Improving the Performance of Multinomial Logistic Regression in Vowel Recognition by Determining Best Regression Coefficients

Shahrul Azmi Mohd Yusof
School of Computing
Universiti Utara Malaysia
Sintok, Malaysia
shahrulazmi@uum.edu.my

Abdulwahab F. Atanda
School of Computing
Universiti Utara Malaysia
Sintok, Malaysia
abdulwahabfu@gmail.com

Husniza Husni
School of Computing
Universiti Utara Malaysia
Sintok, Malaysia
husniza@uum.edu.my

***Abstract*— The performance of Multinomial Logistic Regression (MLR) is highly dependent on the estimated value of its parameters (Regression Coefficients – RCs). However, the usual** maximum likelihood estimation (MLE) **approach of RCs mostly resulted in overfitting the regression model, especially in limited data. Hence alternatives approach (shrinkage) such as Lasso and ridge were proposed. The shrinkage process at times might eliminate important predictors by shrinking the RCs values to zero. We proposed data splitting and swapping approach aimed at eliminating the identified problems in the existing estimation approaches while improving the performance of MLR. Two algorithms were implemented for determining the best set of RCs (DBRCs) which are DBRCs-I and DBRCs-II. Experimental results show that one of the approach- DBRCs-II outperforms the conventional** MLE**, approach by 2.05 % in overall recognition of Malay vowels. Given enough data for training, DBRCs-I swapping techniques can be use as good technique to obtain good RCs faster.**

Keywords*— *Vowel Recognition; Multinomial Logistic Regression; Automatic Speech Recognition; Regression Coefficients.

I. Introduction

Prediction models such as Multinomial Logistic Regression (MLR) are developed to estimate probabilities that an event will occur or to predict the presence or absence of an event. In regression methods, the main purpose of the estimation process is to determine the values of the estimate/regression coefficients (RCs) [1] that will guarantee pattern recognition with high accuracy. Theoretically, the predictability of the MLR model or its ability to generalize to new observation depends to a large extent on the estimated value of RCs [2]. It is therefore pertinent that to obtain high classification accuracy of MLR, the first goal should be to obtain a good estimate of MLR RCs.

Estimation of the RCs is usually done by **maximum likelihood estimation (MLE)** [3]. Experimental results, however, revealed that **MLE** usually resulted in model over-fitting especially in limited data samples. Hence penalized approach that includes Lasso and ridge methods were proposed. However, the shrinkage process of the penalized approach often results in shrinking the RCs to 0, thereby eliminating some important predictors [4, 5]. Based on the importance of RCs to the performance of MLR and the identified shortcomings of the existing estimation approaches, we proposed a simple but effective data sampling approach to estimate RCs that can improve the performance of MLR in the pattern recognition task. Hence, a new approach to determining the best RCs (DBRCs) is developed. The new approach to RCs estimation involves data resampling and swapping (exchanging training and test data). This is done to eliminate overfitting the classifier and consequently improves its performance [4]. In implementing our new approach – DBRCs (to determine best RCs), two approaches were proposed and experimented through algorithms implemented in MLR.

MLR has been used as a classifier in several fields of human endeavours such as speech recognition [6], medical diagnosis [4], and weather forecasting [7]. The proposed approach for RCs is implemented in Malay vowel recognition (MVR) task. Vowel recognition (VR) is a part of the larger automatic speech recognition (ASR) systems. Like any other pattern recognition tasks, VR is aimed at classifying the input speech signal into one of the n numbers of classes of the vowel [8, 9]. Speech-enabled applications are grounded on an effective separation and recognition of phonetic (vowels and consonants) units of speech [10]. The random nature of speech signals due to the higher rate of variability in the phonetic units makes speech recognition a challenging task [11-13]. Therefore, the ability of ASR to effectively recognize phonemes is crucial to the performance of speech-based applications such as speech recognition and speech synthesis [10]

Vowels are the voiced components of the sound of any language and are a significant part of speech as hardly exist a word without a vowel [14]. Vowels can generally be recognized effortlessly, and thus, function as significant cues that enhances the ability of both humans and machines to recognize speech. Hence, the ability to effectively recognize vowels is essential for improved performance of ASR. The standard Malay language unlike English language is made up of six vowels: /a/, /e/, /ə/, /i/, /o/, and /u/ [10, 15, 16].

Performance issues, particularly in terms of low recognition accuracy have remained major impediments to the wider adoption of ASR [17] especially for low resource language such as Malay [18, 19]. Hence, the focus of several ASR researchers has been on how to improve the performance of ASR. Improving the performance of ASR can either be attained at feature extraction (FE) or the level of recognition. Our approach is on recognition level through enhancement of MLR performance by obtaining the best sets of RCs.

II. Determining the Best Regression Coefficients

In this paper, two approaches to the determination of best regression coefficients (DBRCs) are presented. The two approaches which are DBRCs-I and DBRCs-II involves a similar process but differentiated based on the percentage of data used for parameter estimation and testing. Other differences include involves swapping training and testing data that affects the numbers of training and testing repetition respectively. The details of the algorithms for implementing the two approaches to DBRCs are presented in the following subsections.

2020 International Conference on Decision Aid Sciences and Application (DASA) | 978-1-7281-9677-0/20/$31.00 ©2020 IEEE | DOI: 10.1109/DASA51403.2020.9317106

A. DBRCs-I

The first approach to DBRCs is an attempt to eliminate the effect of overfitting the training model. This work proposed an alternative approach to splitting the original data set, into two, but of equal part of 50:50 ratio. The first 50% of the data is used in training the MLR to obtain RCs, while the other 50% data is used to test the trained MLR model using the obtained RCs. This approach also introduces the process of sample swapping in which the first 50% data is used as training data, while the second 50% is used as testing data and vice versa. This approach of data swapping can obtain twice the testing results in which ten (10) sets of RC results are obtained instead of five (5). The algorithm for implementing the first approach to DBRCs named DBRCs-I is as shown in Table 1.

TABLE 1. DBRCS-I ALGORITHM (50:50) FOR OBTAINING MLR REGRESSION COEFFICIENTS RCS

Step 1	Extract 39-MFCC FVs from speech waveform. Label the extracted 39-MFCC features (x) and class membership (y) as $\boldsymbol{D} = \{(\mathbf{x_1}, \boldsymbol{y_1}), (\mathbf{x_2}, \boldsymbol{y_2}), \dots, (\mathbf{x_n}, \boldsymbol{y_n})\}$ where n is the sample size.
Step 2	For each iteration where (k=5) 2.1 Randomized and split $\boldsymbol{D}$ into 50% MLR training set (DTr_i) and 50% testing set (DTe_i) 2.2 Train MLR using DTr_i and obtain the RCs_i 2.3 Test the trained MLR with DTe_i 2.4 Obtain CRs_i, 2.5 Store RCs_i, CRs_i
Step 3	3.1 Switch DTr_i and DTe_i, each as the test set and training set respectively. 3.2 Repeat Steps 2.2 to 2.5 for the switched DTr_i and DTe_i. 3.3 Repeat Steps 2.1 to 3.2 for (k-1) times. 3.4 Determine the best value of RCs_i based on CRs_i.

In implementing the first approach to RCs estimation as shown in the DBRCs-I algorithm displayed in Table 1. Firstly, we extracted 39-MFCC (13-MFCC with first and second derivatives) making a total of 39-dimensional FVs from the speech corpus of the 5 Malay vowels. The second step randomizes the extracted 39-MFCC FVs ($\boldsymbol{D}$) together with their targeted output vowel labels and divided into two equal parts (resampling). The first part which is DTr_i (50% of the data) is used for training while the second part DTe_i (50% of the data) for testing. The MLR classifier was trained using DTr_i samples to obtain the first set of MLR RCs_i. The trained MLR is then evaluated using the test data samples DTe_i. The obtained RCs_i together with its classification rate of CR_i is saved.

The third step involves samples swapping, in which the training and test data samples (DTr_i and DTe_i) were interchanged (swap). The MLR classifier is trained with DTe_i data samples to obtain a new set of RCsi. The DTe_1 trained MLR is then evaluated using DTr_i as testing data. The obtained classification rate is saved as CRs_i alongside RCs_i value. This marks the completion of a cycle in which two pairs of CRs (CRs_1, CRs_2) and RCs (RCs_1, RCs_2) are obtained. The process in the second and third steps was repeated four (4) times to obtain a total of ten (10) different sets of MLR RCs and CRs.

B. DBRCs-II

The DBRCs-II approach follows the conventional method of splitting the data into training and testing sets using a ratio of 70:30. Exactly 70% of the data is used in training MLR to obtain RCsi, while the balance 30% of the data is used to test the trained MLR model to obtain CRsi. The training and test process is repeated ten (10) times to obtain ten sets of RCs and CRs. The DBRCs-II approach to DBRCs is implemented using DBRCs-II algorithm as shown in Table 2.

TABLE 2. DBRCS-II ALGORITHM (70:30) FOR OBTAINING MLR REGRESSION COEFFICIENTS RCS

Step 1	Extract 39-MFCC FVs from speech waveform. Label the extracted 39-MFCC features (x) and class membership (y) as $\boldsymbol{D} = \{(\mathbf{x_1}, \boldsymbol{y_1}), (\mathbf{x_2}, \boldsymbol{y_2}), \dots, (\mathbf{x_n}, \boldsymbol{y_n})\}$ where n is the sample size.
Step 2	For each iteration where (k=10) 2.1 Randomized and split $\boldsymbol{D}$ into 70% training set DTr_i and 30% test set DTe_i 2.2 Train MLR using DTr_i and obtain the RCs_i 2.3 Test the trained MLR with DTe_i 2.4 Obtain CRs_i, 2.5 Store RCs_i, CR_i
Step 3	3.1 Repeat Steps 2.1 to 2.5 for (k-1) times. 3.2 Determine the best value of RCs_i based on CRs_i.

The DBRCs-II algorithm for implementing the DBRCs-II approach to DBRCs is as shown in Table 2. Firstly, we extracted 39-MFCC (13-MFCC with first and second derivatives) making a total of 39-dimensional FVs from the speech corpus of Malay five vowels. The second step randomizes the extracted 39-MFCC FVs (D) together with their targeted output vowel labels and divides into two based on ratio 70:30. The first part which is DTr_i (70% of the data) is used for training while the second part DTe_i (30% of the data) for testing. The MLR classifier was trained using DTr_i samples to obtain the first set of MLR RCs_i. The trained MLR is then evaluated using the test data samples DTe_i. The obtained RCs_i together with its classification rate of CRs_i is saved. In the third step, the process in the second step is repeated 9 (9) times to obtain a total of ten (10) different sets of MLR RCs_i and CRs_i.

III EXPERIMENTAL SETUP

In conducting the experiment involved in this work, two processes of corpus formation and acoustic feature extractions were carried out as follows.

A. Speech Corpus

In this work, a secondary source of speech corpus collected by Azmi (2010a) is used. The speech corpus was obtained from 84 individuals who are students of Universiti Utara Malaysia (UUM) and Universiti Malaysia Perlis (Unimap). The corpus consist of speech from Malay, Chinese, and Indian made up of male and female with a total of 2368 utterances. Each of the speakers read the 6 consonant-vowel (CV) pairs of "Ka", "Ke", "Ki", "Ko", "Ku" and "Kə" representing six standard Malay vowels of /a/, /e/, /i/, /o/, /u/, and /ə/. Each of the CV words was pronounced several times depending on the situation to improve the quality of the recordings.

The recordings were performed in a room with a noise level of about 40 dB at a sampling frequency of 8 kHz. The speech signal is captured by a means of a conventional microphone attached to a laptop that is pre-installed with developed Matlab code for speech signal capturing. After each recording session, the Matlab program checks for the correctness of the utterance to the number of the expected utterances before saving it as a .wav file for further processing.

The details of the elicitation of the speech corpus used in this work are as given in Table 3 below.

TABLE 3. SPEECH CORPUS DESCRIPTION

Respondents	*84 individuals aged between 21-26 years old*
No of utterances	1368
Sampling Frequency	8000Hz
Phrase recorded	"Ka", "Ke", "Ki", "Ko", "Ku" and "Kə"
Environment	Room with 40 dB

Before pre-processing, the speech corpus was subjected to cleaning to ensure that only clear and exact speech samples were used for further processing. Perceptual listening test that involves playing-back the recorded corpus, identifying and removing noisy, unclear or wrongly pronounced files from the corpus was carried out. The perceptual listening test process was done in two stages: 1) The researcher listened and selected candidates' speech files for removal; 2) Two experts in speech recognition was engaged to listen to and confirmed the files to be removed due to vowel utterances clarity quality.

B. Mel-Frequency Cepstrum Coefficients (MFCCs)

MFCCs was developed by [20] and had since remained one
of the most widely used features in ASR [21]. MFCCs are perceptually motivated speech representation which is based on Fourier discrete cosine transform of the log filter bank amplitudes. Modelled after human auditory system, MFCCs is built on Mel-frequency scale where each filter computes the average spectrum around each central frequency. MFCCs has been the most frequently used technique, especially in speech recognition and speaker verification applications. In addition to the regular 13-MFCC coefficients, we added to each of the 13 features cepstral features a delta, and a double delta or acceleration feature. Thereby making a total of 39-MFCC coefficients were extracted for classification purposes. 39-MFCC FVs representing five Malay vowels of /a/, /e/, /i/, /o/, and /u/ were extracted and used for implementing the DBRCs algorithms.

IV RESULT AND ANALYSIS

A. Determining the best Regression Coefficients

The generated MLR CRs_i while testing the MLR model with different ten values of RCs_i obtained by training MLR using the two approaches to DBRCs are shown in Table 4.

TABLE 4. RESULTS OF DBRCS APPROACHES

RCs	**CRs (%)**	
	***DBRCs-I* (50:50)**	***DBRCs-II* (70:30)**
$\mathbf{RCs_1}$	86.46	96.32
$\mathbf{RCs_2}$	93.67	**98.53**
$\mathbf{RCs_3}$	90.94	89.99
$\mathbf{RCs_4}$	92.16	91.09
$\mathbf{RCs_5}$	78.92	89.62
$\mathbf{RCs_6}$	93.75	94.00
$\mathbf{RCs_7}$	92.42	93.63
$\mathbf{RCs_8}$	86.32	84.45
$\mathbf{RCs_9}$	91.07	86.29
$\mathbf{RCs_{10}}$	**94.45**	93.20
Average	**90.02**	***91.71***

In Table 4 displayed the CRs, and average of the two approaches for DBRCs in MVR task based on MLR classifier. For the DBRCs-I approach, the highest CRs of 94.45% is attained using the RCs_{10} value. The least overall CRs of 78.92% was recorded by RCs_5. The overall average CRs for the DBRCs-I approach is 90.02%. As for the DBRCs-II approach, the highest CRs of 98.53% is attained by RCs_2 value, while the least CRs of 84.45% is attained by RCs_8 value. The overall CRs for the DBRCs-II approach is 91.71%. Based on CRs, for the DBRCs-I approach, the best RCs is that produced by RCs_{10}, while for the DBRCs-II approach, the best RCs is that produced by RCs_2.

Based on the overall average CRs of the two DBRCs approaches for different values of CRs_i, DBRCs-II approach obtained the highest CRs, while DBRCs-I approach has the least CRs. The best RCs for approaches DBRCs-I and DBRCs-II are RCs_{10}, and RCs_2 respectively.

Based on CRs of the two approaches to DBRCs as shown in Table 4, we have been able to establish that RCs have significant effects on the performance of MLR. Likewise, the conventional approach of splitting the data i.e. DBRCs-II (70:30) performed better than the proposed (DBRCs-I) 50:50 approach. Although, the DBRCs-I approach halved the repetitions number. Analysis of the two approaches to DBRCs-I and DBRCs-II follows in the next section.

B. Performance of RCs in Malay Vowel Recognition

Sequel to the DBRCs process and subsequent determination of the best set of RCs that produces ten values of RCs for each of the two approaches to DBRCs, classification experiments were conducted using the ten sets of RCs so obtained and the sets of randomized training and test data. Performance evaluation is done to select the best set of RCs and to determine which of the two approaches (DBRCs-I and DBRCs-II) to DBRCs performs better. Tables 5 and 6 shows the CRs for Malay vowels using ten different values of MLR RCs generated by the two approaches (DBRCs-I and DBRCs-II) to DBRCs.

TABLE 5. CLASSIFICATION RESULT FOR RCS OBTAINED FROM DBRCS-I

RCs_i	**CRs of DBRCs-I (%)**					**Avg**
	/a/	**/e/**	**/i/**	**/o/**	**/u/**	
$\mathbf{RCs_1}$	85.35	69.42	100	99.05	78.46	86.46
$\mathbf{RCs_2}$	99.08	94.54	98.82	93.36	82.56	93.67
$\mathbf{RCs_3}$	67.14	100	98.77	93.58	95.24	90.94
$\mathbf{RCs_4}$	88.29	94.74	96.57	94.61	86.57	92.16
$\mathbf{RCs_5}$	99.50	70.62	92.98	93.75	37.77	78.92
$\mathbf{RCs_6}$	99.07	88.20	100	86.45	95.05	93.75
$\mathbf{RCs_7}$	88.15	100	97.62	77.83	98.51	92.42
$\mathbf{RCs_8}$	88.24	96.91	97.63	99.09	49.74	86.32
$\mathbf{RCs_9}$	85.07	99.01	98.13	98.54	74.60	91.07
$\mathbf{RCs_{10}}$	**99.48**	**95.16**	**100**	**87.56**	**90.05**	**94.45**
Avg	89.94	90.86	98.05	92.38	78.85	*90.02*

For the DBRCs-I approach, vowel /a/ attains the highest CRs of 99.50% when RCs is RCs_5 and the least CRs of 67.14% when RCs is RCs_3. The overall average for vowel

/a/ based on the first approach is 89.94%. Vowel /e/ attains CRs of 100% for values of RCs_3 and RCs_7 respectively. The least CRs of 69.42% is attained by vowel /e/ when RCs is RCs_1. The overall average of 90.86% is achieved by the first approach for vowel /e/. Vowel /i/ attains CRs of 100% for values of RCs of RCs_1, RCs_6, and RCs_{10} respectively. The least CRs of 92.98% for vowel /i/ is when RCs is RCs_5. The overall average for vowel /i/ based on the DBRCs-I approach is 98.05%. For vowel /o/, the highest CRs of 99.09% is attained with the value of RCs_8, while the least CRs of 77.83% is obtained when the value of RCs is RCs_7. The overall CRs average of 92.38% is attained for vowel /o/ based on the DBRCs-I approach. Considering the CRs of vowel /u/ based on the DBRCs-I approach to DBRCs, RCs_7 gave the highest CRs of 98.51%, while the least CRs of 37.77% is given by RCs_5. The overall average CRs for vowel /u/ based on the DBRCs-I approach is 78.85%. Based on the overall vowel average, vowel /i/ has the highest CRs of 98.05%, while vowel /u/ has the least CRs of 78.85%. Summarily for the DBRCs-I approach, out of the ten RCs_i generated, the highest overall CRs of 94.45% is attained by RCs_{10}, while the least CRs of 78.92% is attained using by RCs_5. The overall CRs average of 90.02% is achieved using the DBRCs-I approach to DBRCs.

As for the DBRCs-II approach to DBRCs, vowel /a/ attains the highest CRs of 100% when RCs values are RCs_3, RCs_4, and RCs_9 respectively and the least CRs of 80.33% when RCs is RCs_8. The overall average for vowel /a/ based on the DBRCs-II approach is 96.43%. Vowel /e/ attains the highest CRs of 99.27% for the value of RCs_2. The least CRs of 60.63% is attained by vowel /e/ when RCs is RCs_8. The overall average of 88.98% is achieved by the DBRCs-II approach for vowel /e/. Vowel /i/ attains CRs of 100% for values of RCs of RCs_1, RCs_2, RCs_5, RCs_6, and RCs_{10} respectively. The least CRs of 95% for vowel /i/ is when RCs is RCs_4. The overall average for vowel /i/ based on the DBRCs-II approach is 98.41%. For vowel /o/, the highest CRs of 98.51% is attained with the value of RCs_7, while the least CRs 43.80% is obtained when the value of RCs is RCs_9. The overall CRs average of 86.65% is attained for vowel /o/ based on the DBRCs-II approach. Considering the CRs of vowel /u/ based on the DBRCs-II approach to DBRCs, RCs_9 gave the highest CRs of 99.17%, while the least CRs 66.95% of is given by RCs_5. The overall average CRs for vowel /u/ based on the DBRCs-II approach is 88.09%. Based on the overall vowel average, vowel /i/ has the highest CRs of 98.41%, while vowel /o/ has the least CRs of 86.65%. Summarily for the DBRCs-II approach, out of the ten RCs_i generated, the highest overall CRs of 98.53% is attained by RCs_2, while the least CRs of 84.45% is attained using by RCs_8. The overall CRs average of 91.71% is achieved using the DBRCs-II approach to DBRCs.

TABLE 6. CLASSIFICATION RESULT FOR RCS OBTAINED FROM DBRCS-II

RCs_i	**CRs of DBRCs-II (%)**					**Avg**
	/a/	**/e/**	**/i/**	**/o/**	**/u/**	
RCs_1	99.17	93.94	100	94.85	93.65	96.32
RCs_2	**99.65**	**99.27**	**100**	**95.77**	**97.92**	**98.53**
RCs_3	100	81.25	96.94	93.65	78.10	89.99
RCs_4	100	94.74	95.00	80.16	85.58	91.09
RCs_5	90.98	92.45	100	97.73	66.95	89.62
RCs_6	98.31	98.39	100	87.97	85.32	94.00
RCs_7	99.15	91.45	98.15	98.51	80.91	93.63
RCs_8	80.33	60.63	95.92	91.18	94.17	84.45
RCs_9	100	90.43	98.06	43.80	99.17	86.29
RCs_{10}	96.75	87.27	100	82.86	99.14	93.20
Avg	96.43	88.98	98.41	86.65	88.09	91.71

As seen in Tables 5 and 6, different values of RCs yields different CRs for both approaches. This implies that RCs determines the CRs of MLR. For the DBRCs-I approach, RCs_{10} yields the best overall CRs, while for the DBRCs-II approach the best overall CRs is attained by RCs_2. For both approaches to DBRCs, vowel /i/ is the highest recognized, while the least recognized is vowel /u/ and /o/ for DBRCs-I and DBRCs-II approach respectively. On the overall CRs of the two approaches, the overall CRs for the DBRCs-I approach is 90.02%, while the overall CRs for the DBRCs-II approach is 91.71%. Thus, the DBRCs-II approach performs slightly better than the DBRCs-I approach with a performance margin of 1.69%.

From Tables 5 and 6 we extracted the CRs of vowels for each of the best RCs values of both approaches (RCs_{10} for the DBRCs-I approach and RCs_2 for the DBRCs-II approach). The CRs of the best RCs for the two approaches and that of the baseline (**MLE**) together is displayed in Table 7.

Table 7 displayed the CRs for the baseline (**MLE**), DBRCs-I and DBRCs-II approach to DBRCs. Based on CRs as contained in Table 7, the DBRCs-II approach has the highest CRs followed by the DBRCs-I approach, while the baseline has the least CRs for vowel /a/. As for vowels /e/, /o/, and /u/, the DBRCs-II approach has the highest CRs followed by the baseline, while the DBRCs-I approach has the least CRs. In the case of vowel /i/, both approaches attain 100% CRs, while the baseline has the least CRs of 99.71%. For the overall average CRs, the DBRCs-II approach has the highest CRs, followed by the baseline, while the DBRCs-I approach has the least CRs.

TABLE 7. CLASSIFICATION RESULT FOR BASELINE AND DBRCS

Vowels	**CRs (%)**		
	Baseline (MLE)	**DBRCs-I approach**	**DBRCs-II approach**
/a/	98	99.48	99.65
/e/	97.82	95.16	99.27
/i/	99.71	100.00	100.00
/o/	94.43	87.56	95.77
/u/	92.42	90.05	97.92
Avrg	96.48	94.45	98.53

Fig. 1 is the plot of CRs of Malay vowels based on baseline and the two approaches to DBRCs. It shows the CRs and overall average CRs for Malay vowels for baseline and the two approaches to DBRCs.

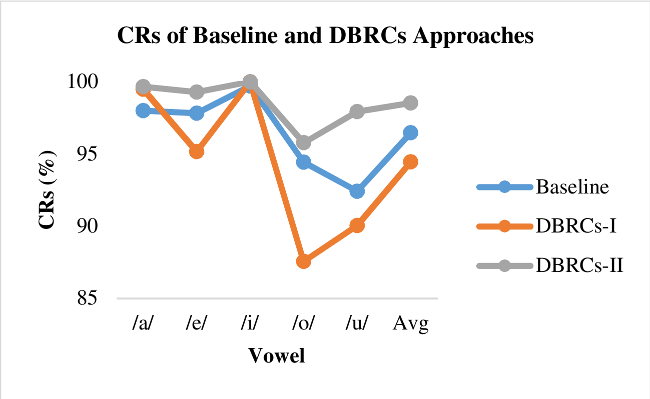

Fig 1. Classification Rates MFCC Baseline, DBRCs-I and DBRCs-II

As observed from Figure 1, DBRCs-II has the highest CRs followed by the baseline while DBRCs-I has the least performance.

V CONCLUSION

In order to improve the performance of MLR in MVR task, two algorithms were developed and implemented to determine the best sets of RCs that can improve the recognition accuracy of MLR. Two versions of the algorithm were designed for implementing DBRCs resulting in two sets of DBRCs (RCs_{10} and RCs_2). Analysis of the two approaches to DBRCs and **MLE**, reveals that DBRCs-II outperforms both **MLE**, and DBRCs-I. Our best DBRCs approach outperforms the conventional **MLE**, by 2.05% in overall CRs for MVR which is significant depending on the application of this technique. Although this is not a consider a new finding, the practical contributions of this work shows that given enough data for training, the DBRCs-I swapping technique can be use to obtain good RCs values faster.

REFERENCES

[1]. Hosmer Jr, D.W., Lemeshow, S., and Sturdivant, R.X.: 'Applied logistic regression' (John Wiley & Sons, 2013. 2013)

[2]. Salillari, D., and Prifti, L.: 'A multinomial logistic regression model for text in Albanian language', Journal of Advances in Mathematics, 2016, 12, (7), pp. 6407-6411

[3]. Best, H., and Wolf, C.: 'Logistic regression': 'The SAGE handbook of regression analysis and causal inference' (Sage Los Angeles, CA, 2015), pp. 153-171

[4]. de Jong, V.M., Eijkemans, M.J., van Calster, B., Timmerman, D., Moons, K.G., Steyerberg, E.W., and van Smeden, M.: 'Sample size considerations and predictive performance of multinomial logistic prediction models', Statistics in medicine, 2019, 38, (9), pp. 1601-1619

[5]. Salaro, R.: 'Multinomial Logistic Regression with High Dimensional Data', Università Ca'Foscari Venezia, 2018

[6]. Azmi, M.Y.S.: 'Development of Malay Word Pronunciation Application using Vowel Recognition', Malay, 2016, 9, (1)

[7]. Moon, S.-H., and Kim, Y.-H.: 'An improved forecast of precipitation type using correlation-based feature selection and multinomial logistic regression', Atmospheric Research, 2020, 240, pp. 104928

[8]. Chang, Y.-p., Chang, R.Y., Lin, C.-Y., and Luo, X.: 'Mandarin tone and vowel recognition in cochlear implant users: Effects of talker variability and bimodal hearing', Ear and Hearing, 2016, 37, (3), pp. 271

[9]. Romera, M., Talatchian, P., Tsunegi, S., Araujo, F.A., Cros, V., Bortolotti, P., Trastoy, J., Yakushiji, K., Fukushima, A., and Kubota, H.: 'Vowel recognition with four coupled spin-torque nano-oscillators', Nature, 2018, 563, (7730), pp. 230-234

[10]. Bora, A., Vajpai, J., and Gaur, S.B.: 'Phonology based Fuzzy Phoneme Recognition', Available at SSRN 3358093, 2019

[11]. Devi, K.J., and Thongam, K.: 'Automatic speaker recognition with enhanced swallow swarm optimization and ensemble classification model from speech signals', Journal of Ambient Intelligence and Humanized Computing, 2019, pp. 1-14

[12]. Srinivas, N.S., Sugan, N., Kar, N., Kumar, L.S., Nath, M.K., and Kanhe, A.: 'Recognition of Spoken Languages from Acoustic Speech Signals Using Fourier Parameters', Circuits, Systems, and Signal Processing, 2019, 38, (11), pp. 5018-5067

[13]. Reid, C.V.: 'Study of locus equations as features for speech classification and recognition', uga, 2016

[14]. R. Hidayat, D. Yulian, A. Bejo and S. Sumaryono, "Comparison of vowel feature extraction on time and frequency domain," *2017 9th International Conference on Information Technology and Electrical Engineering (ICITEE)*, Phuket, 2017, pp. 1-4, doi: 10.1109/ICITEED.2017.8250477.

[15]. Azmi, M.Y.S.: 'An improved feature extraction method for Malay vowel recognition based on spectrum delta', International Journal of Software Engineering and Its Applications, 2014, 8, (1), pp. 413-426

[16]. Ting H.N., Lam Y.M. (2009) Speaker-Independent Malay Vowel Recognition of Children Using Neural Networks. In: Dössel O., Schlegel W.C. (eds) World Congress on Medical Physics and Biomedical Engineering, September 7 - 12, 2009, Munich, Germany. IFMBE Proceedings, vol 25/4. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-03882-2_76

[17]. Gupta, D., Bansal, P., and Choudhary, K.: 'The state of the art of feature extraction techniques in speech recognition': 'Speech and language processing for human-machine communications' (Springer, 2018), pp. 195-207

[18]. Besacier, L., Barnard, E., Karpov, A., and Schultz, T.: 'Automatic speech recognition for under-resourced languages: A survey', Speech Communication, 2014, 56, pp. 85-100

[19]. [19] Desai, V.A., 'Algorithm For Keyword Spotting with Application To Speech Recognition', Ph.D. Thesis, Gujarat Technological University Ahmedabad, 2017.

[20]. [20] Davis, S., and Mermelstein, P.: 'Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences', Acoustics, Speech and Signal Processing, IEEE Transactions on, 1980, 28, (4), pp. 357-366

[21]. [21] Yusnita, M.: 'Investigation of Robust Speech Feature Extraction Techniques for Accents Classification of Malaysian English Speakers'. Ph.D, Universiti Malaysia Perlis, 2014