Is Attention always needed? A Case Study on Language Identification from Speech

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Language Identification (LID), a recommended initial step to Automatic Speech Recognition (ASR), is used to detect a spoken language from audio specimens. In state-of-the-art systems capable of multilingual speech processing, however, users have to explicitly set one or more languages before using them. LID, therefore, plays a very important role in situations where ASR based systems cannot parse the uttered language in multilingual contexts causing failure in speech recognition. We propose an attention based convolutional recurrent neural network (*CRNN with Attention*) that works on Mel-frequency Cepstral Coefficient (MFCC) features of audio specimens. Additionally, we reproduce some state-of-the-art approaches, namely *Convolutional Neural Network* (*CNN*) and *Convolutional Recurrent Neural Network* (*CRNN*), and compare them to our proposed method. We performed extensive evaluation on thirteen different Indian languages and our model achieves classification accuracy over 98%. Our LID model is robust to noise and provides 91.2% accuracy in a noisy scenario. The proposed model is easily extensible to new languages.

CCS Concepts: • Computing methodologies → Speech recognition; Neural networks.

Additional Key Words and Phrases: Language Identification, Convolutional Neural Network, Convolutional Recurrent Neural Network, Attention, Indian Languages

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1 INTRODUCTION

From the inception of research in Natural Language Processing (NLP), researchers have specifically rely on Convolution Neural Networks (CNN) as it utilizes local features effectively. Earlier Recurrent Neural Network (RNN) was effectively used in different NLP domains, but recent use of Transformer has shown promising results which outperforms all previous experimental results. Attention based models are capable of capturing the content-based global interactions.

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Transformer in Question-Answering domain, researcher [Yamada et al. 2020] were able to outperform BERT [Devlin et al. 2019], SpanBERT [Joshi et al. 2020], XLNet [Yang et al. 2019], and ALBERT [Lan et al. 2020]. In Machine Translation domain researcher [Takase and Kiyono 2021] [Gu et al. 2019] [Chen and Heafield 2020] used Transformer and were able to outperform other state-of-the-art (sota) algorithms. In other domain like Language Modelling, Text Classification, Topic Modelling, Emotion Classification, Sentiment Analysis, etc Transformer has widely used.

However, as of yet transformer architectures have not been explored in the domain of Language Identification (LID). Use of LID in texts has been heavily researched [Rijhwani et al. 2017] [Jhamtani et al. 2014] [Mahata et al. 2019] [Mandal et al. 2018], it still is a constraint when dealing with spoken languages.

In this work we focused on using different approaches for Spoken Language Identification. Humans are capable of recognizing almost immediately the language being used by a speaker for voicing an utterance. The task of automatic language identification (LID) is to automatically classify the language used by a speaker in his/her speech. In the era of *Internet of Things*, smart and intelligent assistants (e.g., Alexa¹, Siri², Cortona³, Google Assistant⁴, etc.) can interact with humans with some default language settings (mostly in English) and these smart assistants rely heavily on Automatic Speech Recognition (ASR). However, these virtual assistants fail to provide any assistance in multilingual contexts. To make such smart assistants robust, LID can be used so that the smart assistants can automatically recognize the speaker's language and change its language setting accordingly.

Our approach of identifying spoken language is limited to Indian Languages only because India is world second populated and seventh largest country in landmass and also have dynamic culture. Currently, India has 28 states and 8 Union Territories, where each states and Union Territories has its own language, but none of the language is recognised as the national language of the country. Only, English and Hindi is used as official language according to the Constitution of India Part XVII Chapter 1 Article 343⁵. Currently, only 22 languages have been accepted as regional languages.

Sl. No.	Language	Family	Spoken in				
1	Assamese	Indo-Aryan	Assam				
2	Dongoli	Indo Amron	Assam, Jharkhand, Tripura,				
2	Bengali	Indo-Aryan	West Bengal				
3	Bodo	Sino-Tibetan	Assam				
4	Dogri	Indo-Aryan	Jammu and Kashmir				
5	Gujarati	Indo-Aryan	Gujrat,				
3	Gujaran	IIIuo-Ai yaii	Dadra and Nagar Haveli and Daman and Diu				
			Andaman and Nicobar Islands, Bihar,				
			Chhattisgarh,				
			Dadra and Nagar Haveli and Daman and Diu,				
(Hindi	Indo Amron	Delhi, Haryana, Himachal Pradesh,				
6	піпаі	Indo-Aryan	Jammu and Kashmir,				
		Jharkhand, Ladakh, Madhya Pradesh,					
			Mizoram, Rajasthan, Uttar Pradesh,				
			Uttarakhand				

¹https://developer.amazon.com/en-US/alexa/alexa-voice-service

²https://www.apple.com/in/siri/

³https://www.microsoft.com/en-in/windows/cortana

⁴https://assistant.google.com/

⁵https://www.mea.gov.in/Images/pdf1/Part17.pdf

Sl. No.	Language	Family	Spoken in
7	Kannada	Dravidian	Karnataka
8	Kashmiri	Indo-Aryan	Jammu and Kashmir
9	Konkani	Indo-Aryan	Dadra and Nagar Haveli and Daman and Diu, Goa
10	Maithili	Indo-Aryan	Jharkhand
11	Malayalam	Dravidian	Kerala, Lakshadweep, Puducherry
12	Marathi	Indo-Aryan	Dadra and Nagar Haveli and Daman and Diu, Goa, Maharashtra
13	Meitei	Sino-Tibetan	Manipur
14	Nepali	Indo-Aryan	Sikkim, West Bengal
15	Odia	Indo-Aryan	Jharkhand, Odisha
16	Punjabi	Indo-Aryan	Delhi, Haryana, Punjab
17	Sanskrit	Indo-Aryan	Himachal Pradesh
18	Santali	Austroasiatic	Jharkhand
19	Sindhi	Indo-Aryan	Rajasthan
20	Tamil	Dravidian	Tamil Nadu
21	Telugu	Dravidian	Andhra Pradesh, Puducherry, Telangana
22 Urdu Indo-Arya			Bihar, Delhi, Jammu and Kashmir, Jharkhand, Telangana, Uttar Pradesh

Table 1. List of official languages as per the Eighth Schedule of the Constitution of India, as of 1 December 2007 with their language family and states spoken in.

Table 1 describes the 22 languages designated as Official language according to the Eighth Schedule of the Constitution of India, as of 1 December 2007. Most of the Indian languages originated from Indo-Aryan and Dravidian language family.

It can be seen from the Table 1 that different languages are spoken in different states, however, languages do not obey the geographical boundaries. Therefore, many of these languages, particularly in the neighboring regions, have multiple dialects which are amalgamation of two or more languages.

Such enormous linguistic diversity makes it difficult for the citizens to communicate in different parts of the country. Bilingualism and multilingualism are the norm in India. In this context, an LID system becomes a crucial component for any speech based smart assistant. The biggest challenge and hence an area of active innovation for Indian language is the reality that most of these languages are under resourced.

Every spoken language has its underlying lexical, speaker, channel, environment, and other variations. The likely differences among various spoken languages are in their phoneme inventories, frequency of occurrence of the phonemes, acoustics, the span of the sound units in different languages, and intonation patterns at higher levels. The overlap between the phoneme set of two or more familial languages makes it a challenge for recognition. The low-resource status of these languages makes the training of machine learning models doubly difficult. Every spoken language has its underlying lexical, speaker, channel, environment, and other variations. The likely differences among various spoken languages are in their phoneme inventories, frequency of occurrence of the phonemes, acoustics, the span of the sound units in different languages, and intonation patterns at higher levels. The overlap between the phoneme set of two or more familial languages makes it a challenge for recognition. The low-resource status of these languages makes

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the training of machine learning models doubly difficult. The purpose of our approach is yet to predict the correct spoken language regardless of the above-mentioned constraints.

In this work we proposed Language Identification method for Indian Languages using different approaches. Our LID methods cover 13 Indian languages⁶. Additionally our method is language agnostic. The main contributions of this work can be summarized as follows:

- The method uses Convolutional Neural Network (CNN), Convolutional Recurrent Neural Network (CRNN), and attention based CRNN for the task of LID. We tested 13 Indian languages achieving state-of-the-art accuracy.
- Our model also provides state-of-the-art performance in languages that belong to the same language family as well as in noisy scenarios.

2 RELATED WORKS

Extraction of language dependent features for example prosody and phonemes was widely used to classify spoken languages [Zissman 1996] [Martinez et al. 2011] [Ferrer et al. 2010]. Following the success in speaker verification systems, identity vectors (i-vectors) have also been used as features in various classification architectures. Use of i-vectors requires significant domain knowledge [Dehak et al. 2011] [Martinez et al. 2011]. In recent trends researchers rel on neural networks for feature extraction and classification [Lopez-Moreno et al. 2014] [Ganapathy et al. 2014]. Researcher [Revay and Teschke 2019] used the ResNet50 [He et al. 2016] architecture for classifying languages by generating the log-Mel spectra for each raw audio. The architecture uses cyclic learning rate where learning rate increases and then decreases linearly. Maximum learning rate for a cycle is set by finding the optimal learning rate using fastai [J. 2018].

Researcher [Gazeau and Varol 2018] established the use of Neural Network, Support Vector Machine, and Hidden Markov Model (HMM) to identify different languages. Hidden Markov models converts speech into a sequence of vectors and was used to capture temporal features in speech. Established LID systems [Dehak et al. 2011] [Martinez et al. 2011] [Plchot et al. 2016] [Zazo et al. 2016] are based on identity vector (i-vectors) representations for language processing tasks. In [Dehak et al. 2011], i-vectors are used as data representations for a speaker verification task and fed to the classifier as the input. [Dehak et al. 2011] applied Support Vector Machines (SVM) with cosine kernels as the classifier, while [Martinez et al. 2011] used logistic regression for the actual classification task. Recent years have found the use of feature extraction with neural networks, particularly with Long Short Term Memory (LSTM) [Zazo et al. 2016] [Gelly et al. 2016] [Lozano-Diez et al. 2015]. These neural networks produce better accuracy while being simpler in design compared to the conventional LID methods [Dehak et al. 2011] [Martinez et al. 2011] [Plchot et al. 2016]. Recent trends in developing LID systems are mainly focused on different forms of LSTMs with DNNs. [Plchot et al. 2016] used a 3 layered Convolutional Neural Network where i-vectors were the input layer and softmax activation function as the output layer. [Zazo et al. 2016] used Mel Frequency Cepstral Coefficients (MFCCs) with Shifted Delta Coefficient features as information to a unidirectional layer which is directly connected to a softmax classifier. [Gelly et al. 2016] used audio transformed to Perceptual Linear Prediction (PLP) coefficients and their 1^{st} and 2^{nd} order derivatives as information for a Bidirectional LSTM in forward and backward directions. The forward and backward sequences generated from the Bidirectional LSTM were joined together and used to classify the language of the input samples. [Lozano-Diez et al. 2015] used Convolutional Neural Networks (CNNs) for their LID system. They transformed the input data as an image containing MFCCs with Shifted Delta Coefficient features. The image represents the time domain for the x-axis and frequency bins for the y-axis.

 $^{^6}$ The study was limited to the number of Indian languages for which datasets were available

[Lozano-Diez et al. 2015] used CNN as the feature extractor for the identity vectors. They achieved better performance when combining both the CNN features and identity vectors. [R. and T. 2019] used ResNet [He et al. 2016] architecture for language classification by generating spectrograms of each audio. Cyclic Learning [Smith 2018] was used where the learning rate increases and decreases linearly. Our research differs from the previous works on LID in the following aspects:

- Comparison of performance of CNN, CRNN, as well as CRNN with Attention.
- Extensive experiments with our proposed model shows its applicability both for close language as well as noisy speech scenarios.

3 MODEL ARCHITECTURE

Our proposed architecture consists of three models.

- CNN based architecture
- · CRNN based architecture
- CRNN with Attention based architecture

We made use of the capacity of CNNs to capture spatial information to identify languages from audio samples. In CNN based architecture our network uses four convolution layers, where each layer is followed by ReLU [Nair and Hinton 2010] activation function and max pooling with a stride of 3 and a pool size of 3. The kernel sizes and the number of filters for each convolution layer are (3, 512), (3, 512), (3, 256), and (3, 128), respectively.

In CRNN based architecture the Bi-Directional LSTM consists of a single LSTM with 256 output units were used after the CNN based architecture. The design of the Attention Mechanism is based on Hierarchical attention networks [Yang et al. 2016] which was introduced after the CRNN based architecture. In the Attention Mechanism, contexts of features are summarized with a bidirectional LSTM by going forward and backward.

$$\overrightarrow{o_n} = \overrightarrow{LSTM}(o_n), n \in [1, L]$$

$$\overleftarrow{o_n} = \overleftarrow{LSTM}(o_n), n \in [L, 1]$$

$$o_i = [\overrightarrow{o_n}, \overleftarrow{o_n}]$$

where, L is the number of audio specimens.

The annotations, o_i , build the base for the attention mechanism, and start with a Multi-layer Perceptron. The goal of the mechanism is to learn the model through training with randomly initialized weights and biases. Improved annotations are represented by u_i . The layer also ensures that network doesn't stall with a tanh function. The function 'corrects' the input values between -1 and 1, and also maps zeros to near-zero.

$$u_i = tanh(w_s o_i + b_s)$$

Important annotations are again multiplied by trainable context vector u_s and normalised to w_i by a softmax function. The context weight vector u_s is randomly initiated and jointly learned during the training process.

$$w_i = \frac{exp(u_i^T u_s)}{\sum_i exp(u_i^T u_s)}$$

The sum of these importance weights concatenated x_i with the previously calculated context annotations fed to a fully connected layer with 13 output units serving as a classifier for 13 languages.

Figure 1 provides a schematic overview of the network architecture.

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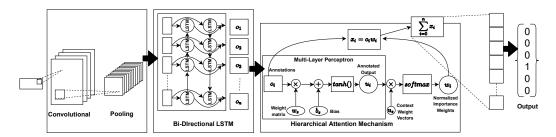


Fig. 1. Figure consists of CNN, LSTM, and Attention Mechanism denoted in different blocks. CNN extracts features from the input audio. The output of the final convolution layer is connected to the LSTM network as the input which is further connected to the Hierarchical Attention Mechanism for adequate learning. The Hierarchical Attention layer is further connected to a softmax classifier.

4 EXPERIMENTS

4.1 Data

For serving input to the neural network, MFCCs of each audio was extracted using the librosa. Sample rate of 8 kHz (8000 Hz) was taken with a Discrete Cosine Transform (DCT) type II as an ortho-normal DCT basis. The number of MFCCs feature extracted is 39, and the Lifter value of 26 used. The first 13 MFCC features for each time steps were used. We used hop-length i.e. window width of 10 msec and sliding window of 25 msec.

4.1.1 Benchmark Data. In the past two decades, development of LID methods has been largely fostered through NIST Language Evaluations (LREs). As a result, the most popular benchmarks for evaluating new LID models and methods are NIST LRE evaluation dataset [Sadjadi et al. 2018]. The NIST LREs dataset mostly contains narrow-band telephone speech. Datasets are typically distributed by the Linguistic Data Consortium (LDC) and cost thousands of dollars. For example, the standard Kaldi [Povey et al. 2011] recipe for LRE072 relies on 18 LDC SLR datasets that cost \$15000 (approx) to LDC non-members. This makes it difficult for new research groups to enter the academic field of LID. Furthermore, the NIST LRE evaluations focus mostly on telephone speech.

As the NIST LRE dataset is not freely available we used the European Language Dataset [Bartz et al. 2017] which is open sourced. The European language (*EU*) dataset contains YouTube News data for 4 major European languages – English (*en*), French (*fr*), German (*de*) and Spanish (*es*). Statistics of the dataset are given in Table 2.

Language	Label	Total Samples	Average Duration (in seconds)
English	en	43,269	684.264
French	fr	67,689	492.219
German	de	48,454	1,152.916
Spanish	es	57,869	798.169

Table 2. Statistics of the European Language (EU) Dataset

4.1.2 Experimental Data. The Indian language (IL) dataset was acquired from the Indian Institute of Technology, Madras⁷. The dataset includes 13 widely used Indian languages. Table 3 presents the statistics of this dataset which we used for our experiments.

Language	Label	Gender	Samples	Total Samples	Average Duration (in seconds)	
Assamese	as	F	8,713	17,654	5.587	
riosamese	us us	M	8,941	17,031	3.307	
Bengali	bn	F	3,253	9,440	5.743	
Dengan	DII	M	6,187	7,110	3.743	
Bodo	bd	F	571	571	25.219	
Gujarati	on.	F	2,396	5,684	13.459	
Gujaran	gu	M	3,288	3,004	13.439	
Hindi	hi	F	2,318	4,636	8.029	
Hillai	111	M	2,318	4,030	0.029	
Kannada	kn	F	1,289	2,578	10.264	
Kaiiiaua	KII	M	1,289	2,370	10.204	
Malayalam	ml	F	5,650	11,300	5.699	
Maiayalalli	1111	M	5,650	11,300	3.099	
Maninuri	mn	F	9,487	17,917	4.169	
Manipuri	mn	M	8,430	17,917	4.109	
Marathi	mr	F	2,448	2,448	7.059	
Odia	0.11	F 3,578		7 151	4.4	
Odia	or	M	3,573	7,151	4.4	
Daiaathani	:	F	4,346	0.125	7.014	
Rajasthani	rj	M	4,779	9,125	7.914	
Tamil	ta	F	3,243	6.060	10.516	
1311111	ı ta	M	3,717	6,960	10.316	
Tolugu	to	F	4,043	6 524	15.395	
Telugu	te	M	2,481	6,524	15.595	

Table 3. Statistics of the Indian Language (IN) Dataset

4.2 Environment

We implemented our architecture using Tensorflow [Abadi et al. 2015] backend. We split the Indian language dataset into training, validation, and testing set, containing 80%, 10%, and 10% of the data, respectively, for each language and gender.

For regularization, we apply dropout [Srivastava et al. 2014] after Max-Pooling layer and Bi-Directional LSTM layer. We use the rate of 0.1. A l_2 regularization with 10^{-6} weight is also added to all the trainable weights in the network. We train the model with Adam [Kingma and Ba 2014] optimizer with $\beta_1=0.9$, $\beta_2=0.98$, and $\epsilon=10^{-9}$ and learning rate schedule [Vaswani et al. 2017], with 4k warm-up steps and peak learning rate of $0.05/\sqrt{d}$ where d is 128. Batch size of 64 with "Sparse Categorical Crossentropy" as the loss function were used.

⁷https://www.iitm.ac.in/donlab/tts/database.php

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4.3 Results on European Language

We evaluated our model in two environments – No Noise and White Noise. According to our intuition, in real life scenarios during prediction of language chances of capturing background noise of chatter and other sounds may happen. For the white noise evaluation setup, we mixed white noise to each test sample which has a strong audible presence but retains the identity of the language.

	No Noise	White Noise
CRNN [Bartz et al. 2017]	0.91	0.63
Inception-v3 CRNN [Bartz et al. 2017]	0.96	0.91
CNN	0.948	0.871
CRNN	0.967	0.912
CRNN with Attention	0.966	0.888

Table 4. Comparative evaluation results (in terms of Accuracy) of our model and the model of [Bartz et al. 2017] on the YouTube News (EU) dataset

Table 4 compares the results of our models on the EU dataset with state-of-the-art models presented by Bartz et al. [Bartz et al. 2017]. Proposed model by [Bartz et al. 2017] consists of CRNN and uses Google's Inception-v3 architecture [Szegedy et al. 2016]. They experimented in four different environments – No Noise, White Noise, Cracking Noise, and Background Noise. All our evaluation results are rounded up to 3 digit after decimal point.

The CNN model failed to achieve competitive results; it provided accuracy of 0.948/0.871 in No Noise/White Noise. In CRNN architecture, our model provides accuracy of 0.967/0.912 on No Noise/White Noise scenario outperforming the state-of-the-art results of [Bartz et al. 2017]. Use of Attention improves over the Inception-v3 CRNN in No Noise scenario, however it does not perform well on White Noise

4.4 Result on Indian Language Dataset

There is no benchmark in LID for Indian Languages against which we can compare our model results. We evaluated system performance using the following evaluation metrics – Recall (TPR), Precision (PPV), f1-score, and Accuracy.

Language		CRNN v	vith Atte	ntion		(CRNN		CNN				
Language	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy	
as	0.989	0.998	0.993		0.995	0.989	0.992		0.991	0.988	0.989		
bn	1	0.9	0.948		1	0.904	0.949		1	0.888	0.941		
bd	0.966	1	0.983		0.966	1	0.983]	0.966	1	0.983		
gu	0.997	0.997	0.997		0.951	0.998	0.974		0.996	0.991	0.994		
hi	0.987	0.991	0.989		0.991	0.991	0.991		0.991	0.974	0.983		
kn	0.977	0.996	0.987		0.996	0.996	0.996		0.973	0.992	0.983		
ml	0.996	0.988	0.992	0.987	0.997	0.99	0.994	0.987	0.99	0.993	0.991	0.983	
mn	0.987	0.999	0.993		0.973	0.999	0.986		0.972	0.998	0.985		
mr	1	1	1		1	1	1		1	0.996	0.998		
or	1	1	1		1	0.999	0.999	1	0.986	0.999	0.992		
rj	0.999	0.993	0.996		0.995	1	0.997	1	0.986	0.996	0.991		
ta	0.929	0.991	0.959		0.975	0.997	0.986		0.946	0.989	0.967		
te	0.979	0.998	0.989		0.982	1	0.991		0.975	0.998	0.986		

Table 5. Experimental Results for Indian Languages

Since one of our major objectives was to measure the accessibility of the network to new languages, we introduced Data Balancing of training data for each class, as the number of samples

available for each class may vary drastically. This is the case for the Indian Language Dataset as shown in Table 3 in which Kannada, Marathi and particularly Bodo have limited amount of data compared to the rest of the languages. To alleviate this data imbalance problem, we used class weight balancing as a dynamic method using scikit-learn [Pedregosa et al. 2011].

PPV, TPR, f1-score and Accuracy scores are reported in Table 5 for the three architectures - CNN, CRNN, and CRNN with Attention. From Table 5 it is clearly visible that both CRNN architecture and CRNN with Attention provide competitive results of 0.987 accuracy.

]	Predicte	d						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	FFV	IFK	Score
	as	1762	0	0	0	0	0	0	4	0	0	0	0	0	0.989	0.998	0.993
	bn	10	850	0	1	0	0	0	18	0	0	0	53	12	1	0.9	0.948
	bd	0	0	57	0	0	0	0	0	0	0	0	0	0	0.966	1	0.983
	gu	1	0	0	566	0	0	0	0	0	0	0	0	1	0.997	0.997	0.997
	hi	0	0	0	0	460	0	4	0	0	0	0	0	0	0.987	0.991	0.989
ਾਫ	kn	0	0	1	0	0	257	0	0	0	0	0	0	0	0.977	0.996	0.987
ctual	ml	0	0	1	0	6	5	1116	1	0	0	0	0	1	0.996	0.988	0.992
¥	mn	0	0	0	1	0	0	0	1790	0	0	0	0	0	0.987	0.999	0.993
	mr	0	0	0	0	0	0	0	0	245	0	0	0	0	1	1	1
	or	0	0	0	0	0	0	0	0	0	716	0	0	0	1	1	1
	rj	4	0	0	0	0	1	1	0	0	0	906	0	0	0.999	0.993	0.996
	ta	5	0	0	0	0	0	0	0	0	0	1	690	0	0.929	0.991	0.959
	te	0	0	0	0	0	0	0	1	0	0	0	0	652	0.979	0.998	0.989

Table 6. Confusion matrix for CRNN with Attention architecture

		Predicted													DDV	PPV TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	PPV	IPK	Score
	as	1746	0	0	0	0	0	0	19	0	0	0	1	0	0.995	0.989	0.992
	bn	8	853	0	28	0	0	0	28	0	0	0	17	10	1	0.904	0.949
	bd	0	0	57	0	0	0	0	0	0	0	0	0	0	0.966	1	0.983
	gu	0	0	0	567	0	0	0	0	0	0	0	0	1	0.951	0.998	0.974
	hi	0	0	0	0	460	0	3	0	0	0	1	0	0	0.991	0.991	0.991
	kn	0	0	1	0	0	257	0	0	0	0	0	0	0	0.996	0.996	0.996
Actu	ml	0	0	1	0	4	1	1119	1	0	0	4	0	0	0.997	0.99	0.994
₹	mn	0	0	0	1	0	0	0	1789	0	0	0	0	1	0.973	0.999	0.986
	mr	0	0	0	0	0	0	0	0	245	0	0	0	0	1	1	1
	or	0	0	0	0	0	0	0	1	0	715	0	0	0	1	0.999	0.999
	rj	0	0	0	0	0	0	0	0	0	0	912	0	0	0.995	1	0.997
	ta	1	0	0	0	0	0	0	1	0	0	0	694	0	0.975	0.997	0.986
	te	0	0	0	0	0	0	0	0	0	0	0	0	653	0.982	1	0.991

Table 7. Confusion matrix for CRNN

								Predicte	:d						PPV TPR	TDD	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	FFV	IFK	Score
	as	1744	0	1	0	0	3	1	13	0	0	0	4	0	0.991	0.988	0.989
	bn	9	838	0	1	1	0	0	35	0	8	5	34	13	1	0.888	0.941
	bd	0	0	57	0	0	0	0	0	0	0	0	0	0	0.966	1	0.983
	gu	2	0	0	563	0	0	0	0	0	1	0	0	2	0.996	0.991	0.994
	hi	0	0	0	0	452	0	10	0	0	0	2	0	0	0.991	0.974	0.983
Б	kn	0	0	0	0	1	256	0	0	0	0	1	0	0	0.973	0.992	0.983
Actual	ml	0	0	1	0	2	2	1122	0	0	0	3	0	0	0.99	0.993	0.991
¥	mn	1	0	0	0	0	0	0	1788	0	0	0	1	1	0.972	0.998	0.985
	mr	0	0	0	0	0	0	0	0	244	1	0	0	0	1	0.996	0.998
	or	0	0	0	0	0	0	0	1	0	715	0	0	0	0.986	0.999	0.992
	rj	1	0	0	0	0	2	1	0	0	0	908	0	0	0.986	0.996	0.991
	ta	3	0	0	1	0	0	0	1	0	0	2	688	1	0.946	0.989	0.967
	te	0	0	0	0	0	0	0	1	0	0	0	0	652	0.975	0.998	0.986

Table 8. Confusion matrix for CNN

Table 6, 7, and 8 shows the confusion matrix for CNN, CRNN, and CRNN with Attention. From Table 6, 7, and 8 it can be observed that Assamese gets confused with Meitei; Bengali gets confused with Assamese, Meitei, Tamil and Telugu; and Hindi gets confused with Malayalam.

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Assamese and Bengali have originated from the same language family and they share approximately the same phoneme set. However, Bengali and Tamil are from different language family but share similar phoneme set. For example, in Bengali **cigar** is *churut* and **star** is *nakshatra* while **cigar** in Tamil is *charuttu* and **star** in Tamil is *natsattira*, which is quite similar. Similarly, Meitei and Assamese share similar phonemes. On close study we observed that Hindi and Malayalam have also similar phoneme set as both the languages borrowed most of the vocabularies from Sanskrit. For example, 'arrogant' is **Ahankar** in Hindi and *Ahankaram* in Malayalam. Similarly, **Sathyu** or commonly spoken as **Satya** in Hindi means 'Truth', which is *Sathyam* in Malayalam. Also the word **Sundar** in Hindi is *Sundaram* in Malayalam, which means 'beautiful'. Table 9 shows the most common classification errors encountered during evaluation.

Table 9. Most common errors

Assamese → Meitei
Bengali → Assamese
Bengali → Meitei
Bengali → Tamil
Hindi → Malayalam

4.5 Result on same language families on Indian Language Dataset

A deeper study into these 13 Indian languages led us to define five clusters of languages based on their phonetic similarity. Cluster internal languages are phonetically similar, close, and geographically contiguous, hence difficult to be differentiated.

- Cluster 1: Assamese, Bengali, Odia
- Cluster 2: Gujarati, Hindi, Marathi, Rajasthani
- Cluster 3: Kannada, Malayalam, Tamil, Telugu
- Cluster 4: Bodo
- Cluster 5: Meitei

Bodo and Meitei are phonetically very much distant from any of the rest of the languages, thus they form singleton clusters. We carried out separate experiments for identification of the cluster internal languages for Cluster 1, 2 and 3, and the experimental results are presented in Table 10.

Cluster	anguage			CRNN with ttention			(CRNN		CNN			
ū	Lang	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy
	as	0.962	1	0.981		0.953	1	0.976		0.953	1	0.976	
1	bn	1	0.926	0.961	0.98	1	0.907	0.951	0.974	1	0.894	0.944	0.971
	or	1	1	1		1	1	1		0.982	1	0.991	
	gu	1	0.998	0.999		1	0.998	0.999		1	0.993	0.996	
2	hi	1	1	1	0.999	1	0.998	0.999	0.999	0.991	0.996	0.994	0.996
-	mr	1	1	1	0.333	1	1	1	0.555	1	0.996	0.998	0.550
		•	-			-	•	-		-	0.770	0.770	
	rj	0.999	1	0.999		0.998	1	0.999		0.995	0.998	0.996	
	rj kn	0.999	_	0.999		0.998	1	0.999		0.995			
3		0.999 1 0.999	1		0 999	0.998	1 1 1	0.999	1		0.998	0.996	0.996
3	kn	1	1 0.996	0.998	0.999	0.998 1 1 1	1 1 1 1	1	1	0.992	0.998 0.988	0.996	0.996

Table 10. Experimental Results of LID for close languages.

It can be clearly observed from Table 10 that both CRNN architecture and CRNN with Attention provide competitive results for every language cluster. For **cluster-1** CRNN architecture and CRNN

with Attention provides accuracy of 0.98/0.974, for **cluster-2** 0.999/0.999, and for **cluster-3** 0.999/1, respectively. CNN architecture also provides comparable results to the other two architectures.

Table 11, Table 12 and Table 13 presents the confusion matrix for cluster 1, cluster 2 and cluster 3, respectively.

From Table 11, we observed that Bengali gets confused with Assamese and Odia, which is quite expected since these two languages are spoken in neighbouring states and both of them share almost the same phonemes. For example, in Odia **rice** is pronounced as *bhata* whereas in Bengali pronounced as *bhat*, similarly **fish** in odia as *machha* whereas in Bengali it is *machh*. Both CRNN and CRNN with Attention perform well to discriminate between Bengali and Odia.

	CRNN and Attention												
		Pı	redicte	d	PPV	TPR	f1						
		as	bn	or	11.	1110	Score						
	as	1766	0	0	0.962	1	0.981						
Actual	bn	70	874	0	1	0.926	0.961						
	or	0	0	716	1	1	1						
	CRNN												
		Pı	redicte	d	PPV	TPR	f1						
		as	bn o		FFV	IFK	Score						
	as	1766	0	0	0.953	1	0.976						
Actual	bn	88	856	0	1	0.907	0.951						
	or	0	0	716	1	1	1						
			C	NN									
		Pı	redicte	d	PPV	TPR	f1						
		as	bn	or	FFV	IFK	Score						
	as	1766	0	0	0.953	1	0.976						
Actual	bn	87	844	13	1	0.894	0.944						
	or	0	0	716	0.982	1	0.991						

Table 11. Confusion matrix for Cluster 1

In Table 12, we observed Gujarati getting confused with Hindi and Rajasthani, similarly Hindi with Rajasthani and Rajasthani with Marathi. In CRNN and CRNN with Attention architecture the confusion is minimised.

	CRNN and Attention												
			Pred	icted		PPV	TPR	f1					
		gu	hi	mr	rj	* * *	1110	Score					
	gu	567	0	0	1	1	0.998	0.999					
Actual	hi	0	464	0	0	1	1	1					
/ictuai	mr	0	0	245	0	1	1	1					
	rj	0	0	0	912	0.999	1	0.999					
				CRN	1								
			Pred	icted		PPV	TPR	f1					
		gu	hi	mr	rj	1 1 1 1	1110	Score					
	gu	567	0	0	1	1	0.998	0.999					
Actual	hi	0	463	0	1	1	0.998	0.999					
Actual	mr	0	0	245	0	1	1	1					
	rj	0	0	0	912	0.998	1	0.999					
				CNN									
			Pred	icted		PPV	TPR	f1					
		gu	hi	mr	rj	1 1 1 1	1110	Score					
	gu	564	2	0	2	1	0.993	0.996					
Actual	hi	0	462	0	2	0.991	0.996	0.994					
Actual	mr	0	0	244	1	1	0.996	0.998					
	rj	0	2	0	910	0.995	0.998	0.996					

Table 12. Confusion matrix for Cluster 2

It can be observed from Table 13 that CNN makes a lot of confusion discriminating among these four languages. Both CRNN and CRNN with Attention prove to be better at discriminating among these languages.

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			CRNN	and A	tentio	n		
			Predi	cted		PPV	TPR	f1
		kn	ml	ta	te	11.	1110	Score
	kn	257	1	0	0	1	0.996	0.998
Actual	ml	0	1130	0	0	0.999	1	0.999
Actual	ta	0	0	696	0	1	1	1
	te	0	0	0	653	1	1	1
				CRNN	Ī			
			Predi	cted		PPV	TPR	f1
		kn	ml	ta	te	FFV	IFK	Score
	kn	258	0	0	0	1	1	1
Actual	ml	0	1130	0	0	1	1	1
Actual	ta	0	0	696	0	1	1	1
	te	0	0	0	653	1	1	1
				CNN				
			Predi	cted		PPV	TPR	f1
		kn	ml	ta	te	11.	111	Score
	kn	255	3	0	0	0.992	0.988	0.99
Actual	ml	1	1125	2	2	0.996	0.996	0.996
2 sectual	ta	1	0	694	1	0.996	0.997	0.996
	te	0	1	1	651	0.995	0.997	0.996

Table 13. Confusion matrix for Cluster 3

From the results in Table 10, 11, 12 and 13, it is quite clear that CRNN (Bi-Directional LSTM over CNN) and CRNN with Attention are more effective for Indian language identification and they perform almost at par. Another important observation is that it is harder to classify the languages in cluster 1 than the other two clusters.

4.6 Ablation Studies

4.6.1 Automatic Class Weight vs Manual Class Weight. Balancing the data using class weights gives better accuracy for CRNN with Attention (98.7%) and CRNN (98.7%), compared to CNN (98.3%) shown in Table 5. We study the efficacy of the architectures by manually balancing the datasets using 100 samples, 200 samples, and 571 samples drawn randomly from the dataset and the results of these experiments are presented in Table 14, 15 and 16, respectively. The objective of the study was to observe the performance of the architectures on increasing the sample size. Since Bodo language has the minimum data (571 samples) among all the languages in the dataset, we perform our experiments till 571 samples.

A comparison of the results in Table 14, 15, and 16 reveals the following observations.

- All the models perform consistently better with more training data.
- CRNN and CRNN with attention perform consistently better than CNN.
- CRNN is less data hungry among the 3 models and it performs the best in the lowest data scenario.

Language	(CRNN v	vith Atte	ntion		-	CRNN				CNN	
Language	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy
as	0.766	0.72	0.742		0.839	0.94	0.887		0.617	0.58	0.598	
bn	0.875	0.7	0.778		0.957	0.9	0.928		0.816	0.8	0.808	
bd	1	1	1		0.962	1	0.98		0.843	0.86	0.851	
gu	0.943	1	0.971		1	0.98	0.99		0.731	0.76	0.745	
hi	0.959	0.94	0.95	1	0.957	0.9	0.928	1	0.778	0.7	0.737	
kn	0.961	0.98	0.97		0.94	0.94	0.94		0.725	0.74	0.733	
ml	0.958	0.92	0.939	0.883	0.923	0.96	0.941	0.932	0.774	0.82	0.796	0.72
mn	0.878	0.72	0.791		0.935	0.86	0.896		0.691	0.76	0.724	
mr	0.906	0.96	0.932	1	0.98	0.96	0.97	1	0.857	0.84	0.848	
or	0.959	0.94	0.949		0.943	1	0.971		0.811	0.86	0.835	
rj	0.782	0.86	0.819		0.894	0.84	0.866		0.605	0.52	0.559	
ta	0.677	0.88	0.765		0.898	0.88	0.889		0.564	0.62	0.590	
te	0.878	0.86	0.869	1	0.906	0.96	0.932	1	0.532	0.5	0.515	

Table 14. Experimental Results for Manually Balancing the Samples for each category to 100.

Language	(CRNN v	vith Atte	ntion			CRNN				CNN	
Language	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy
as	0.941	0.96	0.95		1	0.94	0.969		0.8	0.88	0.838	
bn	0.909	1	0.952		1	0.96	0.98		0.92	0.92	0.92	
bd	0.98	0.96	0.97		0.98	0.98	0.98		0.94	0.94	0.94	
gu	1	1	1		1	1	1		0.918	0.9	0.909	
hi	1	0.98	0.99		1	0.98	0.99		0.956	0.86	0.905	
kn	1	0.98	0.99		1	0.98	0.99		0.878	0.86	0.869	
ml	0.962	1	0.98	0.975	0.893	1	0.943	0.971	0.896	0.86	0.878	0.883
mn	0.979	0.92	0.948		0.907	0.98	0.942		0.754	0.92	0.829	
mr	0.98	0.98	0.98		0.98	0.96	0.97		0.956	0.86	0.905	
or	0.98	1	0.99		1	1	1		0.941	0.96	0.95	
rj	0.96	0.96	0.96	-	1	0.96	0.98		0.86	0.86	0.86	
ta	1	0.96	0.98		0.904	0.94	0.922		0.784	0.8	0.792	
te	1	0.98	0.99		0.979	0.94	0.959		0.935	0.86	0.896	

Table 15. Experimental Results for Manually Balancing the Samples for each category to 200.

Language		CRNN v	vith Atte	ntion		(CRNN				CNN	
Language	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy	PPV	TPR	f1 Score	Accuracy
as	1	1	1		0.983	0.983	0.983		0.967	1	0.983	
bn	1	1	1		1	1	1		0.983	1	0.991	
bd	1	1	1		1	1	1		1	1	1	
gu	1	1	1	1	0.983	1	0.991		0.982	0.931	0.956	
hi	0.983	0.983	0.983		1	1	1		0.893	0.862	0.877	
kn	1	1	1		1	1	1		0.903	0.966	0.933	
ml	1	0.966	0.982	0.988	0.983	1	0.991	0.985	0.914	0.914	0.914	0.945
mn	0.983	1	0.991	1	1	0.983	0.991		0.931	0.931	0.931	
mr	1	1	1	1	0.982	1	0.991		0.965	0.982	0.973	
or	1	1	1		1	0.983	0.991		1	0.966	0.982	
rj	0.919	0.983	0.95	1	0.918	0.966	0.941		0.9	0.931	0.915	
ta	0.964	0.931	0.947	1	0.964	0.914	0.938		0.879	0.879	0.879	
te	1	0.983	0.991	1	1	0.983	0.991		0.982	0.931	0.956	

Table 16. Experimental Results for Manually Balancing the Samples for each category to 571.

Figure 2 graphically shows the performance improvement over increasing data samples. The confusion matrices for the three architectures for the 3 datasets are presented in Table 17-25 in the Appendix.

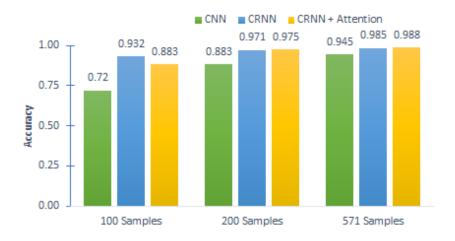


Fig. 2. Comparison of model results for varying dataset size

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5 CONCLUSION

In this work, we proposed a language identification method using CRNN that works on MFCC features of speech signals. Our architecture efficiently identifies the language both in close language and noisy scenarios. We carried out extensive experiments and our architecture produced state-of-the-art results. Through our experiments, we have also shown our architecture's robustness to noise and its extensibility to new languages. The model exhibits the overall best accuracy of 98.7% which improves over the traditional use of CNN (98.3%). CRNN with attention performs almost at par with CRNN, however the attention mechanism which incurs some additional computational overhead does not always result in improvement over CRNN. In future, we would like to experiment with diverse language families and smaller audio samples.

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A CONFUSION MATRICES FOR THE CNN, CRNN AND CRNN WITH ATTENTION ARCHITECTURES FOR THE 3 DATASETS (100, 200 AND 571 SAMPLES)

CNN architecture

							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	1 * * *	1110	Score
	as	29	2	0	1	0	3	0	7	0	0	3	2	3	0.617	0.58	0.598
	bn	2	40	0	0	0	1	1	1	1	0	0	3	1	0.816	0.8	0.808
	bd	0	0	43	1	0	2	0	0	2	0	1	1	0	0.843	0.86	0.851
	gu	1	0	0	38	4	0	0	0	0	0	0	3	4	0.731	0.76	0.745
	hi	2	0	0	2	35	3	3	0	0	2	0	2	1	0.778	0.7	0.737
le le	kn	0	0	1	0	1	37	6	1	0	0	1	0	3	0.725	0.74	0.733
Actual	ml	0	1	0	1	0	3	41	0	0	0	2	1	1	0.774	0.82	0.796
¥	mn	2	2	0	0	0	0	1	38	0	1	0	1	5	0.691	0.76	0.724
	mr	0	0	1	0	0	0	0	0	42	3	4	0	0	0.857	0.84	0.848
	or	0	1	1	0	0	0	0	0	3	43	1	1	0	0.811	0.86	0.835
	rj	2	2	3	1	3	0	1	2	1	2	26	7	0	0.605	0.52	0.559
	ta	5	0	0	3	2	0	0	3	0	0	2	31	4	0.564	0.62	0.590
	te	4	1	2	5	0	2	0	3	0	2	3	3	25	0.532	0.5	0.515

Table 17. Confusion matrix of Manually Balancing the Samples for each category to 100 with CNN

							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	11 4	1110	Score
	as	44	1	0	0	0	0	0	1	0	0	1	3	0	0.8	0.88	0.838
	bn	1	46	0	0	0	0	0	1	0	0	0	2	0	0.92	0.92	0.92
	bd	0	0	47	0	0	1	0	1	0	0	1	0	0	0.94	0.94	0.94
	gu	1	1	0	45	1	0	0	0	0	0	0	0	2	0.918	0.9	0.909
	hi	0	1	0	1	43	1	1	2	0	0	1	0	0	0.956	0.86	0.905
_E	kn	0	0	1	1	0	43	2	1	0	0	0	1	1	0.878	0.86	0.869
Actual	ml	1	0	0	0	0	1	43	2	1	2	0	0	0	0.896	0.86	0.878
¥	mn	2	0	0	0	0	0	1	46	0	0	0	1	0	0.754	0.92	0.829
	mr	0	0	2	0	0	0	1	1	43	1	2	0	0	0.956	0.86	0.905
	or	0	0	0	0	1	0	0	0	0	48	1	0	0	0.941	0.96	0.95
	rj	2	1	0	0	0	1	0	1	1	0	43	1	0	0.86	0.86	0.86
	ta	2	0	0	1	0	2	0	4	0	0	1	40	0	0.784	0.8	0.792
	te	2	0	0	1	0	0	0	1	0	0	0	3	43	0.935	0.86	0.896

Table 18. Confusion matrix of Manually Balancing the Samples for each category to 200 with CNN

							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	11 4	1110	Score
	as	58	0	0	0	0	0	0	0	0	0	0	0	0	0.967	1	0.983
	bn	0	58	0	0	0	0	0	0	0	0	0	0	0	0.983	1	0.991
	bd	0	0	56	0	0	0	0	0	0	0	0	0	0	1	1	1
	gu	0	0	0	54	4	0	0	0	0	0	0	0	0	0.982	0.931	0.956
	hi	0	0	0	0	50	0	2	1	0	0	0	5	0	0.893	0.862	0.877
_E	kn	0	0	0	0	0	56	2	0	0	0	0	0	0	0.903	0.966	0.933
Actual	ml	0	0	0	0	0	4	53	0	0	0	1	0	0	0.914	0.914	0.914
¥	mn	1	0	0	0	0	1	0	54	0	0	0	1	1	0.931	0.931	0.931
	mr	0	0	0	0	0	0	0	0	55	0	1	0	0	0.965	0.982	0.973
	or	0	0	0	0	1	0	0	0	1	56	0	0	0	1	0.966	0.982
	rj	1	1	0	0	0	0	1	1	0	0	54	0	0	0.9	0.931	0.915
	ta	0	0	0	1	1	0	0	1	1	0	3	51	0	0.879	0.879	0.879
	te	0	0	0	0	0	1	0	1	0	0	1	1	54	0.982	0.931	0.956

Table 19. Confusion matrix of Manually Balancing the Samples for each category to 571 with CNN

• CRNN architecture

							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	FFV	IFK	Score
	as	47	0	0	0	0	0	0	1	0	0	1	1	0	0.839	0.94	0.887
	bn	0	45	0	0	0	1	0	0	0	0	0	3	1	0.957	0.9	0.928
	bd	0	0	50	0	0	0	0	0	0	0	0	0	0	0.962	1	0.98
	gu	0	0	0	49	0	0	0	0	0	0	0	0	1	1	0.98	0.99
	hi	0	0	0	0	45	2	2	0	0	0	0	0	1	0.957	0.9	0.928
а	kn	1	0	0	0	0	47	2	0	0	0	0	0	0	0.94	0.94	0.94
Actual	ml	0	0	0	0	1	0	48	0	0	0	1	0	0	0.923	0.96	0.941
Ā	mn	1	2	0	0	0	0	0	43	0	1	1	0	2	0.935	0.86	0.896
	mr	0	0	0	0	0	0	0	0	48	0	2	0	0	0.98	0.96	0.97
	or	0	0	0	0	0	0	0	0	0	50	0	0	0	0.943	1	0.971
	rj	4	0	1	0	0	0	0	0	1	1	42	1	0	0.894	0.84	0.866
	ta	2	0	0	0	1	0	0	2	0	1	0	44	0	0.898	0.88	0.889
	te	1	0	1	0	0	0	0	0	0	0	0	0	48	0.906	0.96	0.932

Table 20. Confusion matrix of Manually Balancing the Samples for each category to 100 with CRNN

							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	FFV	IFK	Score
	as	47	0	0	0	0	0	0	2	0	0	0	1	0	1	0.94	0.969
	bn	0	48	0	0	0	0	0	0	0	0	0	2	0	1	0.96	0.98
	bd	0	0	49	0	0	0	1	0	0	0	0	0	0	0.98	0.98	0.98
	gu	0	0	0	50	0	0	0	0	0	0	0	0	0	1	1	1
	hi	0	0	0	0	49	0	1	0	0	0	0	0	0	1	0.98	0.99
а	kn	0	0	0	0	0	49	1	0	0	0	0	0	0	1	0.98	0.99
Actual	ml	0	0	0	0	0	0	50	0	0	0	0	0	0	0.893	1	0.943
¥	mn	0	0	0	0	0	0	1	49	0	0	0	0	0	0.907	0.98	0.942
	mr	0	0	1	0	0	0	0	1	48	0	0	0	0	0.98	0.96	0.97
	or	0	0	0	0	0	0	0	0	0	50	0	0	0	1	1	1
	rj	0	0	0	0	0	0	0	0	1	0	48	1	0	1	0.96	0.98
	ta	0	0	0	0	0	0	0	2	0	0	0	47	1	0.904	0.94	0.922
	te	0	0	0	0	0	0	2	0	0	0	0	1	47	0.979	0.94	0.959

Table 21. Confusion matrix of Manually Balancing the Samples for each category to 200 with CRNN

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							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	11 4	1110	Score
	as	57	0	0	0	0	0	0	0	0	0	0	1	0	0.983	0.983	0.983
	bn	0	58	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	bd	0	0	56	0	0	0	0	0	0	0	0	0	0	1	1	1
	gu	0	0	0	58	0	0	0	0	0	0	0	0	0	0.983	1	0.991
	hi	0	0	0	0	58	0	0	0	0	0	0	0	0	1	1	1
le l	kn	0	0	0	0	0	58	0	0	0	0	0	0	0	1	1	1
Actu	ml	0	0	0	0	0	0	58	0	0	0	0	0	0	0.983	1	0.991
¥	mn	0	0	0	0	0	0	0	57	0	0	1	0	0	1	0.983	0.991
	mr	0	0	0	0	0	0	0	0	56	0	0	0	0	0.982	1	0.991
	or	0	0	0	0	0	0	0	0	1	57	0	0	0	1	0.983	0.991
	rj	1	0	0	0	0	0	1	0	0	0	56	0	0	0.918	0.966	0.941
	ta	0	0	0	1	0	0	0	0	0	0	4	53	0	0.964	0.914	0.938
	te	0	0	0	0	0	0	0	0	0	0	0	1	57	1	0.983	0.991

Table 22. Confusion matrix of Manually Balancing the Samples for each category to 571 with CRNN

• CRNN with Attention architecture

							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	11 4	1110	Score
	as	36	0	0	0	0	0	0	1	0	0	6	6	1	0.766	0.72	0.742
	bn	1	35	0	0	0	0	0	1	0	0	0	13	0	0.875	0.7	0.778
	bd	0	0	50	0	0	0	0	0	0	0	0	0	0	1	1	1
	gu	0	0	0	50	0	0	0	0	0	0	0	0	0	0.943	1	0.971
	hi	0	0	0	0	47	1	1	0	0	0	0	0	1	0.959	0.94	0.95
a	kn	0	0	0	0	0	49	0	0	0	0	0	1	0	0.961	0.98	0.97
Actual	ml	0	0	0	0	1	1	46	0	0	0	2	0	0	0.958	0.92	0.939
A	mn	5	3	0	1	0	0	0	36	0	1	1	0	3	0.878	0.72	0.791
	mr	0	0	0	0	0	0	0	0	48	0	2	0	0	0.906	0.96	0.932
	or	0	0	0	0	0	0	0	0	3	47	0	0	0	0.959	0.94	0.949
	rj	2	0	0	0	0	0	1	0	2	1	43	1	0	0.782	0.86	0.819
	ta	2	1	0	0	1	0	0	0	0	0	1	44	1	0.677	0.88	0.765
	te	1	1	0	2	0	0	0	3	0	0	0	0	43	0.878	0.86	0.869

Table 23. Confusion matrix of Manually Balancing the Samples for each category to 100 with CRNN and Attention

							P	redict	ed						PPV	TPR	f1
		as	bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	FFV	IFK	Score
	as	48	2	0	0	0	0	0	0	0	0	0	0	0	0.941	0.96	0.95
	bn	0	50	0	0	0	0	0	0	0	0	0	0	0	0.909	1	0.952
	bd	0	0	48	0	0	0	0	0	1	0	1	0	0	0.98	0.96	0.97
	gu	0	0	0	50	0	0	0	0	0	0	0	0	0	1	1	1
	hi	0	0	0	0	49	0	1	0	0	0	0	0	0	1	0.98	0.99
al	kn	0	0	0	0	0	49	1	0	0	0	0	0	0	1	0.98	0.99
Actual	ml	0	0	0	0	0	0	50	0	0	0	0	0	0	0.962	1	0.98
¥	mn	3	0	0	0	0	0	0	46	0	1	0	0	0	0.979	0.92	0.948
	mr	0	0	1	0	0	0	0	0	49	0	0	0	0	0.98	0.98	0.98
	or	0	0	0	0	0	0	0	0	0	50	0	0	0	0.980	1	0.99
	rj	0	2	0	0	0	0	0	0	0	0	48	0	0	0.96	0.96	0.96
	ta	0	1	0	0	0	0	0	0	0	0	1	48	0	1	0.96	0.98
	te	0	0	0	0	0	0	0	1	0	0	0	0	49	1	0.98	0.99

Table 24. Confusion matrix of Manually Balancing the Samples for each category to 200 with CRNN and Attention

	Predicted														PPV	TPR	f1
			bn	bd	gu	hi	kn	ml	mn	mr	or	rj	ta	te	FFV	IFK	Score
Actual	as	58	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	bn	0	58	0	0	0	0	0	0	0	0	0	0	0	1	1	1
	bd	0	0	56	0	0	0	0	0	0	0	0	0	0	1	1	1
	gu	0	0	0	58	0	0	0	0	0	0	0	0	0	1	1	1
	hi	0	0	0	0	57	0	0	0	0	0	0	1	0	0.983	0.983	0.983
	kn	0	0	0	0	0	58	0	0	0	0	0	0	0	1	1	1
	ml	0	0	0	0	1	0	56	0	0	0	1	0	0	1	0.966	0.982
	mn	0	0	0	0	0	0	0	58	0	0	0	0	0	0.983	1	0.991
	mr	0	0	0	0	0	0	0	0	56	0	0	0	0	1	1	1
	or	0	0	0	0	0	0	0	0	0	58	0	0	0	1	1	1
	rj	0	0	0	0	0	0	0	1	0	0	57	0	0	0.919	0.983	0.95
	ta	0	0	0	0	0	0	0	0	0	0	4	54	0	0.964	0.931	0.947
	te	0	0	0	0	0	0	0	0	0	0	0	1	57	1	0.983	0.991

Table 25. Confusion matrix of Manually Balancing the Samples for each category to 571 with CRNN and Attention