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Classification of Analyzed Text in Speech Recognition Using RNN-LSTM in Comparison with Convolutional Neural Network to Improve Precision for Identification of Keywords

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Abstract

Aim: *Text classification is a method to classify the features from language translation in speech recognition from English to Telugu using a recurrent neural network- long short term memory (RNN-LSTM) comparison with convolutional neural network (CNN).*
Materials and Methods: *Accuracy and precision are performed with dataset alexa and english-telugu of size 8166 sentences. Classification of language translation is performed by the recurrent neural network where a number of the samples (N=62) and convolutional neural network were a number of samples (N=62) techniques, the algorithm RNN implies speech recognition that can be compared with convolutional is the second technique.* ***Results and Discussion:*** *RNN-LSTM from the dataset speech recognition, feature Telugu_id produce accuracy 93% and precision 68.04% which can be comparatively higher than CNN accuracy 66.11%, precision 61.90%. It shows a statistical significance as 0.007 from Independent Sample T-test.* ***Conclusion:*** *The RNN-LSTM performs better in finding accuracy and precision when compared to CNN.*

Key-words: Classification, Convolutional Neural Network (CNN), Natural Language Processing, Recurrent Neural Network-Long Short Term Memory(RNN-LSTM), Speech Recognition.

1. Introduction

Speech recognition was an upcoming natural language processing where chatbots and other trending developments are one aspect to be highlighted. Applications such as Chatbots, disable

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people's communication devices, and so on are identified as latest generation utilized applications. The research aim was to prove better accuracy and precision using RNN-LSTM which has Relu and Softmax classifiers for proving best fit models and avoid overfitting. Nowadays speech recognition was the inbuilt feature in smart devices which was used for composing text and recognition of speech patterns. While accessing the speech from the user, the system needs to convert the physical signals into electrical signals which are processed with the help of a system microphone. After transmission of the audio file to the system, the system converts the electrical signals into digital signals such as binary(0,1) (Lee et al. 2021).The application of this proposed system is converting speech to text format(Ning et al. 2020)and translate text format into Telugu sentences(Do, Sakti, and Nakamura 2018) then converting Telugu text into Telugu speech. Users can directly access their voice in English from Telugu. While accessing the Telugu audio system, users can also carry out the audio text and Telugu text for audio reference.

With references from reputed research documents from databases such as IEEE Xplore, Google scholar and Web of Science, etc., to motivate this idea. In the research work the identified 777 journal papers in IEEE Xplore and 497 articles on Google Scholar that relate relevant research work in speech recognition and language translation. The most cited journal follows, based on the speech recognition (Nassif et al. 2019) has a maximum of 206 times authors cite, in his paper, he focused on Deep neural networks which focus on real-time applications and (Afouras et al. 2018) has a maximum of 185 times authors cited, in his paper, he focused on Deep visual audios, in speech recognition using sequence to sequence model, based on language translation (Zhang et al. 2017) has a maximum of 70 times authors cited, in this paper he focused on translating English to Chinese subtitles using sequence to sequence learning and ((Zhang et al. 2017; Su et al. 2018) has a maximum of 15 times authors cite, in this paper he focused on translating Chinese to English and English to German using sequential to sequential model. Based on the literature survey, (Zhang et al. 2017) paper has the best study also Language translation from English to Chinese is done using a sequence to sequence model and can be prepared from one domain of language into another domain of language. Novel Natural Language processing was a major artificial intelligence systems that covered the computation in highlighting the voice interactive responses.

Previously our team has a rich experience in working on various research projects across multiple disciplines (Sathish and Karthick 2020; Varghese, Ramesh, and Veeraiyan 2019; S. R. Samuel, Acharya, and Rao 2020; Venu, Raju, and Subramani 2019; M. S. Samuel et al. 2019; Venu, Subramani, and Raju 2019; Mehta et al. 2019; Sharma et al. 2019; Malli Sureshbabu et al. 2019;

Krishnaswamy et al. 2020; Muthukrishnan et al. 2020; Gheena and Ezhilarasan 2019; Vignesh et al. 2019; Ke et al. 2019; Vijayakumar Jain et al. 2019; Jose, Ajitha, and Subbaiyan 2020). Now the growing trend in this area motivated us to pursue this project.

Speech classification is used for recognition purposes and the data size of speech increases significantly. This was the primary idea for various tasks such as google assistant, amazon echo, apple siri. Classification of speech recognition analyses the frequency and amplitude in the audio signals which helps to perform the classification of phrases. The primary goal of work is speech classification in language translation from english-telugu for improving the accuracy and precision using RNN-LSTM and comparing the better translations that have been proved with the encoder-decoder model that can avoid underfitting in translating the phrases. To identify the gender classification from Alexa voice dataset a Novel speech-id classification was used to predict the text based on languages using distinct procedures that can identify from the given input.

2. Materials and Methods

The research work was carried out in Saveetha School of Engineering, SIMATS, where the laboratory facilitates high configuration systems in the Data Analytics laboratory used to obtain the experimental results. The number of groups identified for the study were two with the sample size used for experimenting speech to text recognition using English Corpora is 62 and 62 with 156 samples as existing and proposed two groups.(Melcher 2003; Tabossi, Scott, and Burani 1991). The computation is performed using G-power 0.8 with alpha value is 0.05 and beta value is 0.2 with a confidence interval at 95%.

The dataset used was Alexa timing and converted sentences from the English language to Telugu sentences where the dataset size was 16332. It consists of 8166 English sentences and 8166 Telugu sentences. The complete data of “English and Telugu” has been extracted from kaggle.The translated text using novel speech-id classification based on dependent variables that have produced 93% of accuracy.

Jupyter Notebook was used for executing the proposed work. Algorithms are compatible with 64-bit, the system should support a minimum of 8GB RAM and 1TB ROM for processing the data and Intel i3 Processor. Python language (3.8.3) has been used for executing each cell in the proposed system.

2.1 Sample Preparation Group 1 [Proposed Algorithm - Recurrent Neural Network]

(Mou, Ghamisi, and Zhu 2017)Recurrent Neural Network is the technique where the program was executed in sequential to sequential (seq2seq) manner. Long short term memory is the technique where the system stores the output as input and pre processes the input to the next iteration. It helps to model the connection of multiple hidden layers. Initially, padding will remove unnecessary words at the beginning of the sentence. Followed by padding, tokenizing is the process of breaking down the whole sentence into tiny units which helps the program to clear understanding of the text while developing natural language processing. Encoder-decoder model in recurrent neural networks is the program where the neural machine translation was performed in classical machine translation methods with the first sequence model consisting of the input sequence in the encoder and the second sequence model consisting of the target sequence. The activation functions in this encoder- decoder model are ReLu and Softmax functions. The Relu activation function helps the model to learn the non-linear dependencies and its range is $[0,\infty]$ followed by a range of Softmax functions is [0,1].

2.2 Sample Preparation Group 2[Comparison Algorithm - Convolutional Neural Network]

(Mou, Ghamisi, and Zhu 2017; Shelhamer, Long, and Darrell 2017) The Convolutional neural network is the process of executing the program in a forward direction similar to a feed-forward neural network. Word embedding is the process of identifying the different words which have the same meaning and helps in identifying the representation of words that can perform the various tasks. In convolutional layer, filtering is the input with the activation function and extracting the specific features in the layer. A Fully connected layer is the process of executing the program where all the multilayer perceptrons can be interconnected and execute the program to give output followed by user instructions. The Softmax function is one of the activation functions which is used in this convolutional neural network. The advantage of this softmax activation function is that it gives the output as either 0 or 1. The range of softmax functions is [0,1].

The data collection for this work system is as follows, input audio file is encrypted and converted into electrical signals. Using machine code the electrical signals convert into binary code. The binary code consists of zeros and ones which can help the computer need to understand the data. Using the encoder-decoder model the ReLu (Rectified linear units) activation function encrypts the input file into hidden layers and processing with the weights and bias.

For statistical implementation here the software is called IBM SPSS V26.0. Statistical package for social sciences is used for statistical calculations such as mean, standard deviation, significance and also plot the graphs etc., The independent variables are speech_id and gender in speech_id and the dependent variables are English _id, loss of keywords, accuracy, and precision. In comparison with both RNN-LSTM and CNN, RNN-LSTM has more accuracy and precision (93,68.04) when compared to CNN accuracy and precision(66.11, 61.90).

3. Results

Table 3 represents the Mean, Standard Deviation and Standard error mean are classified based on speech and translated text for training loss, accuracy and precision of the data. The accuracy of RNN-LSTM is better when compared to CNN.

Table 4 represents the significance of the data and standard error difference, where significance value of Accuracy for RNN-LSTM has 0.007 and CNN has 0.007. The significance value of precision for RNN-LSTM has 0.002 and CNN has 0.002. Fig. 1 represents the RNN-LSTM and CNN comparison of accuracy and precision value. RNN-LSTM has more accuracy with 93.00 and precision has 68.04 when compared to CNN accuracy with 66.11 and precision has 61.90.

Table 1 - Pseudocode for RNN-LSTM

RNNencoder-decoder algorithm
Input: encoder_tokens of input
Function RNNenc-dec(E,D):
1. X → encoder_input //Input_layer
2.H → X(seq) //Forward RNN
3.H ←decoder_target_tokens(LSTM) // Backward RNN
4.H= H(Forward RNN) + H(Backward RNN)
5. return H,H(:,-1);
Output: decoder_target_tokens

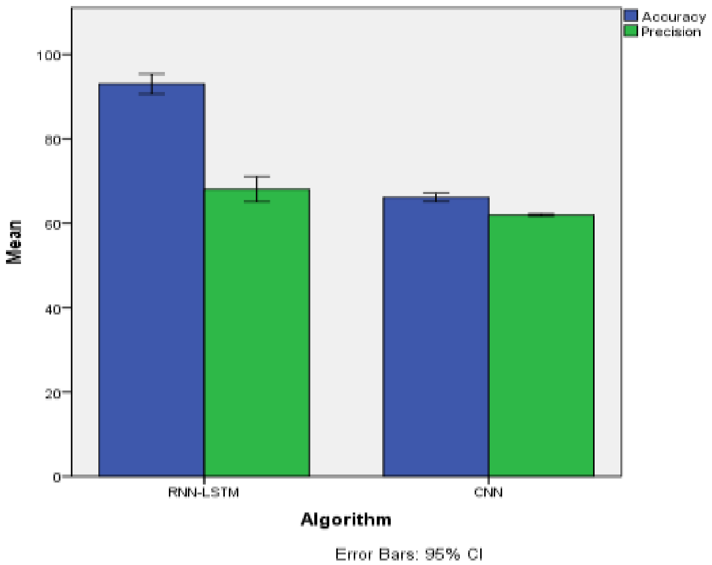
Table 2 - Pseudocode for CNN

CNN algorithm
Input: word_embedding_tokens of input
Function CNN(x):
1.Input → word_embedding_tokens //Input layer
2.H0 → max_poolin_tokens(conv) //convolutional layer
3.H1→ target_tokens(fully_con) //fully connected layer
4. H= H1
5.return Input,H
Output: target_tokens for input

Fig. 1 represents the comparison of accuracy and precision with a significance value interval of 95% for RNN-LSTM and CNN. RNN-LSTM holds the accuracy of 93% compared with CNN has 66.11%. The precision of RNN-LSTM has 68.04% compared with CNN has 61.90%.

In performing the statistical analysis of 62 samples, RNN-LSTM obtained 9.415 standard deviation with 1.196 standard error while CNN obtained 3.947 standard deviation with 0.501 standard error(Table 3). The significance value smaller than 0.001 showed that our contention holds good. The independent variables change the input values with the corresponding dependent variables as output values(Fig. 1).

Fig. 1 - Simple Bar graph for Comparison of Accuracy and Precision



Representing the higher RNN-LSTM in terms of mean, accuracy comparison with CNN. Variable results with its standard deviation ranging from 90 lower to 95 higher RNN where CNN standard deviation ranging from 65 lower to 70 higher. There is a significant difference between RNN-LSTM and CNN algorithms ($p<0.005$ Independent sample test).X-axis:RNN-LSTM vs CNN Y-axis: Mean of accuracy and precision for identification of keywords ± 1 SD with 95 % CI

Table 3 - The statistical calculation such as mean, std. deviation and std. error mean for RNN-LSTM and CNN. Loss, accuracy, and precision are the parameters used in the t-test. The mean accuracy of RNN-LSTM is 93.00 and CNN is 66.11. The mean precision of RNN-LSTM is 68.04 and CNN is 61.90. T-Test for comparison for RNN-LSTM Std.Error Mean(1.660) and CNN (0.419)

	Algorithm	N	Mean	Std.Deviation	Std.Error Mean
Loss	RNN-LSTM	62	15.36	13.069	1.660
	CNN	62	11.95	3.298	.419
Accuracy	RNN-LSTM	62	93.00	9.415	1.196
	CNN	62	66.11	3.947	.501
Precision	RNN-LSTM	62	68.04	11.722	1.489
	CNN	62	61.90	1.086	.138

Table 4 - The statistical calculations for independent samples test between RNN-LSTM and CNN ($p<0.005$). This independent samples test consists of significance as 0.007, significance(2-tailed), mean difference, std.error difference, and lower and upper interval difference. The sig(2-tailed) for accuracy and precision is 0.002. Independent samples T-test is applied for comparison of RNN-LSTM and CNN with the confidence interval as 95% and level of significance as 0.05

		Leven's test for equality of variances f	Leven's test for equality of variances Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error	Lower of 95% Confidence interval difference	Upper of 95% Confidence interval difference
Accuracy	Equal variance assumed	7.468	.007	20.738	122	.000	26.886	1.296	24.320	29.453
	Equal variances not assumed			20.738	81.803	.000	26.886	1.296	24.307	29.465
Precision	Equal variance assumed	99.715	.002	4.112	112	.000	6.148	1.495	3.188	9.108
	Equal variances not assumed			4.112	62.047	.000	6.148	1.495	3.160	9.137

3.1 Discussion

The statistical mean precision value obtained by the proposed system(RNN-LSTM) is 68.04 and the significance value is less with 0.002. For CNN statistical mean precision value is 61.90 and the significance value is less with 0.002.The RNN-LSTM is with better accuracy and precision when compared to CNN.

(Lee et al. 2021) system implemented for automatic speech recognition using softmax function using encoder-decoder model. A model is created which has no hyperparameters. By using this model overfitting can be reduced and the training process can be done easily. (Ning et al. 2020)in this research a system for localizing the video clips using sequence to sequence model. The author created a model using bi-directional recurrent neural network which is used in two phrases such as the video language matching and concatenating the video language into video content frames. In this system researcher provides an efficient model which performs the translating of the videos which is implemented by sequence to sequence model in RNN. (Do, Sakti, and Nakamura 2018) For this problem research model which consists of continu translation of sequence to sequence and combining these models into single embedding, and this experiment can show the one word delay instead of full sentence delay in translation.

According to the discussion surveys of (Lee et al. 2021),(Ning et al. 2020), (Do, Sakti, and Nakamura 2018) the researchers designed a system for recognition of audio and translation using RNN technique which shows a wide range of outcomes. Research using RNN technique for language translation in speech recognition indicates higher accuracy and precision. So, study of the research observed that RNN shows comparatively better results in language translation in speech recognition.

Our institution is passionate about high quality evidence based research and has excelled in various fields ((Vijayashree Priyadharsini 2019; Ezhilarasan, Apoorva, and Ashok Vardhan 2019; Ramesh et al. 2018; Mathew et al. 2020; Sridharan et al. 2019; Pc, Marimuthu, and Devadoss 2018; Ramadurai et al. 2019). We hope this study adds to this rich legacy.

The training of input takes time for execution as speech id, audio frequency are being extracted. The extraction of features based on sequence flow and word to text processor. The future work of this research is to design a model for processing more number of speech id as well as language translation can be done in multiple languages such as tamil, malayalam, hindi, french etc., Increasing the audio compatibility for user audio accessing signals.

4. Conclusion

The prediction accuracy of RNN-LSTM models is high when compared to CNN in speech recognition. Recurrent neural networks have precision higher compared with CNN.

Declarations

Conflict of Interest

No conflict of interest in this manuscript.

Author Contribution

Bathaloori Reddy Prasad - Methodology, Text to speech analysis, Writing original manuscript, Mrs.N.Deepa, - Review and editing, Supervision and Validation.

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