Design and Implementation of a Phonological Analyzer for the Irula Language: A Computational Approach to Endangered Language Preservation

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Abstract: Irula is a South Dravidian language spoken by a small tribal community in India and is critically endangered due to a decreasing number of speakers and the assimilation of its speakers into dominant regional languages such as Tamil and Malayalam. This research focuses on creating a phonological analyzer that utilizes Mel-Frequency Cepstral Coefficients (MFCC) for feature extraction, aiming to tackle the computational limitations faced by the Irula language. The study evaluates the performance of two machine learning models, Bi-LSTM and SVM, in classifying audio data from Irula, Tamil, and Malayalam. Additionally, it explores the phonological systems of these closely related languages, emphasizing articulatory features, variations in consonants, and retroflex articulations. The findings indicate that the SVM model surpasses the Bi-LSTM model, achieving a classification accuracy of 90%. This project contributes to the preservation of endangered languages and enhances the field of low-resource language processing by creating a computational framework for analyzing the phonological features of Irula. The results also open avenues for additional research in computational linguistics and phonetics, particularly for languages that are underrepresented.

1 INTRODUCTION

The legacy and culture of a region is carried in its languages which provides a sense of social identity. However, many of the original Dravidian languages that are native to India are in danger of becoming extinct because of a lack of preservation and a drop in speakers.The Irula community is an indigenous tribal group belonging to the South Dravidian language family, primarily residing in four southern Indian states: Andhra Pradesh, Karnataka, Kerala, and Tamil Nadu. Their estimated population is around 200,000 individuals(The Criterion: An International Journal in English, 2024). According to the 2011 census, Irula, a South Dravidian tribal language, is an endangered language, with 12,000 speakers in Kerala currently (Kerala Institute for Research Training and Development Studies of Scheduled Castes and Scheduled Tribes (KIRTADS), 2017). The speakers from a small hamlet in Kerala's Attapadi region are the subject of our attention. In the domains of computational linguistics and natural language processing, Irula is considered a zero-resource language. This study aims to solve this problem by creating the first phonological analyzer specifically designed for the Irula language. The goal is to determine whether the provided audio data is from the sister Dravidian languages of Tamil, Malayalam, or Irula.

Code mixing or code-switching refers to the juxtaposition of linguistic units from two or more languages in a single conversation or sometimes even a single utterance. It is the transfer of linguistic elements or words from one language to another or mixed together. Native speakers, mostly tribal people, are attempting to switch to the main-stream languages of their area, resulting in code mixing. The main external factors causing language endangerment among the Irula people are cultural, educational, and economic subjugation. Internal factors, such as the community's rejection of its own language and the general decline of group identity, also contribute to this issue. The Irula tribal communities link their traditional language and culture to their precarious social and economic status. They now feel that their languages are useless and should not be preserved. In

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their pursuit to combat discrimination, achieve financial stability, and enhance social mobility for themselves and their children, they have relinquished their languages and traditions. However, they are unaware that they risk losing their identity if they are unable to communicate in their native tongue. In such a situation, it became crucial to preserve and strengthen the root language, or Irula, from both a cultural and a computational standpoint. Irula presents a significant obstacle due to the absence of any digital corpus or documentation. The objective of this project is to create computational tools for Irula that will significantly influence the field of low-resource language processing and help preserve the language.

Proto-Dravidian refers to the linguistic reconstruction of the common ancestor of the Dravidian languages indigenous to the Indian subcontinent. This language set has descendants in Irula, Tamil, and Malayalam. Analyzing these three languages reveals clear commonalities in syntax, semantics, and lexicon. The phonological system is where the degree of divergence appears. These parallels and discrepancies are examined in this study. It also emphasizes how the phoneme inventory and sound patterns of these languages have changed over time.

Malayalam has a more significant phonetic distinction for every consonant. Irula, which is more like Tamil, has distinct phonological characteristics, as evidenced by the change in where some consonants are articulated. These changes emphasize how each language's phonetics—particularly its fricatives and retroflexes—make these sister languages distinct. The aim of this study is to assess and analyze the phonological distinctions that exist. Irula shares phonetic similarities with Tamil and Malayalam, but it also has distinctive phonetic characteristics, such as consonantal shift and phoneme simplification. For instance, the word ”singam” in Tamil means ”lion,” whereas the word ”simham” in Malayalam indicates both phonological and lexical diversity. Irula is closely connected to languages like Malayalam, as seen by the term ”shivaya,” which is pronounced similarly. This word is pronounced ”sivaya” in Tamil, and ”chivaya,” ”shivaya,” or ”sivaya” in Irula. This research focuses on phonetic differences, as well as syntactic and grammatical similarities.

This effort also aims to analyze the similarities and differences between these languages. Despite having a similar lexicon and grammatical organization, their phonetic components differ greatly. Fricatives and retroflexes aid in the development of a thorough phonological model that precisely differentiates between these languages. Vowel articulation and phonetic markers offer a strong foundation for examining these languages' development. The necessity for instruments that can precisely record the phonetic variety among the proto-Dravidian languages and aid in their preservation is discussed in this work.

Section II provides an overview of related research in phonological analysis, emphasizing studies that focus on language preservation and linguistic diversity, especially concerning low-resource languages. This section reviews prior work on acoustic feature extraction, phoneme segmentation, and the creation of language models specifically designed for endangered languages. Section III describes the methodology of this study, including the dataset utilized for phonological analysis, feature extraction methods like MFCC, and the models used for phonetic comparison. Section IV presents the results from the acoustic analysis, highlighting both the similarities and differences in phonetic characteristics among Malayalam, Tamil, and Irula while assessing the effectiveness of various feature extraction techniques. Section V assesses the phonological models based on their ability to identify language-specific features, particularly regarding their role in preserving Irula. Finally, Section VI concludes with a discussion on the implications of these findings for linguistic research and outlines potential directions for future work, such as incorporating machine learning techniques for automatic phoneme segmentation and developing speech-to-text systems for low-resource languages.

2 RELATED WORKS

The majority of the existing computational linguistics literature on voice analysis concentrates on languages with abundant resources or extensive documentation. However, research on resource-centered and endangered languages has brought attention to the need for computational tools designed specifically for these languages. Speech segmentation and pronunciation modeling are the subjects of two studies that are particularly relevant to this endeavor.

The first study segmented voice samples using a hybrid segmentation system that integrated signal processing and machine learning methods(Prakash et al., 2016). particularly Speech data is divided into syllable-level segments using a hidden Markov model (HMM), which is initialized using the global average variance. Along with examining the distribution of acoustic qualities among the languages, the study also examined the acoustic characteristics of syllables in six Indian languages. and determine the parallels and discrepancies The study's findings demonstrate how these models could enhance TTS systems and speech technologies for low-resource and polyglot languages. However, the lack of variation in language, dialect, and speakers makes research difficult. Having trouble understanding natural or loud speech also adds to it.

For compatibility with Indian languages, a second study created a pronunciation model that includes spelling and pronunciation techniques transferred from UTF-8 to ISCII(Singh, 2006). The model employs Dynamic Time Warping (DTW) for string alignment and incorporates telemetry to gauge phonetic similarity. Spell checking is one of the many applications that the model supports. Normalization of text and identification of related terms. The results demonstrate how standardizing a phonemic orthographic framework for the Brahmi script has improved natural language processing for Indian languages. However, issues like resource efficiency were identified. limited pronunciation format presentation and language generalization.

Hegarty et.al. (2019) phonetic comparison offers crucial tools for comprehending the phonetic diversity of languages. An online database and tools for analyzing phonetic similarities and contrasts between languages are made available by this project(Nallanthighal et al., 2021). It is a useful tool in the field of comparative linguistics. Dialectics and sociolinguistics "Phonetics Comparison" emphasizes the difficulty of developing phonetics resources for those with low proficiency despite its wide breadth. This project's technique, which includes the capacity to search, filter, and examine phonetic data, establishes a standard for recording and examining the phonological characteristics of underrepresented languages.

Tohru et al. represent the overview of evolution of speech recognition, speech synthesis, and machine translation.Key approaches include a minimum mean square error (MMSE) estimator with a Gaussian mixture model (GMM) and a particle filter to reduce noise and interference(Shimizu et al., 2008). An MDLSSS algorithm determines the number of parameters based on training data size using the maximum description length criterion. Despite well-trained models, factors like speaker variability and background noise can still cause errors, which are mitigated by applying generalized word posterior probability (GWPP) for post-processing. The translation process uses TATR and EM modules, with TATR leveraging translation examples and employing probabilities and penalties when necessary.The XIMERA speech synthesis engine, trained on large corpora from Japanese, English, and Chinese speakers, uses an HMM-based statistical prosody model to produce natural pitch patterns without heavy signal processing. Evaluation across the BTEC, MAD, and FED corpora ensures the system's robustness in various speaking styles. Results indicate high accuracy (82-94 percentage for Chinese) and BLEU scores (0.55-0.74) for Chinese-Japanese and Chinese-English translations. The paper concludes that integrating these advanced techniques significantly enhances the performance and consistency of speech recognition, synthesis, and machine translation systems

Nallanthighal et al. investigates the connection between speech's respiratory effort and phoneme formation. The results of the study on the respiratory patterns linked to particular phonetic classes provide insights into the physical components of speech production, despite the controlled setting and small sample size(Heggarty et al., 2019). These observations could help with the phonological analysis of Irula by examining the differences in respiratory effort between the language's phonetic components. However, the accuracy of lung volume changes—which is crucial for practical applications—is limited by the absence of calibration in respiratory data measurement.

While previous studies have examined various methods for phonological analysis and language preservation, there has been limited research comparing machine learning models for phonetic analysis in low-resource languages such as Irula. Furthermore, the automation of phonological feature extraction using models like BiLSTM and SVM has not been extensively studied, particularly in the context of Indian languages. This research seeks to fill this gap by assessing BiLSTM and SVM models for phoneme segmentation and comparing the acoustic properties of Malayalam, Tamil, and Irula. The aim is to enhance the accuracy of phonological analysis tools for endangered languages and evaluate the feasibility of these models for automating phonetic feature extraction in less-explored languages.

3 METHODOLOGY

MFCCs are used (Han et al., 2006)(Paulraj et al., 2009)in this study's methodology to extract phonetic features from audio recordings of considered languages Malayalam, Tamil and Irula.Both deep learning model and a machine learning model were implemented to classify the phoneme analysis for Irula, Malayalam, and Tamil. The procedure can be divided into several key steps, including dataset preparation ,feature extraction, train the model, and evaluation.

3.1 Dataset Preparation

We gathered voice samples from one male and one female speaker of each language for our study, resulting in a total of six participants. For dataset development, we collected one hundred comparable words from Irula, Malayalam, and Tamil. These words share similarities in phonology, morphology, and semantics. The recordings are made by native speakers of the respective languages and saved in WAV format.

3.2 Feature Extraction

The participants' voice signals were(Paulraj et al., 2009) captured. at a sample rate of 16 kHz. The audio samples were processed using MFCC, a popular method for extracting phonetic characteristics in audio sources . The audio samples were examined using MFCC(Han et al., 2006), a commonly employed method for extracting phonetic features from (Paulraj et al., 2009) audio sources. The primary objective of MFCC is to mimic human auditory perception. For each audio file, thirteen MFCC coefficients—an established standard in speech processing research—were extracted. Consequently, each audio frame generated a total of thirteen MFCC features, effectively capturing essential phonetic traits.

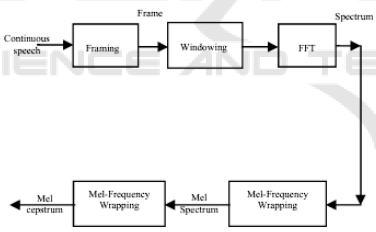

Figure 1: An illustration of the MFCC block

The components of MFCC(Roul and Rath, 2023) feature extraction algorithm:

3.2.1 Frameblocking

The continuous voice stream is segmented into frames of N samples, with neighboring frames overlapping by M samples (where M is less than N). The first frame contains the original N samples. (mfc, 2023)(Paulraj et al., 2009). This pattern continues as the second frame overlaps the first by M samples and begins M samples after it. This process continues until each spoken phrase is captured in either a single frame or multiple frames(mfc, 2023)(Paulraj et al., 2009) . Typically, N and M are set to 256 and 100, respectively(mfc, 2023)(Paulraj et al., 2009) .

3.2.2 Windowing

Windowing reduces spectral distortion and signal discontinuities at the start and end of each frame by smoothly tapering the signal to zero(Paulraj et al., 2009). When N denotes the number of samples in each frame(Paulraj et al., 2009), the resulting signal is obtained through this windowing technique(mfc, 2023)(Paulraj et al., 2009). The Hamming window,is usually utilized.

3.2.3 Fast Fourier Transform

After applying a Hamming window to reduce spectral leakage, the Fast Fourier Transform (FFT) is used to convert the signal from the time domain to the frequency domain. The FFT is an efficient algorithm designed to compute the Discrete Fourier Transform (DFT) for a set of N samples, $\{x_n\}$. In contrast to the DFT, which has a computational complexity of $O(N^2)$, the FFT optimizes this to $O(N \log N)$ by taking advantage of the symmetry and periodicity of complex exponentials.

3.2.4 Mel-Frequency Wrapping

The frequency characteristics of spoken sounds do not conform to a conventional linear scale(Paulraj et al., 2009). As a result, a specialized scale known as the "Mel" scale is utilized to relate perceived pitch to an actual frequency f measured in Hertz (Hz)(Paulraj et al., 2009). On this scale, frequencies below 1000 Hz are spaced linearly, while those above 1000 Hz shift to a logarithmic spacing. Typically, the number of coefficients obtained from the Mel-frequency spectrum, represented as K, is commonly set at 20(Paulraj et al., 2009).

3.2.5 Cepstrum

The logarithmic time is again transformed from the Mel spectrum, resulting in the MFCCs(Han et al., 2006). For the specified frame analysis, the cepstral representation of the speech spectrum provides an effective depiction of the signal's local spectral characteristics(Paulraj et al., 2009). The Discrete Cosine Transform (DCT) can be applied to convert the real-number Mel spectrum coefficients into the(Paulraj et al., 2009) temporal domain.

Using the previously described method, a set of MFCCs is computed for each 30 ms speech frame(Paulraj et al., 2009), incorporating overlap. The DCT coefficients for each speech input are extracted and used as the feature set for the neural network(Paulraj et al., 2009) model.

3.3 Model Architecture and Training

3.3.1 Bi-LSTM

A specific type of recurrent neural network (RNN), known as bi-LSTM (bidirectional long short-term memory)(Subramanian et al., 2023) , is capable of processing sequential data in both frontward and backward directions(Nama, 2018). By combining bidirectional processing with the strengths of LSTM, this model can effectively integrate both the previous and next context of the input sequence(Madamanchi et al., 2024). This bidirectional approach significantly reduces the risk of losing important information that may be influenced by factors present in the opposite direction.

To evaluate the performance of a simplified BiLSTM model, the Keras framework was employed for building and training the architecture. The input data was enhanced with Gaussian noise by adding random values with a mean of 0 and a standard deviation of 0.1 to the training dataset. This augmentation aimed to introduce variability and improve the model's robustness.

The model architecture was constructed using a sequential layout. The initial layer featured a BiLSTM with 128 units, configured to avoid returning intermediate sequences, thus ensuring a compact representation of the input data. To avoid overfitting, a Dropout layer with a probability of 0.5 was added to deactivate nodes during training.

Subsequently, a dense layer with 32 units and a hyperbolic tangent activation function was incorporated. This choice differed from the commonly used ReLU activation function, allowing for an assessment of how an alternative activation mechanism influences the model's learning process. The output layer consisted of a dense layer with a softmax activation function, generating probabilities for each class corresponding to the number of target categories in the one-hot encoded labels. The model was compiled using the Adam optimizer, with categorical cross-entropy as the loss function and accuracy as the evaluation metric. To minimize computational demands, training was performed on a smaller subset of data, consisting of only 100 samples. The model underwent training for 10 epochs with a batch size of 32. These adjustments, including the reduced dataset size and training duration, were implemented to investigate the model's performance under resource-constrained conditions.

3.3.2 Support Vector Machine

Support Vector Machine (SVM) is a powerful supervised learning method that is mainly used for classification purposes.(Nair et al., 2019). It works by figuring out the best hyperplane—or decision boundary in higher dimensions—to divide various data point classes(Nair et al., 2019)(Ratnam et al., 2021). The primary goal of Support Vector Machines (SVM) is to maximize the distance between the nearest data points from different classes, known as support vectors. (Nair et al., 2019). This strategy improves the model's resilience and its ability to generalize to new data. (Nair et al., 2019)(Ratnam et al., 2021). MFCCs are frequently used to capture audio characteristics, leading to a feature space that is typically high-dimensional, with 13 coefficients for each time frame. Given that SVMs perform well in high-dimensional settings, they are particularly suitable for tasks such as sound or vowel classification. We implemented SVM using the Scikit-learn library , applying a linear kernel function that is effective for high-dimensional feature spaces like the MFCCs utilized in this study. SVM is recognized for its efficacy in sound and vowel categorization tasks(Nair et al., 2019)(Ratnam et al., 2021).

4 EVALUATION AND RESULT

4.1 Comparison between Irula, Malayalam and Tamil

Table 1: Comparison between Irula and its Sister Languages.

Weight 1	Weight 2	Weight 3	Language	Phoneme
-576.296	42.311	-4.741	Malayalam	[a]
-442.539	51.198	7.521	Irula	[a]
-463.308	73.609	-2.683	Tamil	[a]
-563.650	24.217	17.235	Malayalam	[i]
-384.451	49.462	-1.058	Irula	[i]
-429.236	60.565	21.706	Tamil	[i]
-609.626	68.138	30.401	Malayalam	[u]
-431.740	46.375	2.256	Irula	[u]
-458.865	85.762	20.168	Tamil	[u]
-573.000	30.000	7.720	Malayalam	[e]
-367.637	53.044	-8.653	Irula	[e]
-4.732	57.919	13.994	Tamil	[e]
-538.000	62.500	25.600	Malayalam	[o]
-386.394	63.102	3.869	Irula	[o]
-418.050	89.870	18.211	Tamil	[o]

4.2 Evaluation

In this task, we assess both models using evaluation metrics such as precision, recall, and F1-score(Tang et al., 2020). Specifically, in this multi-class classification task, these metrics help us in evaluating the model's performance(Tang et al., 2020). Precision is a statistical metric employed to assess the effectiveness of a classification model, especially in identifying true positive predictions(Tang et al., 2020). Recall is a performance metric that measures a model's capability to accurately identify all pertinent instances within a dataset(Tang et al., 2020). The F1 Score is a statistical metric that integrates two essential evaluation measures: precision and recall. It reflects their harmonic mean, offering a single value that balances both the accuracy (precision) and comprehensiveness (recall) of a model's predictions(Tang et al., 2020).

4.3 Result

The performance of the phonological analyzer was evaluated using two machine learning models: Bi-LSTM and SVM. The models were assessed based on their classification reports and confusion matrices, which provide insights into the predictive accuracy and error patterns.

The classification performance of the models is summarized in Tables 2 and 3, which provide detailed metrics, including precision, recall, F1-score, and support for each class.

Table 2: Classification report for Bi-LSTM.

Class	Precision	Recall	F1-Score	Support
Irula	0.85	0.92	0.89	38
Malayalam	0.86	0.86	0.86	37
Tamil	0.90	0.69	0.78	13

Table 3: Classification report for SVM.

Class	Precision	Recall	F1-Score	Support
Irula	0.95	0.97	0.96	38
Malayalam	0.89	0.86	0.88	37
Tamil	0.77	0.77	0.77	13

To further evaluate the performance of both models, a Confusion Matrix was employed. These matrices are presented in Figures 2 and 3 for the Bi-LSTM and SVM models, respectively.

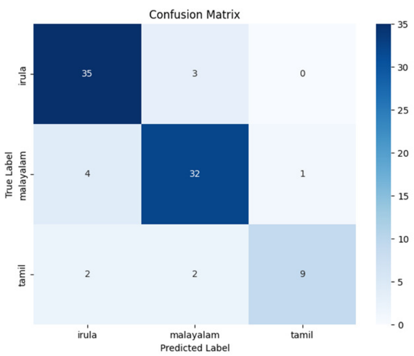

Figure 2: Confusion Matrix for Bi-LSTM

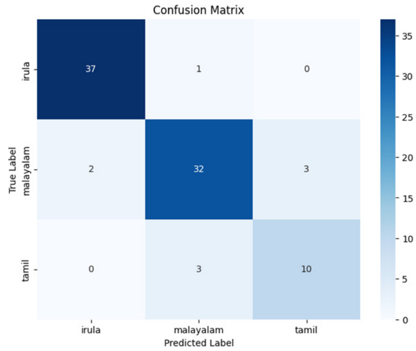

Figure 3: Confusion Matrix for SVM

5 CONCLUSION

This study presents an innovative approach to analyzing and classifying speech data from five individuals into three distinct classes based on articulatory features such as tongue position, tension, and lip placement (front, middle, and rear). MFCCs for feature extraction, the research assessed the performance of Bi-LSTM and SVM. The empirical analysis reveals that the SVM model outperformed the Bi-LSTM in classification accuracy, highlighting its potential as a robust method for phonological analysis.

This research not only showcases computational advancements but also has significant implications for the preservation of Irula, an endangered language with a rich linguistic heritage. By combining computational methodologies with linguistic analysis, it establishes a foundational framework for studying Irula and offers a scalable approach for other low-resource languages. By emphasizing the phonological differences and common features among Irula, Tamil, and Malayalam, this work contributes to the advancement of computational phonology and linguistics.

Furthermore, it highlights the urgent need to develop tools for preserving and analyzing endangered languages in the digital age. The framework presented here is anticipated to support future research in phonological modeling, language preservation, and computational applications for low-resource languages, ensuring that their cultural and academic legacies endure.

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