentary, kids' voice, medical talk show, biography, sports, and 7 regional dialects from all the major divisions in Bangladesh such as Barisal, Chittagong, Dhaka, Mymensingh, Noakhali, Rajshahi, and Sylhet. The regional dialects are mainly obtained from region-specific dramas. There are essentially two types of talk shows we consider in this work: political and medical related. On political talk shows, politicians argue about political matters, while on medical talk shows, medical practitioners discuss medical-related topics and frequently employ scientific jargon. Some domains, such as television news, parliamentary speeches, and documentaries, incorporate both read and spontaneous speech, while others, such as drama, class lectures, political talk shows, interviews, kid's voices, and medical talk shows, consist predominantly of spontaneous speech. The audio book and biographical domains only contain read speech. For each of the domains, there are approximately 30 minutes of speech, except for the dialect domain, which has around 10 minutes of speech per dialect.

We download broadcast speech as waveform audio file format (WAV) using the youtube-dl command. We remove commas and brackets from the original audio file names and replace spaces with underscores to avoid potential errors. To make the corpus consistent, each audio file is then converted to a bitrate of 256 kbps and a 16 kHz mono channel WAV file. After that, each audio file is divided into segments based on silence intervals. We use a silence threshold of -40 dBFS (consider it silent if quieter than -40 dBFS) and 0.2 seconds as the minimum length of silence (the shortest period of silence before a split can happen). Our dataset contains audio files of varying lengths. The lengths of the audio files range from 0.7 to 35 seconds. After preparing the audio files, we use the Google STT system to get the transcripts of those speeches [5]. Two professional native Bangladeshi human annotators with linguistic expertise then manually correct the transcriptions. The corresponding text transcriptions are stored in plain text file format (.txt). The final dataset contains 9802 utterances and 7.2 hours of speech. The detailed statistics of BanSpeech is shown in Table 5.
4. ASR MODEL ARCHITECTURE

4.1 Input Feature

For the CNN, three types of features are used as input to the acoustic model in different experiments: mel-frequency cepstral coefficients (MFCC), mel-frequency spectral coefficients (MFSC) and power-spectrum. MFCCs are widely used input feature in ASR. MFSC refers to the log-energy directly computed from the mel-frequency spectral coefficients without applying Discrete Cosine Transform (DCT). Power-spectrum features have been used in acoustic modeling in recent works [13]. Although 13 MFCCs are generally considered sufficient for extracting acoustic features, we experiment with different numbers of MFCCs to see its impact on WER using our Bangla speech corpus. Non-stationary speech signal is split into smaller windows or frames where it can be assumed as stationary. Different frame sizes and frame strides can affect the WER which we also investigate in this work.

4.2 Acoustic Model Development

There are several variations in the architecture for conducting numerous experiments. In the case of our baseline CNN model, MFCC feature vectors are fed into the CNN. Our baseline architecture consists of mainly convolutional layers and fully connected layers. Our architecture includes 20 convolutional layers (two dimensional) each with a kernel size of 8*1. In the first convolutional layer, 18 MFCCs are mapped to an embedding space of size 256 and stride size 2 is used only for this layer. In the rest of the convolutional layers, there are 256 input channels and 256 output channels (feature maps) and feature extraction through convolution operation is done by 256 filters with stride size 1. Each of the convolutional layers is followed by ReLU activation function to add non-linearity to the network and dropout to address the over-fitting problem. The dropout probability is 0.1. Lastly, two fully-connected layers are attached after converting multi into one dimensional shape by flattening the input tensors for the classification of character-level tokens.

Apart from the baseline architecture, we train several acoustic models incorporating the following normalization techniques:

4.1.1 Batch Normalization

Training a deep neural network is often difficult to converge and time consuming as it suffers from internal covariate shift. Batch normalization is a technique that normalizes the means and variances of layer inputs and thus reduces internal covariate shift and speeds up training [14]. Moreover, it allows us to use larger learning rates by reducing the importance of initial weights and minimizing the risk of vanishing/exploding gradient. It can serve as a regularizer to some extent. Batch normalization is computed using

\[
BN_{\gamma\beta}(x) = \gamma \frac{x-E[x]}{\sqrt{Var[x]+\epsilon}} + \beta
\]

where \(E[x]\) and \(Var[x]\) denotes the mean and variance of the mini-batch computed over the training data. Layer input \(x\) is first normalized by subtracting the mini-batch mean and then dividing by the mini-batch variance. \(\epsilon\) is a small value used for mathematical stability. \(\gamma\) and \(\beta\) are learnable parameters to scale and shift the normalized value.

4.1.2 Weight Normalization

Although batch normalization has brought about breakthroughs in this era of deep learning approaches, the performance of this technique depends on the mini-batch size and it is quite difficult to implement it on recurrent architectures. Weight normalization, first proposed by [15], reparameterizes the weight vectors by separating the norm of the weight vectors from its direction and thus enables faster convergence of stochastic gradient descent (SGD) optimization. In a typical neural network, output from each neuron is calculated using the following equation:

\[
y = \phi(w \cdot x + b),
\]

Here \(y\) is the output of the neuron, \(w\) is a \(p\)-dimensional weight vector, \(x\) is a \(p\)-dimensional input vector, \(b\) is a scalar bias and \(\phi(.)\) is an activation function. According to weight normalization method, weight vector \(w\) is normalized using

\[
w = \frac{v}{\|v\|}
\]
Eq. 3 optimizes a scalar term $g$ and a $p$-dimensional vector $v$. Here, $\|v\|$ stands for the Euclidean norm of $v$.

4.1.3 Layer Normalization

Layer normalization is a technique which enables smoother gradients, speeds up training and results in better accuracy by normalizing the distributions of intermediate layers [16]. It is computed using the following equations:

$$h = g \odot F(x) + b$$  \hspace{1cm} (4) \\
$$F(x) = \frac{x - \mu}{\sigma}$$  \hspace{1cm} (5) \\
$$\mu = \frac{1}{H} \sum_{i=1}^{H} x_i$$  \hspace{1cm} (6) \\
$$\sigma = \sqrt{\frac{1}{H} \sum_{i=1}^{H} (x_i - \mu)^2}$$  \hspace{1cm} (7)

Here $x = (x_1, x_2, x_3, \ldots, x_H)$ denotes the $H$-dimensional input vector, $h$ is the output of Layer normalization, $\odot$ is the scalar product operation, $\mu$ is the variance and $\sigma$ is the standard deviation. $g$ and $b$ are the gain and bias respectively with the same dimension $H$.

5 EXPERIMENT SETUP

5.1 Speech Corpus

We train an ASR model on SUBAK.KO which contains 241 hours of transcribed Bangladeshi Bangla speech data [1]. This corpus has 229 hours of clean read speech and only 12 hours of broadcast speech. Clean read speeches are recorded from 33 native Bangladeshi Bangla male speakers, 28 native female speakers, and 2 L2 speakers. The detailed description of this corpus can be found in the work of Kibria et al. [1]. The same train, dev and test splits used in the original paper have been used in our study. The train, dev and test set contain 200.28 hours, 20.54 hours and 20.30 hours of speech data, respectively. For training the acoustic model, we utilize the wav2letter++ speech processing toolkit [17].

5.2 Language Model

Samin et al. investigated N-gram word-level LMs for the morphologically rich language Bangla and found that high-order N-grams (e.g. 5-gram) can lead to lower WERs for Bangla ASR [6]. Thus, we use the same 5-gram word-level language model trained on the same text corpus prepared by Ahmad et al. [18]. The text corpus contains 10.6 million unique words and 602.5 million total number words.

6 RESULTS & DISCUSSION

In this section, we present the results and discuss the input feature extraction, acoustic modeling experiments, and empirical evaluation of our Bangla ASR model on BanSpeech.

6.1 Experiments on Input Feature Extraction

Three input feature extraction methods from audio signals such as MFCC, MFSC and Power Spectrum are implemented to build Bangla ASR models trained with our baseline deep CNN network and CERs/WERs are compared. Figure 1 illustrates the outcome of this experiment. MFCC technique gets slightly lower WER of 22.34% compared to MFSC which obtains 22.39% WER. Comparing the CERs, however, MFSC gets a slight edge with 6.34% CER than MFCC with 6.38% CER. On the other hand, using Power Spectrum features, the ASR model performs worse, getting a WER of 23.21% and a CER of 6.73%.
Since we get lower WER using MFCC, we conduct further experiments with it by changing the number of MFCCs for each frame. The WERs are calculated using SUBAK.KO dev and test sets and shown in Figure 2. We observe substantial variation in WERs while altering the number of MFCCs from 10 to 24. Initially, with increasing the MFCCs from 10 to 21, we can constantly improve the WERs from 26.20% to 22.34%. Taking 24 MFCCs per frame, however, slightly degrades the ASR performance with 22.53% WER. Similar phenomenon is observed on the dev set as well. These results suggest that a higher number of MFCCs (e.g. 21 MFCCs) generally ensures lower WER in the case of clean read speech training data.

Table 1 presents the impact of windowing on CERs and WERs for a deep CNN-based ASR model. As seen from Table 1, frame size and frame stride have a strong impact on the ASR performance as well as the computational cost. Setting the frame size to 30 ms and stride to 20 ms provides the lowest WER of 20.51% and CER of 6.04%. This setting also reduces the training time to only 17.44 hours. Based on this experiment, we suggest experimenting with the frame sizes and strides to find the suitable setting for each dataset while developing an ASR model.

6.2 Acoustic Modeling Experiments

The performance of Neural Networks rest on the amount of data and the complexity of the networks/number of parameters. We split the SUBAK.KO train set and prepare 5 subsets containing 40 hours, 80 hours, 120 hours, 160 hours, and 200 hours of speech data. Using each of the subsets, we train three ASR models with 10, 15, and 20 convolutional layers. The correlation between training data size and number of convolutional layers is shown in Table 2. In the case of 40 hours of training data, the CNN model with 15 convolutional layers outperforms the models with 10 layers and 20 layers, getting a WER of 47.94% and CER of 16.45%. The advantage of the deep CNN with 20 convolutional layers becomes more apparent as we increase the amount of data. Using 200 hours of train data, CNN with 10, 15, and 20 convolutional layers obtain 25.04%, 19.23%, and 17.79% WERs, respectively.
Table 1. Impact of windowing on CERs and WERs calculated using an acoustic model trained with deep CNN and evaluated on the SUBAK.KO test set

| Frame size (in ms) | Frame Stride (in ms) | CER  | WER  | Training Time (in hours) |
|-------------------|---------------------|------|------|--------------------------|
| 25                | 10                  | 6.63 | 23.15| 31.11                    |
| 25                | 20                  | 6.21 | 20.76| 17.44                    |
| 30                | 10                  | 6.62 | 23.12| 31.11                    |
| 30                | 15                  | 6.06 | 20.87| 22.56                    |
| 30                | 20                  | 6.04 | 20.51| 17.44                    |
| 30                | 25                  | 6.89 | 22.99| 15.22                    |

Table 2. The correlation of training dataset size and the number of convolutional layers measured on CER/WER using SUBAK.KO test set

| Hours of Train Data | CNN 10 Layers | CNN 15 Layers | CNN 20 Layers |
|---------------------|---------------|---------------|---------------|
|                     | CER | WER  | CER  | WER  | CER  | WER  |
| 40                  | 18.17 | 54.30 | 16.45 | 47.94 | 18.67 | 52.32 |
| 80                  | 11.84 | 38.72 | 10.81 | 34.16 | 11.14 | 34.07 |
| 120                 | 9.43  | 31.57 | 8.09  | 26.13 | 7.95  | 25.03 |
| 160                 | 8.13  | 27.66 | 6.79  | 22.02 | 6.33  | 19.94 |
| 200                 | 7.27  | 25.04 | 5.86  | 19.23 | 5.61  | 17.79 |

Table 3. CER/WERs calculated on the SUBAK.KO test set for several normalization techniques. Here, B.N., W.N., and L.N. refers to batch normalization, weight normalization, and layer Normalization, respectively.

| Model                  | Test CER | Test WER |
|------------------------|----------|----------|
| Baseline CNN           | 6.04     | 20.51    |
| CNN+batch norm.        | 5.83     | 19.78    |
| CNN+weight norm.       | 5.95     | 20.32    |
| CNN+layer norm.        | 5.41     | 18.89    |
| CNN+B.N.+W.N.          | 5.96     | 20.14    |
| CNN+L.N.+B.N.+W.N.     | 5.55     | 19.29    |

In Table 3, we provide the CERs and WERs on the SUBAK.KO test set for several types of normalization techniques integrated to our CNN model with 15 convolutional layers. To implement that, the normalization method is applied to each convolutional layer, precisely after the dropout layer in each convolutional layer. Here, baseline CNN refers to the model where no normalization is applied. By adopting normalization, our model achieves lower WERs and CERs compared to our baseline. Using layer norm, we get 18.89% WER whereas applying batch norm and weight norm, 19.78% and 20.32% WERs can be obtained, respectively. While training a CNN with both batch norm and weight norm, our ASR model is able to get 20.14% WER. By building a model incorporating all of these normalization techniques (e.g. layer norm, batch norm, and weight norm), we achieve 19.29% WER. From this experiment, it can be concluded that CNN with layer norm outperforms the rest of the models.

Table 4 presents the CERs and WERs of acoustic models trained with Deep Speech 2 and our best-performing CNN-CTC [1][13]. Same SUBAK.KO training set has been used for both models and these two models are evaluated on the same SUBAK.KO test set as well. To train the best-performing CNN-CTC, we use MFCC features with 19 coefficients, set the frame size to 30 ms and stride to 20 ms, leverage 20
that the current Bangla ASR systems are not prepared to deal with extremely deviant Bangla dialects.

Table 4 reports the evaluation of our Bangla ASR on BanSpeech. There are in total 19 domains, among which seven of them are highly deviant dialectal speech from seven regions in Bangladesh and two domains (e.g. audiobooks and biography) contain mostly clean read speech. The statistics of each of the domains such as audio length in minutes, number of samples, and vocabulary size, number of OOV words and OOV rate in reference to SUBAK.KO, CERs, and WERs for our ASR model and Google STT are provided. OOV rate of a domain is calculated from dividing the vocabulary size of that domain by the total vocabulary of the SUBAK.KO train and dev sets. For example, the audiobooks domain has a vocabulary of 2314 and the vocabulary of the SUBAK.KO train and dev sets is 37301. There are 401 words in that domain which are unavailable in SUBAK.KO. Dividing 401 (number of OOV words) by 2314 (vocabulary size) provides us with a 17.33% OOV rate. For each of the domains, the OOV rate is greater than 10% which implies the difficulty of building a robust ASR model on the morphologically rich language Bangla.

6.3 Performance Evaluation of Bangla ASR on BanSpeech

Table 4. Comparison between Deep Speech 2 and CNN-CTC. Both of the acoustic models are trained on the SUBAK.KO train set and evaluated on the SUBAK.KO test set. CERs and WERs are calculated with and without applying a 5-gram LM.

| Model                  | CER Without LM | WER Without LM | CER With 5-gram LM | WER With 5-gram LM |
|------------------------|----------------|----------------|--------------------|--------------------|
| Deep Speech 2 [1]      | 7.92           | 27.06          | 6.59               | 15.78              |
| CNN-CTC                | 5.29           | 16.69          | 2.98               | 5.09               |

Table 5 reports the evaluation of our Bangla ASR on BanSpeech. There are in total 19 domains, among which seven of them are highly deviant dialectal speech from seven regions in Bangladesh and two domains (e.g. sports, drama, medical talk show, and medical) have higher OOV rates of more than 20% in reference to SUBAK.KO. For these three domains, the performance of our ASR system is the worst with more than 50% WERs. More specifically, there are 65.88% WER and 42.87% CER for drama, 54.81% WER and 31.05% CER for medical talk shows, and 56.53% WER and 31.49% CER for sports. Drama domain is extremely challenging for the ASR model since the speeches are as spontaneous as how native speakers use Bangla in daily lives with varied types of speaking styles and fast speaking rate. SUBAK.KO is not prepared for the medical domain ASR and thus there exists many OOV words which hampers the ASR performance. The sports domain contains a substantial amount of code-switching speeches in English and Bangla, thus we argue that the CER and WER is also high. It is worthwhile to mention that SUBAK.KO is not a code-switching corpus. The two domains namely audiobooks and biography contain mostly clean read speech and their OOV rates are 17.33% and 18.03%, respectively. The WERs and CERs of these two domains are better than the rest of the domains with 28.45% WER and 14.46% CER for audiobooks and 19.22% WER and 7.19% CER for biography. These results confirm that an acoustic model trained on clean read speech corpus provides better results on read speech test set and performs badly with spontaneous speech. The parliament speech domain has the lowest OOV rate of 11.31% and the WER and CER are 29.25% and 19.16%, respectively. Apart from these three domains (e.g. audio books, biography, and parliament speeches) with less than 30% WERs, the following domains have WERs in between 30% to 40%: tv news, class lecture, political talk shows, interview, documentary, and kids’ voice.

Using the Google STT engine [5], among the 12 domains excluding the dialectal ones, we observe more than 50% WER for 5 domains, namely, drama, class lecture, kids’ voice, medical talk shows, and sports. Moreover, Google STT is unable to achieve less than 30% WER for any domain except for biography for which the WER is 29.80%. Similar to SUBAK.KO-based ASR performance, the best two domains in which Google STT performs comparatively well are biography (29.80% WER) and audio books (36.31% WER). Google STT, however, obtains less WERs on 9 out of 12 domains in comparison to our ASR system trained on SUBAK.KO. The three domains where Google STT gets slightly higher WERs than our ASR system are drama, medical talk shows, and sports.

Both Google STT and our ASR system perform poorly on the seven dialectal domains with more than 60% WERs. However, Google STT gets lower WERs on 5 of those 7 domains compared to our ASR system. For the Rajshahi regional dialect, both ASR systems perform comparatively well with 63.37% WER for Google STT and 68.86% WER for our ASR system. Compared to other regional dialects from Bangladesh studied in this work, Rajshahi dialectal speech is less deviant from the standard Bangladeshi Bangla speech. These results imply that the current Bangla ASR systems are not prepared to deal with extremely deviant Bangla dialects.
Table 5 CERs/WERs measured for our deep CNN-based acoustic model trained on SUBAK.KO with a 5-gram LM and Google STT system. These models are evaluated on BanSpeech

| Domain            | Length (in minutes) | Number of samples | Vocabulary size | SUBAK.KO AM + 5-gram LM | Google STT |
|-------------------|---------------------|-------------------|-----------------|-------------------------|------------|
|                   |                     |                   |                 | OOV rate (%)            | CER        | WER        | CER        | WER        |
|                   |                     |                   |                 |                         |            |            |            |            |
| TV news           | 30.0                | 596               | 1403            | 183                     | 13.04      | 20.32      | 36.35      | 17.28      | 36.72      |
| Parliament speech | 30.0                | 609               | 1582            | 179                     | 11.31      | 19.16      | 29.25      | 24.27      | 46.63      |
| Audio books       | 30.0                | 985               | 2314            | 401                     | 17.33      | 14.46      | 28.45      | 13.58      | 36.31      |
| Drama             | 30.0                | 715               | 1397            | 312                     | 22.33      | 42.87      | 65.88      | 45.17      | 63.52      |
| Class lecture     | 30.0                | 375               | 1120            | 188                     | 16.79      | 22.95      | 39.32      | 34.86      | 53.79      |
| Political talk show | 30.0           | 823               | 1749            | 230                     | 13.15      | 22.13      | 37.28      | 20.18      | 44.40      |
| Interview         | 30.0                | 558               | 1606            | 254                     | 15.82      | 20.91      | 36.51      | 18.08      | 38.22      |
| Documentary       | 30.0                | 640               | 1581            | 223                     | 14.10      | 22.73      | 38.43      | 22.92      | 40.86      |
| Kids’ voice       | 30.0                | 1143              | 1634            | 232                     | 14.20      | 29.27      | 37.79      | 47.55      | 65.85      |
| Medical talk shows| 30.0                | 788               | 1194            | 388                     | 32.50      | 31.05      | 54.81      | 29.94      | 51.36      |
| Biography         | 29.3                | 670               | 1747            | 315                     | 18.03      | 7.19       | 19.22      | 10.40      | 29.80      |
| Sports            | 30.0                | 766               | 1661            | 346                     | 20.83      | 31.49      | 56.53      | 31.91      | 52.48      |
| Barisal dialect   | 10.8                | 129               | 688             | 220                     | 31.98      | 62.22      | 88.33      | 75.02      | 88.03      |
| Chittagong dialect| 10.5                | 154               | 589             | 99                      | 16.81      | 51.06      | 68.94      | 71.23      | 88.38      |
| Dhakaiya dialect  | 10.5                | 189               | 690             | 246                     | 35.65      | 49.95      | 78.47      | 52.99      | 73.42      |
| Mymensingh dialect| 8.6                 | 141               | 810             | 369                     | 45.56      | 54.73      | 87.08      | 68.34      | 85.61      |
| Noakhali dialect  | 10.2                | 93                | 725             | 215                     | 29.66      | 44.61      | 70.58      | 56.73      | 76.73      |
| Rajshahi dialect  | 10.1                | 229               | 543             | 96                      | 17.68      | 44.89      | 68.86      | 40.80      | 63.37      |
| Sylhet dialect    | 10.0                | 199               | 503             | 95                      | 18.89      | 50.62      | 85.16      | 51.80      | 71.19      |

7 CONCLUSION AND FUTURE SCOPE

In this study, we introduce a multi-domain Bangla ASR evaluation benchmark, named BanSpeech, consisting of 7.2 hours of speech data and 9802 utterances from 19 distinct domains. This dataset has been utilized to evaluate our ASR system trained on SUBAK.KO, which was developed by collecting recording scripts from 40 text-domains following the reception and production criteria set for text-domains. Empirical evaluation suggests that SUBAK.KO-based ASR can perform considerably well in domains containing mostly read speech, such as audiobooks, biography etc. On the other hand, this model is not well-trained for perceiving spontaneous speech, as seen by its high WERs in domains such as drama, talk shows, sports etc. The number of out-of-vocabulary words for such domains with predominantly spontaneous speech is also substantial. Moreover, the ASR model has considerable difficulty transcribing major dialects in Bangladesh. However, our ASR model outperforms the Google STT engine evaluated on BanSpeech on 9 out of 12 regular domains and 11 out of 19 domains including the dialectal ones. This paper also reports the experimental results on feature extraction techniques, normalization methods integrated into the deep CNN architecture, and the impact of convolutional layers in respect of different training data sizes. We find that the MFCC technique with a high number of coefficients and the layer normalization strategy can improve the performance of SUBAK.KO-based ASR. The limitation of our work is that the dialectal domains contain only 10 minutes of speech or around 93-229 utterances per dialect, which might not be sufficient to evaluate a model. Due to resource constraints (e.g., time and cost), the size of these domains cannot be expanded. However, if resources were available, expanding them would be a promising next step. Another limitation is that gender parity cannot be determined in our dataset in terms of number of speakers. However, due to the random selection of audio sources within a domain from
YouTube, we expect a significant number of utterances from both male and female speakers. From our findings, we recommend compiling a spontaneous Bangla speech corpus considering distinct domains. Furthermore, we would leverage self-supervised learning by pretraining a model on a large dataset and then fine-tuning it with the smaller datasets containing major dialects in Bangla to solve the dialectal issue.

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