Speech-Based Recognition of Gujarati Numerals Using Supervised Learning

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Abstract—*In the realm of computer science, the significance of speech synthesis and speech recognition has surged, particularly in enhancing computers' comprehension of human speech, notably in languages such as English. This paper delves into a specialized model tailored to identify spoken Gujarati numerals. By capitalizing on the efficacy of Mel-Frequency Cepstral Coefficients (MFCC) as fundamental features, and harnessing the classification prowess of Support Vector Machine (SVM) and Random Forest algorithms separately, our proposed model achieves commendable results. With an average accuracy rate of approximately 87% using SVM and 88.40% using Random Forest individually, our model adeptly demonstrates its proficiency in accurately discerning spoken Gujarati numerals ranging from 0 to 20. This study substantially contributes to the advancement of spoken language processing in under-explored linguistic contexts.*

Keywords—speech recognition, MFCC, spoken Gujarati numeral, Supervised Learning, SVM.

1. INTRODUCTION

Speech recognition is a transformative process that empowers computers to identify spoken words across languages, converting them into text. However, its efficacy relies on a comprehensive vocabulary and clear enunciations. Mel-Frequency Cepstrum Coefficients (MFCC) capture audio attributes, pivotal in speech recognition, where Hidden Markov Models (HMMs), deep neural networks (DNNs), and convolutional neural networks (CNNs) decode language intricacies. For speaker identification, Gaussian Mixture Models (GMMs), support vector machines (SVMs), and deep neural networks discern individuals via vocal imprints. Music genre classification leverages SVMs, random forests, and deep learning to categorize audio tracks using MFCC features. The succinct MFCC representations underscore their indispensability across auditory analyses.

In machine learning, the choice of classification algorithm significantly impacts model performance. Support Vector Machines (SVMs) stand out due to robustness, versatility, and handling complex datasets. As a discriminative model, SVMs excel at identifying optimal decision boundaries in high-dimensional spaces, suited for pattern recognition, classification, and regression. This paper delves into SVM selection, unraveling principles and advantages positioning SVMs as a preferred choice in predictive modeling.

This research compiles audio samples across diverse demographics uttering Gujarati numerals 0 to 20. Utilizing MFCC and SVM/Random Forest classifiers, the study transforms spoken language to text. It aims to bridge auditory-textual comprehension, facilitating accurate recognition and transcription of spoken Gujarati numerals. Through advanced speech processing techniques, this endeavor contributes to linguistic understanding and technological capabilities in less-explored linguistic contexts.

Gujarati, an Indo-Aryan language with roots in Sanskrit, holds significance as the native tongue of Gujarat, an Indian state, and its associated territories. As one of India's 22 official and 14 regional languages, it is officially recognized within Gujarat and neighboring regions. Notably, Gujarati encompasses 12 vowels, 34 consonants, and a set of 10 digits, making it linguistically intricate.

2. LITERATURE REVIEW

In this section, we provide an overview of relevant research endeavors focused on speech recognition for Gujarati digits.

- In 2017, Pooja Prajapati and Miral Patel introduced a study showcasing the utilization of Mel-Frequency Cepstral Coefficient (MFCC) for feature extraction in the realm of speaker identification for isolated Gujarati digits. [1].
- In 2019, they extended their work by employing the MFCC feature extraction technique to capture distinctive traits from voice samples. Following the extraction of features from voice signals, the subsequent step involved pattern matching through the utilization of the Vector Quantization (VQ) method. [2].
- In a paper by Bazzi and Katabi, the focus was on the identification of individual spoken digits through the utilization of Support Vector Machines (SVM) as a classifier. Notably, their approach yielded a

commendable accuracy of 94.9% through the application of the SVM classifier [3].

– In their research paper, Patel and Desai delved into the realm of recognizing isolated spoken Gujarati numerals. Their work centered around the development of a numerical model employing MFCC feature extraction technique and DTW classification. Impressively, their model yielded an average accuracy rate of 71.17% specifically for Gujarati numerals. [4].

– In 2010, Patel and Rao [1] introduced a research paper that focused on enhancing the recognition of speech signals through the utilization of frequency spectral information, specifically employing Mel frequency. Their approach aimed to improve the representation of speech features within a Hidden Markov Model (HMM) based recognition framework. [6].

– Pinto and Sitaram [9] proposed two Confidence Measures (CMs) in speech recognition: one based on acoustic likelihood and the other based on phone duration and have a detection rate of 83.8% and 92.4% respectively [7].

English Numerals	Pronunciation	Gujarati Numerals	Pronunciation
0	Zero	૦	શૂન્ય (shuunya)
1	One	૧	એક (ek)
2	Two	૨	બે (be)
3	Three	૩	ત્રણ (traṇ)
4	Four	૪	ચાર (chaar)
5	Five	૫	પાંચ (pããch)
6	Six	૬	છ (chha)
7	Seven	૭	સાત (saat)
8	Eight	૮	આઠ (aaṭh)
9	Nine	૯	નવ (nav)
10	Ten	૧૦	દસ (das)
11	Eleven	૧૧	અગિયાર (agiyaar)
12	Twelve	૧૨	બાર (baar)
13	Thirteen	૧૩	તેર (ter)
14	Fourteen	૧૪	ચૌદ (chaud)
15	Fifteen	૧૫	પંદર (pãdar)
16	Sixteen	૧૬	સોળ (soḷ)
17	Seventeen	૧૭	સત્તર (sattar)
18	Eighteen	૧૮	અઢાર (aḍhaar)
19	Nineteen	૧૯	ઓગણિસ (ogṇis)
20	Twenty	૨૦	વીસ (viis)

Fig. 1. English and Gujarati Numerals and Pronunciation

3.PROPOSED SYSTEM

The focus of our research lies in the development of a specialized speech recognition model tailored specifically for the recognition of Gujarati numerals. The model operates in an isolated word paradigm, ensuring its effectiveness across various speakers without being dependent on any particular speaker's voice. Illustrated in Figure 1, we present a comprehensive block diagram detailing the architecture of our proposed model, designed to accurately recognize isolated Gujarati numerals when spoken by diverse speakers. The initial step involves capturing spoken numerals through a microphone, transforming them into .wav files. These files are then passed to the pivotal phase of our proposed model: feature extraction. Here, we employ the MFCC (Mel-Frequency Cepstrum Coefficient) technique, which processes the .wav files and yields distinctive feature vectors for spoken Gujarati numerals. The MFCC method encompasses essential stages like framing, windowing, Fast Fourier Transform (FFT), Mel Frequency encapsulation, and culminates in computing the Discrete Cosine Transform (DCT) for the feature vector. Framing segments the speech waveform, treating it as stationary with consistent statistics. To mitigate signal irregularities at frame beginnings and endings, a Hamming window is applied. Subsequently, FFT converts each N-sample frame from temporal to frequency domains. In sum, this process efficiently condenses spoken numeral data into representative feature vectors, forming a key foundation for our research. The Mel-frequency Wrapping process is applied to derive a mel-scale spectrum from the signal's frequency domain. Subsequently, the log mel spectrum is reversed to the time domain, yielding the crucial outcome known as Mel Frequency Cepstrum Coefficients (MFCC).

In the classification phase, our research leverages the combined power of Support Vector Machines (SVM) and the Random Forest algorithm. These two advanced techniques play a pivotal role in effectively categorizing and labeling the preprocessed speech data. Support Vector Machines are employed to create decision boundaries that optimally separate different classes of spoken Gujarati numerals in a high-dimensional space. This allows the SVM to accurately classify new instances based on their proximity to these decision boundaries.On the other hand, the Random Forest algorithm capitalizes on an ensemble of decision trees to collectively determine the most suitable class for each input.By aggregating the outputs of multiple trees, Random Forest enhances the model's robustness against overfitting and noise, resulting in a more dependable classification performance. The synergistic integration of these algorithms enables our model to achieve exceptional accuracy and reliability in recognizing and attributing spoken numerals to their respective Gujarati numeral classes.

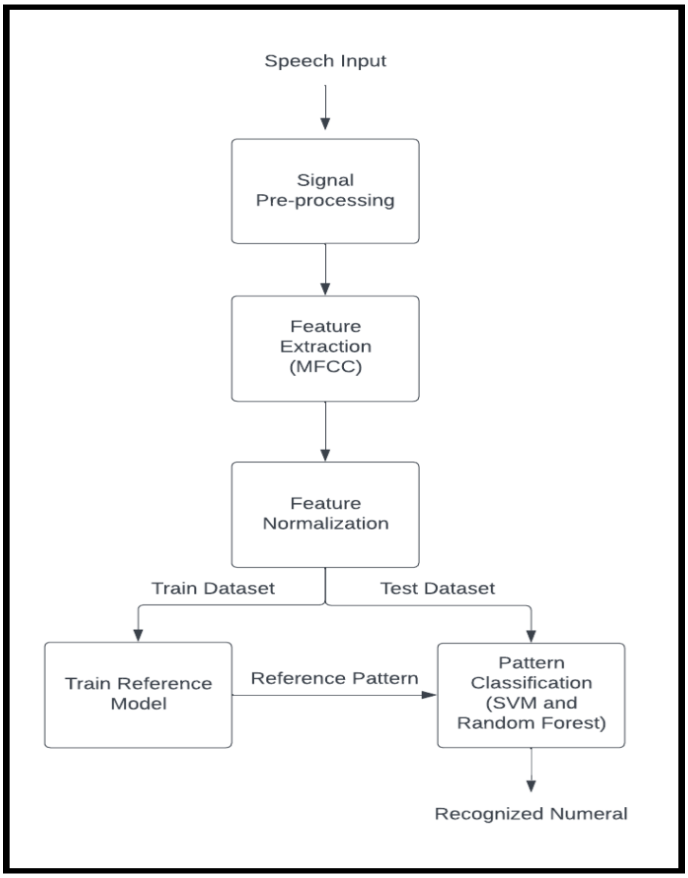

Fig. 2. Block diagram of proposed model

4. METHODOLOGY

This study revolves around the comprehensive collection of speech samples representing all Gujarati numerals, as articulated by diverse individuals spanning various age groups and regions. Our generating dataset accumulating of total 21 recording(0 to 20) from each 51 speakers that makes a sum of 1071 samples, encompassing both male and female, and encompassing numerals from 0 to 20 which is available on (https://drive.google.com/drive/u/0/folders/174lRZIkxUDSX1_eIylEB7XAEzlte8e4s). The initial phase involved the transformation of analog speech signals into digital .wav files. These .wav files were then accessed utilizing the "librosa" module. To enhance data quality, noise reduction techniques were implemented alongside the removal of minimal silence intervals within audio recordings.

Our methodology also encompassed the careful division of audio files into distinct, isolated numerical instances. This procedure ensured minimal silence at both the onset and conclusion of each segment, effectively employed via the "Audacity" tool. The crux of feature extraction was executed through the Mel-Frequency Cepstrum Coefficient (MFCC) technique, rendering rich feature vectors from audio files. For optimal model performance, normalization of MFCC values was achieved using the Min-Max Scaler.

The heart of our classification system lies in the application of Support Vector Machines (SVM) and the Random Forest model. These models were trained on the processed data, finely tuned to recognize and categorize the spoken Gujarati numerals. By iteratively enhancing classification accuracy, this methodology presents a robust approach to numeral identification in varied acoustic contexts. This comprehensive approach contributes to the burgeoning field of spoken language processing and underscores the efficacy of combining advanced techniques to achieve notable results.

5. EXPERIMENTAL RESULTS

The recorded speech utterances were acquired without the constraint of a quiet or noise-proof environment, subsequently requiring noise reduction procedures. To assess the effectiveness of the proposed model, the speech materials used in the experiment consisted of spoken Gujarati numeral samples from a diverse set of 51 speakers spanning various age groups. Each speaker articulated the numerals 0 to 20, resulting in a collective corpus of 1071 speech samples.

For experimental purposes, two distinct datasets were formulated: a training dataset comprising 80% of the samples, and a test dataset encompassing the remaining 20%. Furthermore, based on the age of the speakers, they were categorized into two groups. The accuracy rate of individual spoken Gujarati numerals was calculated using Equation (1) as outlined below:

$$\text{Accuracy Rate} = \frac{\textit{Number of Correctly Classified Samples}}{\textit{Number Of Digits In The Train Dataset}}$$

Furthermore, the average accuracy rate for all Gujarati numerals is computed by summing the individual accuracies of each numeral and then dividing the total by 20. This provides a consolidated measure of the overall performance across all numerals.

5.1 SVM based classification

Figure 3 [5] illustrates the accuracy rates achieved when comparing each test Gujarati numeral against the corresponding train Gujarati numeral. To illustrate this, let's focus on the outcome for numeral zero (0). The data presented in Figure 3 demonstrates that the test numeral zero (0) exhibits a successful match with the train numeral zero (0) on 8 occasions. To elaborate, out of the total of 9 test instances of numeral zero, only 1 instance does not match with the train numerals. This discrepancy arises from its single correspondence with numeral eight (8). As a result, the accuracy rate for the test numeral zero (0) is computed using the equation (1) as follow:

$$\text{Accuracy Rate} = \frac{8}{9} x\ 100 = 88.89\%$$

$$\text{Accuracy Rate} = \frac{10}{14} x\, 100 = 71.42\%$$

Similarly, an exploration of accuracy rates can be extended to encompass the remaining numerals. This investigation aims to uncover the precision levels associated with each distinct numeral. Notably, numerals such as two (2), three (3), four (4), seven (7), nine (9), eleven (11), twelve (12), thirteen (13), fifteen (15), seventeen (17), and twenty (20) have demonstrated remarkable success rates of 100%. Equally commendable, numerals zero (0), eight (8), and fourteen (14) have achieved success rates surpassing 80%. Impressively, numeral six (6) exhibits a success rate exceeding 90%.In contrast, numerals one (1) and sixteen (16) have achieved success rates below 70%. Aggregating these results, the mean accuracy rate across all numerals stands at a commendable 87%. These outcomes collectively shed light on the varying degrees of recognition precision across the spectrum of numerals under consideration.

	Train Numerals																					
Test Numerals	૦	૧	૨	૩	૪	૫	૬	૭	૮	૯	૧૦	૧૧	૧૨	૧૩	૧૪	૧૫	૧૬	૧૭	૧૮	૧૯	૨૦	Accuracy Rate(%)
૦	8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	88.89
૧	0	9	0	0	0	2	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	64.28
૨	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૩	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૪	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૫	0	2	0	0	0	7	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	70
૬	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	1	0	0	0	93.75
૭	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૮	0	0	0	0	0	0	1	0	5	0	0	0	0	0	1	0	0	0	0	0	0	71.42
૯	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	100
૧૦	0	0	0	0	0	0	0	1	0	0	11	0	0	0	1	1	0	0	0	1	0	73.33
૧૧	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	100
૧૨	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	100
૧૩	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	0	100
૧૪	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	1	0	0	0	85.71
૧૫	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	100
૧૬	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	5	0	0	5	0	45.45
૧૭	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	100
૧૮	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	7	0	0	77.78
૧૯	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	2	0	0	9	0	75
૨૦	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	12	100

Fig.3. Accuracy Rate Of Gujarati Numerals For Train And Test Dataset Using SVM

5.2 Random Forest based classification

Figure 4 [5] illustrates the accuracy rates achieved when comparing each test Gujarati numeral against the corresponding train Gujarati numeral. To illustrate this, let's focus on the outcome for numeral zero (0). The data presented in Figure 4 demonstrates that the test numeral zero (0) exhibits a successful match with every train numeral zero (0) and the test numeral one (1) exhibits a successful match with every train numeral zero (0) and the test numeral one (1) exhibits a successful match with the train numeral zero (0) on 10 occasions. To elaborate, out of the total of 14 test instances of numeral zero, Due to its occurrence of 3 times with numeral five (5) and 1 time with numeral twelve (12), the accuracy rate for test numeral one (1) is determined by applying Eq. (2), as elaborated below:

$$\text{Accuracy Rate} = \frac{10}{14} x\, 100 = 71.42\%$$

$$\text{Accuracy Rate} = \frac{8}{9} x\, 100 = 88.89\%$$

Likewise, the accuracy rate assessment can extend to the remaining numerals. Let's investigate the precision levels associated with each distinct numeral. Numerals zero (0), three (3), four (4), seven (7), nine (9), eleven (11), twelve (12), fourteen (14), fifteen (15) and seventeen (17) have accomplished success rates of 100%. Numerals two (2), five (5), six (6), thirteen (13), eighteen (18), nineteen (19) and twenty (20) have surpassed an 80% success rate. Conversely, numerals sixteen (16) have achieved accuracy below 50%. The collective mean accuracy rate across all numerals stands at 88.40%.

	Train Numerals																					
Test Numerals	૦	૧	૨	૩	૪	૫	૬	૭	૮	૯	૧૦	૧૧	૧૨	૧૩	૧૪	૧૫	૧૬	૧૭	૧૮	૧૯	૨૦	Accuracy Rate(%)
૦	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૧	0	10	0	0	0	3	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	71.42
૨	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	90
૩	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૪	0	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૫	0	1	0	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	90
૬	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	1	0	0	0	93.75
૭	0	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0	0	0	0	0	0	100
૮	0	0	0	0	0	0	1	0	5	1	0	0	0	0	0	0	0	0	0	0	0	71.42
૯	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0	0	0	0	100
૧૦	0	0	0	0	0	0	0	1	0	1	11	0	0	0	0	1	0	0	0	2	0	73.33
૧૧	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	100
૧૨	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	100
૧૩	0	1	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	85.71
૧૪	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	0	0	0	100
૧૫	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	0	0	0	0	0	100
૧૬	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	6	0	45.45
૧૭	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	0	100
૧૮	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	8	0	0	88.89
૧૯	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	10	0	83.33
૨૦	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	11	91.66

Fig. 4. Accuracy Rate Of Gujarati Numerals For Train And Test Dataset Using Random Forest Model

We conducted experiments using various dataset sizes: 300,600 and 1071 instances corresponding average accuracy rates were found to be 78.87%, 84%, 87% in the case of SVM model and 74.64%, 79.33%, and 88.40% in the case of Random Forest classifier model respectively. These findings highlight that augmenting the dataset size leads to a proportional enhancement in the average accuracy rate for the cases. This implies that a greater number of speech samples directly contributes to an improved performance of the system.

In our investigation, we sought to benchmark our model for identifying spoken Gujarati numerals against existing literature. A study by Bharat C. Patel and Apurva A. Desai [5] showcased a model employing the K-Nearest Neighbor (K-NN) classifier, achieving a success rate of 78.13% with a substantial dataset of 6000 speech samples. In comparison, our model outperformed this result significantly, achieving greater accuracy with a smaller dataset of just 1071 samples. Specifically, our model demonstrated an average accuracy of 87% using

Support Vector Machine (SVM) and an even higher accuracy of 88.40% using the Random Forest Classifier. This suggests the efficacy of our approach, not only in terms of accuracy but also in resource efficiency, highlighting the potential for advancements in spoken numeral identification for Gujarati and similar languages. Deemagarn and Kawtrakul [8] introduced a speech recognition system for speaker-independent Thai connected digits. The system achieved an average recognition rate of 75.25% for known length strings and 70.33% for unknown length strings. In a separate study, Rathinavelu A. and colleagues [9] created a model for recognizing speech in Tamil stops. Their experiments, utilizing a trained neural network, resulted in an average accuracy rate of 81%.

6. CONCLUSION AND FUTURE WORK

In this study, the recognition system that is suggested was tested on various datasets with differing sizes. The system was evaluated on our own generated dataset of 1071 speech samples, encompassing a diverse set of speakers for both training and testing. The accuracy for numerals from 0 to 10 using SVM stands at 85% when considering speakers aged between 5 to 60 years, using a dataset of 561 samples. Additionally, the Random Forest Classifier achieves an accuracy of 88.78% for the same conditions. The accuracy for numerals from 11 to 20 using SVM stands at 93.13% when considering speakers aged between 5 to 60 years, using a dataset of 561 samples. Additionally, the Random Forest Classifier achieves an accuracy of 85% for the same conditions. Cumulatively, across the range of numerals from 0 to 20, Support Vector Machine (SVM) exhibits an accuracy rate of 87%, while the Random Forest classifier achieves an accuracy of 88.40%. This performance is observed within the age group of 5 to 60 years, utilizing a dataset comprising of 1071 instances. Hence, it can be inferred that the Random Forest classifier outperforms the SVM across the spectrum of Gujarati numerals ranging from 0 to 20. The highest accuracy rates were observed for the majority of Gujarati numerals, while the lowest accuracy rates were encountered specifically for the numeral sixteen (16) in each of the SVM and Random Forest classifier models.

Our model, as proposed, attains a notable level of accuracy even with a limited dataset. Further improvements in accuracy can be anticipated by expanding the dataset, thereby indicating the potential for enhanced performance. The model presented is currently designed to operate exclusively with discrete isolated Gujarati numerals. In forthcoming developments, there is potential to adapt this algorithm to encompass continuous spoken Gujarati numerals, as well as extending its applicability to both isolated and continuous spoken Gujarati words.

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