International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 03 | March - 2023 Impact Factor: 7.185 ISSN: 2582-3930

Review of Automatic Language Identification System in Indian languages from the Non-Uniform Region

KARTHIKA M R
M3 Signal Processing
Dept. of Electronics and Communication
College of Engineering Trivandrum
tve21ecsp10@cet.ac.in

Prof. ANU GEORGE
Assistant Professor
Dept. of Electronics and Communication
College of Engineering Trivandrum
anugeorge@cet.ac.in

Abstract—The process of language identification involves automatically detecting which natural language(s) are given in a speech sample. Using automatic language recognition, an audio clip can be recognised as being spoken in a specific language (LID). Identifying the language correctly from a given speech sample is the language identification system's fundamental purpose. There are two types of systems they are explicit language identification and implicit language identification. The phoneme sequence used in the explicit language recognition system is produced from a speech sample. Language is determined using the phoneme sequence that is retrieved. There is no need to identify the phoneme in the implicit language recognition method, which determines using certain speech properties. The language identification process involves training and a classifier model. the first step is to extract the speech sample using phonemes then it is trained using classifiers. Data are randomly collected from male and female peoples in society.

Index Terms—Language identification (LID), Mel-frequency cepstral coefficients (MFCC), broad phoneme classifier (BPC),Neural network, support vector machine (SVM), LDA, CNN,i-vector,GMM Super Vector(GSV),Factor Analysis(FA),Native Language Identification (NLI),Stylistically Related Text Samples (SSTs),Deep Dumb Multi Layer Perceptron (DDMLP), Deep Convolutional Neural Network (DCNN), and Semi-supervised Generative Adversarial Network(SSGAN),Gated Recurrent Units (GRUs),Hidden Markov models (HMMs),phone error rate (PER),Convolutional and Long Short Term Memory Recurrent (CLSTM), Neural Networks ,Singing Language Identification (SLID),Automatic Speech Recognition (ASR).

I. INTRODUCTION

Language identification system uses a list of supported languages to identify the languages spoken in audio. There are many applications for language identification (LID): stan-dalone language recognition for the situations in which you only need to recognise language from an audio source.There are multiple statistical methods for identifying languages that classify the data using various methods. Comparing the text's compressibility against those of texts in a collection of well known languages is one method. This strategy is referred to as a distance measurement based on mutual information. Numerous traits can be associated with language, but the most significant ones are that it is arbitrary.

II. LITERATURE REVIEW

A. Language Identification

Automatic language identification can be a method for identifying the language spoken in an audio signal. (LID). One of the most fundamental and important LID processes is feature extraction. The main paradigms of research in feature extraction methods are presented in this review, which will give researchers a thorough understanding of feature extraction methods for upcoming LID studies. Every language has a unique set of phonemes. Thus, combining these phonemes under the control of phonotactics will aid in differentiating languages, LID is the recognition and implementation of these variation among languages. LID has applications in many areas like language translation system, in the airport for helping multinational travelers. An automatic language identification system could also serve as a front- end for a multilingual translator that accepts speech as input in a variety of languages.

1) Acoustic phonetics: : This field examines acoustic characteristics of spoken sounds. Features like linear prediction coefficients (LPC), perceptual linear predictive (PLP), and Mel-frequency cepstral coefficients are typically used to represent it (MFCC).

2) Phonotactics: It examines how several phonemes mix to form a language. The phonotactic rules differ between languages.

3) Prosody: Depending on the pitch, intonation, and duration of the phones, it differs from language to language.

4) Vocabulary: It is the vocabulary that each language uses. Each language has a set vocabulary.

5) Morphology: The study of morphology explains the structure of words in languages.

6) Syntax and semantics : It explains the guidelines and precepts that give words their significance when they are combined into clauses, sentences, and phrases.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 03 | March - 2023 Impact Factor: 7.185 ISSN: 2582-3930

Multiple characteristics and classifiers can be used to solve automatic language identification challenges. Here are expla-nations of some of them as they pertain to this study.

B. Features of the LID

Low-level features and high-level features are the two cat-egories of features. Low-level aspects include acoustics, pho-netics, phonotactics, and prosody. The existence of language-specific information is more prevalent in high-level features like morphology, syntax, and semantics than in low-level features. The extraction of higher level features is challenging since this demands audios with a big set of language. Acoustic characteristics explain the unprocessed sound of spoken lan-guage. Better representations of auditory information can be found in the cepstrum derived from Mel-frequency cepstral coefficients (MFCC) and perceptual linear models (PLMs).

In the paper Yuanyuan Yang et.al[1] language identification techniques based on underlying acoustic features are examined along with the emergence and evolution of phoneme-level features both domestically and internationally. Features are extracted and models are established as part of research on dialect identification technology based on language recogni-tion techniques. Additionally, it emphasises the recent ad-vancements in i-phoneme-based dialect detection technolo-gies. The 1970s saw the development of a number of use characteristic language recognition systems, which can be further divided into phoneme-based and lower-level acoustic methods. The phoneme-level feature-based modeling approach is time-consuming and expensive. Based on the bottom layer's acoustic properties, language analysis progresses through three stages: In comparison to the conventional i-vector, the Gaus-sian Model Universal Better performance is achieved us-ing the GMM-UBM Background Model, GSV, FA, DNN-based techniques, end-to-end mechanisms, and attention-based mechanisms(Factor Analysis). Language recognition technol-ogy has been the foundation for dialect identification progress. Similar to how speech recognition technology has developed, Technology for dialect recognition likewise uses language recognition as its foundation.

The author Tharindu Ranasinghe et al.[2] Most of this research focuses on English, in part because the majority of the accessible annotated datasets have English data. In order to create predictions in low-resource languages,this study employ cross-lingual contextual word embeddings and transfer learning to existing English datasets. In Arabic, Bengali, Dan-ish,Greek, Hindi, Spanish, and Turkish, It make projections based on analogous data. The outcomes across all languages support how well-suited transfer learning and cross-lingual contextual embeddings are used in this assignment.The best outcomes attained by competitors in the three competitions are surpassed by the XLM-R with transfer learning, which exceeds all other approaches studied here. Furthermore, Bengali's results demonstrate that, even when the labels don't directly correspond to the projected dataset, transfer learning may be used to obtain great performance on off-domain and off-task data. Given the wide range of phenomena, annotation techniques, and criteria utilised in offensive language datasets, this enables fascinating new study directions. Furthermore, interested in determining whether testing morphologically rich languages like Arabic and Turkish might benefit from language-specific preprocessing, such as segmentation.

R. Ojha et al.[3] has done recently, a number of end-to-end systems with acoustic models developed at the grapheme or phoneme level have also been researched. In order for these systems to perform well at recognition, they either need they employ language models or pronunciation dictionaries frequently or a lot of data. In this study, acoustic models for speech recognition are developed using phonetic information in an effort to lessen the reliance on data or external models. Based on how humans produce speech, the phonetic character-istics of a sound characterize that sound. To identify phonetic features in a particular speech stream, multi-label classification models are created. The models for phoneme identification use the detected phonetic features as well as the auditory features as input.

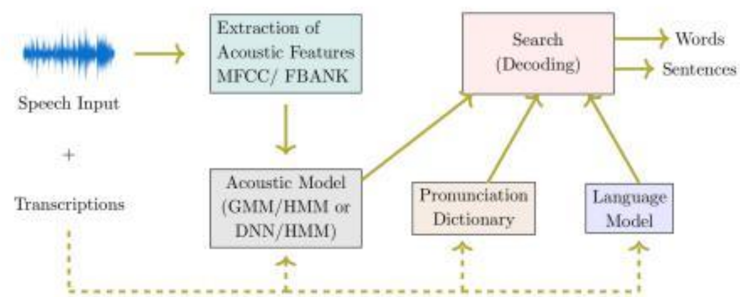

Fig 1. Conventional framework for ASR

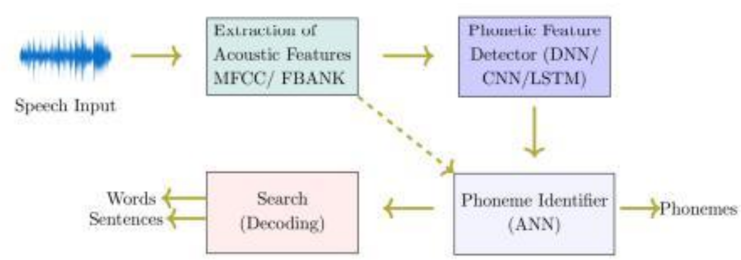

Fig. 1. Phonetic feature detection based framework for ASR [3]

L. Renault et al.[4] has proposed phoneme recognition is carried out using an acoustic model trained on Connectionist Temporal Classification (CTC) with multilingual data, fol-lowed by language classification using an estimation-based recurrent model for phonemes. With record-breaking perfor-mances, the entire pipeline is trained and assessed using a sizable dataset that is made available to the public. Also included is the initial SLID findings for languages outside the group. Examine con- temporary phonetic methods using recurrent models for both phoneme recognition and language classification for SLID on polyphonic music. The suggested system performs better than previous state-of-the-art SLID methods and metadata-based approaches when trained on a publically accessible multi- lingual dataset. The CTC-based acoustic model considerably helps the performance enhance-ment in both closed-set and open-set environments.

The author Y. Karunanayake et al.[5] today, content-based voice classification has many different applications. These include spoken command recognition and speech topic identi-fication. All of these applications use ASR to transform spoken language into text. However, it takes a lot of resources to develop a language-specific ASR system. Despite the fact that there are over all of these speeches- related applications can only use the most popular languages, like English, out of the 6000 possible languages due to data availability. Previous studies have investigated how to categorise speech while considering data shortages. All of these techniques, though, have their own drawbacks. This provides a Tamil and Sinhala speech purpose categorization algorithm based on English phonemes. create phoneme probability features using a pre-trained English ASR model to ascertain the intentions of utterances made in Tamil and Sinhala, both of which have sparse speech corpora.

C. Automatic LID classifiers

LID can be seen as a task that combines language recog-nition and training for pattern recognition. There is research being done on the HMM, GMM, and ANN. The description of SVM and ANN-based systems for identifying Indian lan-guages. Two applications for deep neural networks (DNNs) were suggested in another study using these networks. Initially, the DNN functioned as a fully integrated LID classifier, assessing voice data and forecasting the likelihood of various input languages. The bottleneck features needed for an i-vector system were gathered using a DNN in the second step. During testing, the DNN system outperformed the i-vector systems in place for short-duration utterances.

1) Using HMM: K. R. Moabkela et al [6] has proposed HMMs are used to build multilingual acoustic models that can accom-modate multiple languages in one utterance. To ascer-tain the phoneme commonalities among the target languages, sug- gest two phoneme clustering techniques. SVM technology is used to classify language identity based on probability scores derived from phoneme occurrence segments.A mixed-language voice corpus for Sepedi and English was used for the experiments. Measure the PER and LID classification accuracy performance of the ASR-LID system independently. lower PER was reached on a system that employed a data-driven phoneme clustering method and was modelled with 32 Gaussian mixtures per state. With regard to code-switched and monolingual speech, the suggested multilingual ASR-LID system has produced respectable recognition and classification accuracy.

2) Using SVM: The most common and often utilised meth-ods for recognising speech emotion are SVMs with non-linear kernels. An SVM with a non-linear kernel uses a kernel mapping function to transfer the input feature vectors into a higher dimensional feature space. In order to make classifiers that are non-linear in the original space linear in the feature space, the suitable non-linear kernel functions must be chosen.

C. Yarra et al.[7] has proposed automatic identification of problematic non-native English speakers (L2) who originate from one of the eleven L1 origins. Different sets of linguistic units are chosen and utilised to compute supra-segmental fea-tures by taking into account the acoustic and prosodic changes within and across these sets in order to assess the effects of each variance in L1 pronunciation on L2 pronunciation. Utilize these characteristics to build a multiclass classifier made up of 55 binary (one vs. another) support vector machine (SVM) classifiers. Two feature selection strategies (FSSs) based on the Fisher discriminant ratio are used to find the best set of features for each binary classifier (FDR). The first approach takes into account the characteristics that improve the effectiveness of each binary classifier. The second approach, however, chooses the attributes by enhancing the performance of a multi-class classifier; an algorithm is offered for this. Non-native spoken English in the ETS corpus experiments is run on the 4099 files. The test set's unweighted average recall (UAR) for each choice is calculated when the proposed features are combined with FSSs.In order to help MCC determine the speaker's native language, suggest an FDR-based feature se-lection technique for acoustic and prosodic features. Utilizing a pairwise method, combine 55 SVM BCs to create an 11-class classifier. a technique for learning characteristics and setting the parameters for each BC separately. Use FDR to choose a subset of the features based on acoustic, prosodic, and linguistic properties.

The authors J. S. Anjana et al [8] in their work two su-pervised learning algorithms used in a language identification system are compared for their performance metrics. In order to classify data, formant feature vectors and Mel frequency cepstral coefficients are extracted. Using two distinct features, a method for identifying the language in the speech was put into place, and performance metrics were researched. Both SVM and LDA classifiers were employed in the classification process. It can infer from this study that different languages have different speech properties. It may be said that the LDA classifier outperforms the SVM classifier significantly for the dataset under consideration.

In the paper Srinivasan Sengamedu et al.[9] have presented implicit understanding of these elements exists in neural language models. A system to identify problems with code quality using neural language models. It employs local or repository-specific models to handle conventions specific to a given repository. The models have a low false positive rate for identifying actual code quality problems. A single framework for coding was created using an unsupervised neural language model to discover many categories of code quality issues that may result in poor code readability and maintainability. have created an automated method that detects a significant percentage of these problems a low false positive rate in open-source repositories have also outlined the process for customizing global models for particular repositories and examined the local models that resulted. It's difficult to use unsupervised language models to find According to a recent study that examines the gap between contemporary machine learning models and conventional static analysis techniques, many academically fascinating research publications have little practical real-world relevance.

Raheem Sarwar et al.[10] by examining text samples pro-duced in authors' non-native languages, NLI attempts to determine the writers' native tongues. The learner corpora are needed for the majority of current studies, which focus on this project for educational purposes, such as learning a second language. Since the authors of this essay are proficient non-native speakers of a second language, it presents a de-manding scenario for NLI in the user-generated content (UGC) space. Existing NLI research with UGC I relies on content-specific/social-network features and may not be generalizable to other domains and datasets, (ii) is unable to capture the variations of language-usage patterns within a text sample, and (iii) is not linked to any outlier handling strategy. Due to immigration and economic policy, a sizable portion of the population has picked up non-English second languages, hence it is important to evaluate how NLI with UGC can be applied to other languages. A topic-independent feature space, enabling the generalizability of our method to a wide range of topics and datasets, in contrast to existing systems. This provides a strategy based on our feature space that reduces the impact of outliers in the data and aids in capturing the variability of language-usage patterns within a text sample. To be more precise, we identify the top k SSTs from the corpus and represent each text sample as a point set. then use the iden-tified top-k SSTs to train the probabilistic k nearest neighbors' classifier to estimate the authors' native languages. This article examines native language identification in the difficult setting of competent and proficient non-native English speakers and assesses its application to other languages like French and German. To carry out this inquiry, three new corpora should be created, each written in a different language—in this case, English, French, and German. Since our technique does not rely on social network properties or content-specific attributes, it is more generalizable to various domains and datasets than competing systems.

3) Using DNN: Data on spontaneous speech was gathered from regional radio broadcasts in each language and used in this study. There are numerous noises in this spontaneous dataset. As a result, appropriate feature extraction and classi-fication techniques are needed to create a reliable language identification system.In this study, three features—dynamic prosody, phonotactic features based on parallel phonemes, and acoustic features based on the i-vector—are used to identify languages. These features are combined on the DNN.Due to the restricted standard corpus for Indonesian and its regional languages, future studies may want to develop voice corpora with more linguistic diversity. A dialect recognition task is also intriguing to look into. [11]

By utilizing CLSTMNN, which can boost feature extrac-tion and capture longer temporal relationships, this paper aims to enhance classic DNN x-vector language identification (LID) performance. A two-dimensional attention process is something else we suggest. Our approach, which differs from traditional in order to produce weighted averages and standard deviations, one-dimensional time attention adds a frequency attention mechanism to weight various frequency bands differently. Using this mechanism, which is trained or fused separately or in combination, can focus attention on either time or frequency information. First, the results of the experiments demonstrate that CLSTM can perform noticeably better than a conventional DNN x-vector imple-mentation. Second, The recommended frequency is used when the number of frequency bands matches the size of the feature attention strategy and performs better than time attention. In addition, frequency-time feature merging is not as effective as frequency-time score merging, which exhibits gains for modest frequency dimensions. It was found that score-level mergers of the two dimensions outperformed feature-level mergers in all evaluations. [12]

For this, a wide phoneme classifier automatically determines the broad phoneme labels approximant (A), closure (C), frica-tives (F), nasals (N), plosive/stop (P), voiced stop (B), vowels (V), and silence (S) (BPC). Using Mel-frequency cepstral coefficients and custom features, it is a DNN-based classifier (MFCC). Speech is initially chopped at each silent area using labels received from BPC in order to automatically partition it into smaller regions. At the conclusion of each vowel, it is divided once more. As a result, little non-uniform patches are produced, some of which include phoneme combinations that might be unique to the language of the utterance. Only a predetermined number of frames with a specific mix of phonemes are chosen from each location. Using characteristics from 12 fixed frames of non-uniform regions in 13 dimensions, a DNN classifier is trained to execute LID. For 10-second test utterances from four different languages, average accuracy is found. Increasing the length of the test utterance results in an improvement in accuracy. Higher classification accuracy is also a result of using more training instances.[13].

4) Using GAN: GAN has recently demonstrated promising results for language identification (LID). In this study, take advantage of the capabilities of GAN networks augment the LID model by first pairing them with DNN-based i-vector approaches, and then by conditional generative adversarial net (cGAN) classification. First, i- vectors are extracted from the output posteriors of a pre-trained DNN for automatic sound identification using a widely utilised method called phoneme-dependent deep bottleneck features (DBF) (ASR). To successfully optimise cGAN parameters after classify-ing these i-vectors using cGAN by including both language identification and verification signals as supervision. First, the results demonstrate that when 49-dimensional i-vectors are employed, cGAN methods considerably outperform DBF DNN i-vector approaches, but not when 600-dimensional i-vectors are utilised. Additionally advantageous is training a cGAN discriminator network for direct categorization for short utterances with both high- and low-dimensional i-vectors.[14]

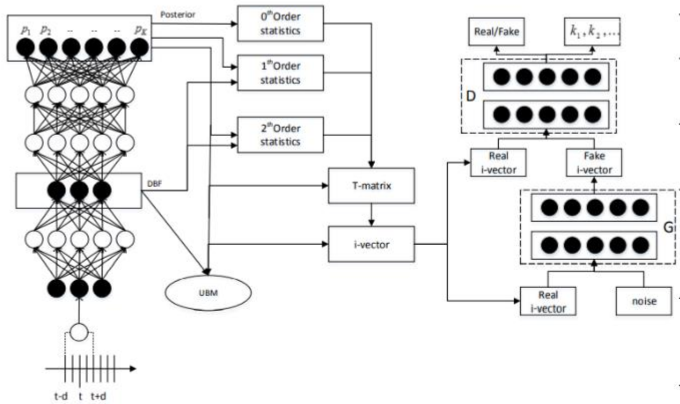

Fig. 2. LID using GAN [14]

5) Using LSTM: This present the FuzzyGCP ensemble architecture, which is developed to extract spoken languages from sound samples using deep learning.In order to increase precision to the highest level, Using a DDMLP,DCNN, and SSGAN, this architecture combines the categorization princi-ples of each network (SSGAN). Finally, ensemble learning using the Choquet integral is applied to predict the final output, which is the language class. four common bench-mark datasets, including two datasets in Indian languages and two datasets in other languages, were used to evaluate our approach.Future scope could be improved by utilizing less computationally intensive designs and some feature selection algorithms. To create an ensemble, use sequential models like LSTMs, GRUs. On the datasets investigated in this study, a detailed examination of the x-vector and i-vector-based models with appropriate hyperparameter tuning can be taken into consideration. [15]

D. Result Analysis

E. Application

The primary areas of study in audio processing and retrieval include automatic speech recognition, music information re-trieval, environmental sound recognition, and audio segmen-tation. As a preprocessing phase in audio analysis, audio segmentation divides various sound kinds, such as speech, mu-sic, environmental sounds, silence, and combinations of these sounds. The subdomains of audio segmentation include speech and music segmentation, speech and non-speech segmentation, and quiet detection.

The development of mood-driven human-computer inter-faces may benefit from recent approaches that try to recognise and evaluate stress and other emotions in spoken language. Age detection from speech and gender detection are further areas of voice processing. Speech analysis in medical appli-cations is a cutting-edge method for identifying illnesses that have an impact on spoken language.

Among other things, bioacoustic pattern recognition deals with the detection and retrieval of animal sound like bird song

CLASSIFIERS	DATASET	FEATURE EXTRACTION	ACCURACY
CTC	Closed set scenario Open set scenario	Phoneme	76.71% 56.25%
HMM	The monolingual speech set data for Sepedi and English	Phoneme Mapping	87.3%
SVM	ETS corpus of Non-Native Spoken English	Acoustics and prosodic	54.8%
DNN	Prosodically guided Phonetic Engine for searching speech databases in the Indian language	MFCC	93.97
GAN	NIST LRE07 Closed set language detection spanning 14 languages	Acoustic Features	49%
LSTM	VoxForge IIT hyderbad IIT madras Mass	MFCCs,spectral bandwidth, spectral contrast, spectral roll-off, spectral flatness, spectral centroid,Polynomial features,Tonnetz	68.00% 95.00% 81.51% 98.75%

Fig. 3. Comparison of result

and whale calls as well as the acoustic monitoring of animals in the wild.

III. Conclusion

A group of Indian languages is categorized using an ar-tificial language identification technique. For the purpose of automatic LID, the system makes use of phonotactics from different languages. A broad phoneme classifier is used to generate broad phoneme labels for a voice signal. Using neural networks is one method of approaching the issue. Better subset accuracy is provided by algorithms for multi-label classification based on DNN, CNN, and LSTM. When developing speech recognition systems with little training data, models for detecting phonetic aspects in speech can be employed to recognize speech that is too articulated or not native. To improve the system’s performance, the present work can be expanded to include more attributes and attribute combinations.

References

[1] Yuanyuan Yang, Kailei Li, Rui Guo and Yun Yan. 2018. Research on the development of automatic dialect identification technology based on language recognition. In AIAM’ 20: 2020 2nd International Conference on Artificial Intelligence and Advanced Manufacture, October 15–17, 2020, Manchester, United Kingdom. ACM, New York, NY, USA.

[2] Multilingual Offensive Language Identification for Low-resource Lan-guages Authors: Tharindu Ranasinghe, Marcos Zampieri ACM Transac-tions on Asian and Low-Resource Language Information ProcessingVol-ume 21Issue 1January 2022 Article No.: 4pp 1–13

[3] R. Ojha and C. C. Sekhar, ”Multi-label Classification Models for Detection of Phonetic Features in building Acoustic Models,” 2019 International Joint Conference on Neural Networks (IJCNN), 2019, pp. 1-8.

[4] L. Renault, A. Vaglio and R. Hennequin, ”Singing Language Identifica-tion Using a Deep Phonotactic Approach,” ICASSP 2021 - 2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2021, pp. 271-275.

[5] Y. Karunanayake, U. Thayasivam and S. Ranathunga, "Sinhala and Tamil Speech Intent Identification From English Phoneme Based ASR," 2019 International Conference on Asian Language Processing (IALP), 2019, pp. 234-239.

[6] K. R. Moabkela, "A Multilingual ASR of Sepedi-English Code-Switched Speech for Automatic Language Identification," 2019 International Multidisciplinary Information Technology and Engineering Conference (IMITEC), 2019, pp. 1-8.

[7] C. Yarra, A. Rao M.V. and P. Kumar Ghosh, "Automatic Native Language Identification Using Novel Acoustic and Prosodic Feature Selection Strategies," 2018 15th IEEE India Council International Conference (INDICON), 2018, pp. 1-6.

[8] J. S. Anjana and S. S. Poorna, "Language Identification From Speech Feature Using SVM and LDA," 2018 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), 2018, pp. 1-4.

[9] Srinivasan Sengamedu and Hangqi Zhao. 2022. Neural Language Mod-els forCode Quality Identification. In Proceedings of the 6th International Workshop on Machine Learning Techniques for Software Quality Eval-uation (MaLTeSQuE'22), November 18, 2022, Singapore, Singapore. ACM, New York, NY, USA.

[10] Raheem Sarwar, Attapol T. Rutherford, Saeed-Ul Hassan, Thanawin Rakthanmanon, and Sarana Nutanong 2020. Native Language Identifi-cation of Fluent and Advanced Non-Native Writers. ACM Trans. Asian LowResour. Lang. Inf. Process. 19, 4, Article 55 (April 2020).

[11] M. S. Saputri and M. Adriani, "Identifying Indonesian Local Languages on Spontaneous Speech Data," 2019 International Conference on Ad-vanced Computer Science and Information Systems (ICACSIS), 2019, pp. 247-254.

[12] Miao, X., McLoughlin, I., Yan, Y. (2019) A New Time-Frequency Atten-tion Mechanism for TDNN and CNN-LSTM-TDNN, with Application to Language Identification. Proc. Interspeech 2019, 4080-4084.

[13] G. Unnikrishnan, A. George and L. Mary, "Non-uniform Region Based Features for Automatic Language Identification," 2021 Fourth Interna-tional Conference on Microelectronics, Signals Systems (ICMSS), 2021, pp. 1-6, doi: 10.1109/ICMSS53060.2021.9673629.

[14] X. Miao, I. McLoughlin, S. Yao and Y. Yan, "Improved Conditional Generative Adversarial Net Classification For Spoken Language Recognition," 2018 IEEE Spoken Language Technology Workshop (SLT), 2018, pp. 98-104.

[15] FuzzyGCP: A deep learning architecture for automatic spoken language identification from speech signals Avishek Garain a, Pawan Kumar Singh b, Ram Sarkar a Department of Computer Science and Engineering, Jadavpur University, Kolkata 700032, West Bengal, India, Department of Information Technology, Jadavpur University, Kolkata 700106, West Bengal, India

[16] W. Xiong, L. Wu, F. Alleva, J. Droppo, X. Huang and A. Stolcke, "The Microsoft 2017 Conversational Speech Recognition System," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2018, pp. 5934-5938.

[17] C. Anjanendu, A. George and L. Mary, "Language Identification Using Gender Dependent GMM-UBM for Three Indian Languages," 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), 2018, pp. 510-513.

[18] K. Abainia, "Toward Accurate Social Media Language Identification: Combining Language Features with a Graphical Approach," 2018 3rd International Conference on Pattern Analysis and Intelligent Systems (PAIS), 2018, pp. 1-7.

[19] Indian Native Language Identification - INLI 2018 Authors: Anand Kumar M,Barathi Ganesh HB, Soman KP, Ajay SG, Proceedings of the 10th annual meeting of the Forum for Information Retrieval Evaluation December 2018 Pages 11–15

[20] Phonetic Temporal Neural Model for Language Identification Zhiyuan Tang, Dong Wang, Yixiang Chen, Lantian Li, Andrew Abel, Zhiyuan Tang, Dong Wang, Yixiang Chen, Lantian L,IEEE/ACM Transactions on Audio, Speech and Language Processing Volume 26Issue 1 January 2018 pp 134–144