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Voice Outperforms Text in Identifying Personality Traits in Bangla: A Comparative Study

Md Omar Faruk[1], Anik Paul[2], and Md Aminur Rahman[3]
Department of Computer Science and Engineering (CSE)
Ahsanullah University of Science and Technology (AUST), Dhaka, Bangladesh
Email- f.omarfaruk01@gmail.com[1], anikpal219@gmail.com[2], aminur.rahman.rsd@gmail.com[3]

***Abstract*—In recent years, the exploration of personality traits through both text and speech has garnered significant attention, offering valuable insights into psychological profiling, human-computer interaction, and personalized services. Previous studies have primarily focused on identifying personality traits from user-written text. Although some efforts have been made to detect personality traits using Bangla text, the results have been largely unsatisfactory. Despite the fact that there is a well-established relationship between speech and personality traits, there is no research on automatically determining personality traits from Bangla speech. To address this gap, we have conducted an in-depth study that highlights the effectiveness of Bangla voice-based models. Our findings have revealed that these models outperform text-based models in accurately detecting personality traits, showing significant potential in this domain. We compiled a substantial dataset of Bangla speech recordings, covering diverse demographic backgrounds and personality traits. Utilizing state-of-the-art deep learning models, we proposed two advanced systems for personality trait detection from Bangla speech, specifically employing VGG19 and ResNet50 architectures. Our deep learning framework incorporated convolutional neural networks to capture temporal dependencies and spectral features inherent in speech. Through extensive experimentation, we evaluated the efficacy of our approach on the speech dataset and compared it to text-based methods presented in [1]. Our results demonstrated promising outcomes, confirming the practicality of using voice for personality trait detection in Bangla. Notably, the VGG19 model emerged as the top performer, achieving an accuracy score of 79.17%, which is much higher than text based methods.**

Keywords—Voice analysis, Text analysis, Personality traits detection, Bangla language, VGG19, ResNet50

I. INTRODUCTION

Understanding human traits, particularly personality traits, has been a longstanding pursuit across various disciplines, ranging from psychology to artificial intelligence. Personality traits, such as openness, conscientiousness, extroversion, agreeableness, and neuroticism, play pivotal roles in shaping individuals' behaviors, decisions, and interactions. The ability to accurately detect and analyze these traits offers invaluable insights into human cognition, social dynamics, and personalized services. With the rapid advancements in technology, especially in machine learning and natural language processing, researchers have explored novel methodologies for personality traits detection, utilizing a range of modalities such as text, speech, and physiological signals. Traditionally, text-based approaches, including self-report questionnaires and textual analysis, have been the primary means of assessing personality traits. However, the emergence of voice-based analysis presents an intriguing alternative with its potential to capture small details in communication that may not be evident in text alone. The motivation behind comparing voice and text-based modalities for detecting personality traits arises from the fact that text-based models have shown very poor results with Bangla. Improving these results is crucial to making the models suitable for practical applications. Voice analysis offered the advantage of capturing para-linguistic cues, such as intonation, pitch, and rhythm, which are integral to personality expression. In contrast, text analysis provided a wealth of linguistic data, allowing for detailed semantic analysis and textual patterns.

By clarifying the methodologies, datasets, and evaluation metrics employed in this comparative analysis, we aimed to provide comprehensive insights into the relative merits of voice and text analysis in advancing our understanding of personality traits. Through this exploration, we sought to contribute to the broader discourse on the role of modalities in personality traits detection and pave the way for future research directions in this domain.

This paper is structured as follows: Section II reviews related works, Section III discusses the dataset, and Section IV details our proposed methodology, including a description of the proposed architecture. Finally, Sections V presents the result analysis, followed by the conclusion in Section VI.

II. RELATED WORKS

In recent years, natural Language Processing (NLP) has been extensively employed in personality detection, emotion recognition, and abusive speech detection. While most research has focused on English, there is comparatively less work on non-English languages, such as Bangla, highlighting the need for more research in this domain [1]. Research like [5] explores machine learning algorithms for automatic personality recognition, emphasizing the importance of linguistic features in improving prediction accuracy. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been particularly effective in learning high-level representations from text data, as shown in [3], significantly enhancing personality trait prediction accuracy. Emotion detection, which is closely tied to personality traits, has been widely studied. Papers like [9] and [8] explore how emotions expressed in written communication can be classified using deep learning techniques, showing that emotion recognition is essential in understanding affective states and linking them to personality traits. In the context of abusive speech detection, same as like [13] and [14] propose machine learning

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algorithms for identifying abusive language in text comments. The work in [13] highlights the importance of automated systems for cyberbullying prevention, while [14] examines classifiers like Support Vector Machines (SVMs) and Random Forests across multilingual datasets, including Bangla. Several studies have demonstrated the effectiveness of deep learning models in personality detection. For example, a semi-supervised deep embedded clustering model achieved a high accuracy of 95.90% by learning feature representations and cluster assignments simultaneously [26]. The use of transfer learning models, including BERT, ELMo, and ULMFiT, has significantly improved personality classification, as noted in [27], highlighting the potential of pre-trained models to enhance performance. Furthermore, transfer learning models such as ERNIE and RoBERTa have been applied to personality trait classification, outperforming existing methods by over 3%, as mentioned in [29]. These studies demonstrate the potential of leveraging pre-trained language models for improved results in personality trait detection. The work in [28] investigates the role of feature selection algorithms—Pearson correlation coefficient (PCC), correlation based feature subset (CFS), information gain (IG), symmetric uncertainty (SU), and chi-squared (CHI)—in reducing the dimensionality of linguistic, psycholinguistic, and social network features, thereby improving the prediction performance for the Big Five personality traits. Recent work emphasizes the importance of multimodal data (text, audio, and visual) and transfer learning for personality detection. Key speech characteristics are highlighted in the study by [25], such as pitch and speech rate, that correlate with personality traits based on the Myers-Briggs Type Indicator (MBTI) model. These studies collectively advance the understanding of personality prediction across different modalities. While extensive research has focused on detecting human personality traits in English, there is comparatively less work addressing personality trait detection in Bangla, highlighting the need for more studies in this area.

III. Dataset

We used a novel dataset sourced from Rudra et al. [1] to detect human personality traits. Firstly, we delved into the Personality Traits Dataset, which comprised 3000 labeled text instances categorized into five distinct classes: extroversion, agreeableness, openness, conscientiousness, and neuroticism. This dataset provides a rich resource of textual data features sourced from various media such as social media, online interactions, and written communication. For the voice dataset, we curated an extensive audio dataset comprising 2989 recordings for personality trait detection in Bangla from Rudra et al. [1], as illustrated in Figure 1. We converted the original text based dataset into audio format. Each audio sample in our dataset was labeled with one of the Big Five personality traits [20], namely openness, conscientiousness, extraversion, agreeableness, and neuroticism. We converted text data into audio data using a microphone, with the help of 10 individuals who lent their voices. Among them, 7 were male and 3 were female, all aged between 20 and 28. By reading the Bangla text aloud, we transformed it into a Bangla audio dataset. Additionally, this diverse group of participants from Dhaka and Chattogram allowed us to analyze how personality is conveyed through speech. Each audio sample

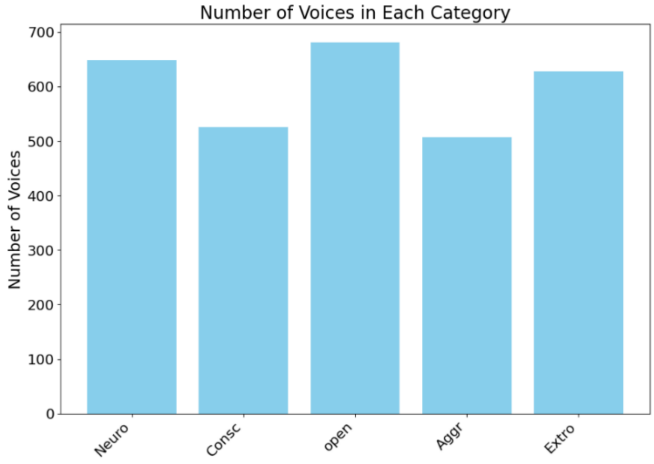

Fig. 1: Distribution of Classes in the Dataset

was labeled with the corresponding personality trait. The dataset will be available upon request.

IV. Methodology

Voice for Detecting Personality Traits: To detect human traits from voice, we planned a structured methodology encompassing dataset creation, noise reduction, feature ex traction, model implementation, performance evaluation, and statistical analysis. We undertook the task of building a complete Bangla voice dataset, meticulously selecting recordings that represented different personality traits such as Openness, Conscientiousness, Extroversion, Neuroticism, and Agreeable ness. Subsequently, we employed noise reduction techniques to preprocess the audio recordings, aiming to enhance signal clarity by minimizing background noise interference, thus improving the quality of the dataset.

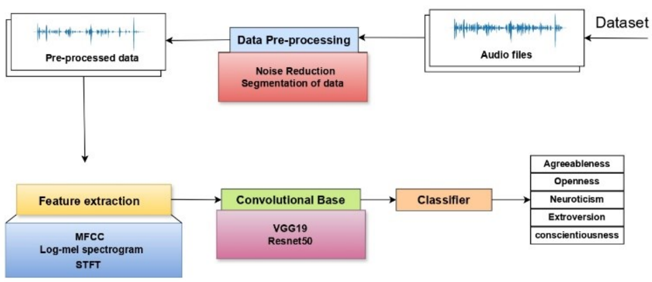

Fig. 2: Methodology for Classification of Personality Traits from Voice

As demonstrated in Figure 2, for feature extraction phase, we utilized three prominent techniques: Mel Frequency Cepstral Coefficients (MFCC), Log-mel spectrogram, and Short-Time Fourier Transform (STFT). MFCCs captured vocal tract characteristics, while Log-mel spectrograms represented the frequency content of the audio signals, and STFT provided a time-frequency representation of audio signals, capturing how spectral content evolved over time. Moving forward, we implemented two state-of-the-art deep learning architectures, VGG-19 and ResNet50, for personality trait detection. These models were trained using the extracted MFCC, Log-mel spectrogram, and STFT features as input. We have evaluated the performance of the trained models using appropriate metrics such as accuracy, precision, recall, and F1-score. Additionally, we conducted a comparative analysis between the VGG-19 and ResNet50 architectures to assess their efficacy in personality trait detection using Bangla voice data. To ensure the robustness and generalization capability of the models, we employed cross-validation techniques. Furthermore, statistical analysis was performed to identify any significant differences in performance between the VGG-19 and ResNet50 models.

A.Data Preprocessing:

In the data preprocessing phase, we undertook two essential steps to prepare the Bangla voice dataset for personality trait detection. This included noise reduction and segmentation of the data into fixed-length segments.

1) Noise Reduction: Ensuring the quality and reliability of our dataset was paramount, so we implemented noise reduction techniques to minimize unwanted noise interference in our audio recordings. This step was crucial as it significantly improved signal clarity and enhanced the effectiveness of subsequent processing stages. Various noise reduction algorithms and filters were applied to attenuate unwanted noise components while ensuring the integrity of the speech signals , as shown in Figure 3, which compares the audio sample before and after the noise reduction process.

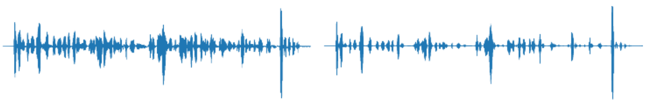

Fig. 3: Before Noise Reduction (Left) & After Noise Reduction (Right)

We explored three effective noise reduction methods: the noisereduce Python library, librosa's spectral gating, and Wavelet Transform Denoising, all of which are widely used in audio signal processing to enhance audio quality by reducing unwanted noise. Noisereduce and librosa both utilize spectral gating for noise reduction in audio processing. Noisereduce is specifically designed for noise reduction and offers a pre-packaged, user-friendly implementation, making it straightforward to use. In contrast, librosa provides greater flexibility, allowing for noise reduction through manual implementation, which is more suitable for advanced users seeking detailed control over the process. After thorough evaluation, we found that the noisereduce Python library, when combined with MFCC features and the VGG19 model, achieved the highest accuracy. Consequently, we chose to use the noisereduce Python library for the remainder of our work to maintain consistency and optimize performance.

2) Segmentation of Data in Fixed Length: After noise reduction, we segmented the audio data into fixed-length segments of 39 milliseconds to ensure uniform processing and facilitate feature extraction. The choice of 39 ms is based on its ability to capture the stationary characteristics of speech, as human speech typically exhibits stable features over such short intervals [22]. This segmentation divided the continuous audio recordings into shorter, equal-duration segments, simplifying the subsequent feature extraction and model training processes. The 39 ms segments strike a balance between capturing detailed speech features and maintaining computational efficiency. Segmenting the data into these fixed-length segments maintained the temporal coherence of the original recordings, enabling efficient processing and analysis. This preprocessing step laid the foundation for extracting meaningful features from the audio data and training accurate personality trait detection models.

B. Feature Extraction:

We employed three prominent techniques: Mel Frequency Cepstral Coefficients (MFCC), Log-Mel-Spectrogram, and Short-Time Fourier Transform (STFT). By extracting MFCCs, log-Mel spectrograms, and STFT from the Bangla voice dataset, we obtained rich feature representations that captured relevant information for personality trait detection. These features served as input to our deep learning models, enabling them to learn and distinguish between different personality traits based on the inherent characteristics of the voice data.

1) Mel Frequency Cepstrum Coefficient (MFCC): We utilized Mel Frequency Cepstral Coefficients (MFCCs) as the primary feature extraction technique for analyzing Bangla voice data. These MFCCs were extracted with a maximum length size of 39, chosen to balance capturing essential vocal tract characteristics and spectral information from the audio signals while maintaining computational efficiency. The length of 39 coefficients ensures that sufficient detail is retained to represent the acoustic properties of speech, making it effective for subsequent analysis and modeling.

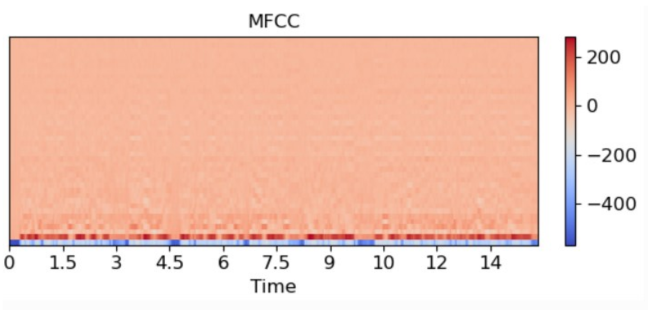

Fig. 4: Mel Frequency Cepstrum Coefficient (MFCC)

By representing the frequency content and temporal dynamics of the voice data in a concise and informative manner, these MFCC features served as effective inputs for personality trait detection models Through this approach, we aimed to leverage the rich information encoded in MFCCs to accurately discern patterns associated with different personality traits in the Bangla language.

2) Log-Mel-Spectrogram: These log-mel spectrograms were computed with a maximum length size of 39, effectively

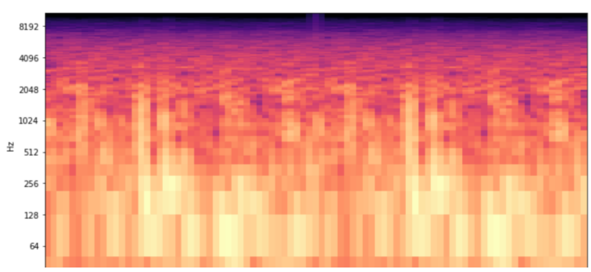

Fig. 5: Log-Mel-Spectrogram

capturing the spectral characteristics and frequency content of the audio signals. By representing the distribution of spectral energy in a logarithmic scale, log-mel spectrograms provided a compact yet comprehensive representation of the voice data.

3) Short-Time Fourier Transform: The STFT was computed with a window size of 39, providing a time frequency representation of the audio signals. By capturing the spectral content and its evolution over time, STFT offered detailed insights into both the temporal and frequency domains of the voice data.

C. Deep Learning Based Models:

We initially explored regular machine learning models like SVM and KNN to detect personality trait from Bangla voice. But models built upon these features turned out not up to mark due to their incapability of handling high-dimensional and complex features coming from MFCC, Log-Mel Spectrograms, and Short-Time Fourier Transform (STFT). As SVM and KNN did not perform well, as shown in Table-1, we explored deep learning architectures like VGG-19 and ResNet50, which are known for their performance on tasks that involve hierarchies of different features.

Table 1: Performance of Machine Learning Models on Voice

Features	SVM	KNN
MFCC	68%	66%
Log-Mel-Spectrogram	61%	43%
STFT	62%	42%

These models are renowned for their effectiveness in image classification due to VGG-19's deep, straightforward architecture and ResNet50's innovative use of residual connections. Both were adapted to process features extracted from the audio data, including Mel Frequency Cepstral Coefficients (MFCC), Log-Mel Spectrograms, and Short Time Fourier Transform (STFT). We ran both VGG-19 and ResNet50 architectures with the extracted MFCC, Log-Mel Spectrograms and STFT features.

Both models successfully capture key features from the voice data, effectively learning patterns that are crucial for accurate personality trait detection. This comprehensive approach allowed us to explore the models' performance in learning intricate patterns and relationships within the voice data, enhancing our understanding of personality trait detection using deep learning techniques in the context of Bangla language analysis.

1) VGG-19: The model was trained for 25 epochs using different features like MFCC, log-mel spectrogram, and STFT, with a batch size of 32 samples per iteration. The initial learning rate was set to 0.0001 to facilitate gradual convergence during training. Additionally, dropout regularization with a rate of 0.5 was incorporated to mitigate overfitting and improve generalization performance. This configuration allowed us to effectively leverage the VGG-19 architecture to learn intricate patterns from the audio data representations and enhance the accuracy of personality trait detection in the Bangla language.

2) ResNet50: The model was trained for 15 epochs with MFCC features and 25 epochs with log-mel spectrogram and STFT features, using a batch size of 32 samples per iteration. The initial learning rate was set to 0.0001 to ensure stable convergence during training. The decision to use 15 epochs for MFCC features with ResNet50 was based on the model's efficiency and faster convergence, which allowed it to capture the necessary patterns within fewer epochs compared to VGG 19. However, for the more complex log-mel spectrogram and STFT features, 25 epochs were used to ensure the model had sufficient time to learn the intricate patterns. By leveraging the ResNet50 architecture, we aimed to effectively capture these patterns and improve the accuracy of personality trait detection in the Bangla language.

V. RESULT ANALYSIS

Text for Detecting Human Traits: In the study by Rudro et al. [1], various machine learning methods were tested for classifying text into five personality categories. From Table 2, it can be observed that Among statistical methods, Decision Tree performed poorly (Macro Average F1 Score of 0.22), while MultinomialNB and SVC performed better (0.30 and 0.31, respectively). Deep learning methods outperformed them, with FastText and C-LSTM achieving the highest scores (0.36 and 0.37, respectively), demonstrating superior effectiveness in personality classification.

Table 2: Performance Comparison of Various Models on Text

Models	Recall	Precision	F1 Score	Accuracy
Statistical Machine Learning Models				
Decision Tree	0.23	0.27	0.22	0.24
SGD	0.27	0.26	0.26	0.26
Random Forest	0.29	0.29	0.29	0.29
MultinomialNB	0.30	0.36	0.30	0.31
SVC	0.32	0.31	0.31	0.32
Deep Learning Based Models				
MLP	0.27	0.27	0.27	0.27
FastText	0.36	0.37	0.36	0.37
C-LSTM	0.36	0.37	0.37	0.37

The study by Islam et al. [19] assessed various models for predicting personality traits from Bangla text. The large BanglaBERT variant by Bhattacharjee achieved the highest performance with 47.93% accuracy and an F1 score of 48.41% at the 8th epoch. The base BanglaBERT model also performed well, with 46.6% accuracy and an F1 score of 0.4666. Combining BanglaBERT embeddings with LSTM improved accuracy to 43.62%, while the BERT+BiLSTM model reached 47.10% accuracy and an F1 score of 0.4665 at the 15th epoch. Traditional models like MLR, trained on TF-IDF features, achieved 40.96% accuracy, outperforming deep learning models in this context. XGBoost showed the best performance among tree-based models with 34.99% accuracy, while SVC achieved 39.80% accuracy.

Voice for Detecting Human Traits: The experimental results evaluated personality trait detection using Bangla voice data with VGG-19 and ResNet50 models, trained on MFCC, log-mel spectrogram, and STFT features. From Table 3, it is evident that VGG-19 achieved the highest accuracy with 79.17% on MFCC, 78% on STFT, and 65% on log-mel spectrogram features, indicating MFCC as the most effective feature set.

Table 3: Accuracy of Deep Learning Based Models on Voice

Features	VGG19	Resnet50
MFCC	79.17%	73.91%
Log-Mel-Spectrogram	65%	70.76%
STFT	78%	76.34%

ResNet50 also performed best with 73.91% accuracy on MFCC, 76.34% on STFT, and 70.76% on log-mel spectrogram features, suggesting MFCC slightly outperformed log-mel spectrogram.

In the study by Rudro et al. [1], the deep learning methods FastText and C-LSTM achieved the highest scores, with F1 Scores of 0.36 and 0.37, respectively. The study by Islam et al. [19] highlighted that the large BanglaBERT variant by Bhattacharjee achieved the highest performance with 47.93% accuracy and an F1 score of 0.4841. The BERT+BiLSTM model reached 47.10% accuracy and an F1 score of 0.4665. Despite their promise, these models require substantial pre training on diverse datasets to generalize well, particularly in noisy text environments like social media. However, traditional deep learning models and statistical machine learning methods did not perform as well, often hindered by the noisy nature of social media texts and the need for larger datasets. In contrast, the experimental results using Bangla voice data for personality trait detection showed significantly better performance. Two deep learning models, VGG-19 and ResNet50, were evaluated using MFCC, log-mel spectrogram, and STFT features. The VGG-19 model achieved the highest accuracy of 79.17% with MFCC features, while ResNet-50 also performed well, achieving up to 76.34% accuracy with STFT features. These results indicate that MFCC features are particularly effective for voice-based personality trait detection. The superior performance of voice-based models compared to text based models can be attributed to the rich expressive cues in voice data, such as tone, pitch, and rhythm, which are absent in text data. Feature extraction techniques like MFCC and STFT capture these nuances effectively, leading to higher accuracy, as shown in Table-4. The deep learning architectures used, VGG-19 and ResNet-50, are adept at handling the complex patterns in audio signals, further enhancing performance.

Table 4: Best Accuracy for Text and Voice-Based Models

Models	Type	Best Accuracy
BanglaBERT Large + BiLSTM	Text	47.10%
VGG19 (MFCC)	Voice	79.17%
VGG19 (STFT)	Voice	78%

In summary, the findings demonstrate that voice-based models are more effective than text-based models for detecting human personality traits in Bangla. The higher accuracy rates of VGG-19 underscore the potential of utilizing auditory features for more reliable and accurate personality trait detection.

VI. Conclusion

Comparing voice-based and text-based models on the same content shows that voice-based models are more effective. Notably, the voice-based models achieve a remarkable accuracy of 79.17%, outperforming their text-based counterparts in detecting human traits. This finding highlights the potency of utilizing voice data for trait detection, indicating its superiority over text data in this particular task. Moving forward, it is imperative to prioritize the exploration and utilization of voice based models for personality trait detection, as they offer a more effective and reliable means of understanding and analyzing human behavior and characteristics.

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