

the attribute's weight based on its contribution, making this method more flexible for prediction. Therefore, it is improbable that the learning data process will fail because MARS uses the selected attribute on the associated basis function. Furthermore, because MARS employs filtered important attributes to reduce processing time and significantly increase processing speed, the learning model on MARS can accurately and effectively analyze each feature [35], [36].

C. Optimal Base Function Selection in MARS Models

For optimal basis selection, both forward and backward stepwise procedures are possible [37]. The purpose of the forward stepwise method is to construct a model by adding truncated spline basis functions (knots and interactions), which will result in a model containing the greatest possible number of basis functions [38]. The forward stepwise process is a hidden layer in MARS, and the value obtained from forward stepwise will be used to determine if backward stepwise modeling is feasible.

1) *Forward Stepwise*: Forward stepwise is enabled on MARS to select the maximum number of basic functions. $\frac{1}{n} \sum_{i=1}^n (y_i - \hat{f}(x_i, \alpha))^2$ is a function used as a basis function selection criterion to obtain the minimum average sum of square residuals. To obtain the minimum ASR value, divide the number of parameters for the C(M) model by n observations minus 1 of this function, which is the ASR dividing value. The following are the forward stepwise steps in the process of selecting the basis function:

Initialization and constant-coefficient conjecture

$$B_0 = 1$$

Assuming there are $K + 1$ basis functions $B_0, B_1(x), \dots, B_k(x)$, add two new basis functions:

$$B_{k+1}(x) = B_1(x) + [x_{1(k,l)} - x_{1^*(k,l)}]_+^m$$

$$B_{k+1}(x) = B_1(x) - [x_{1(k,l)} - x_{1^*(k,l)}]_+^m$$

Where $B_k(x)$ is the initial function basis (parent), $x_{1(k,l)}$ is a variable not included in the basis function $B_k(x)$, and $x_{1^*(k,l)}$ is the knot point.

$$x_{i(k,l)}^* \in \{x_{i(k,l)}\}, i = 1, \dots, n \quad (7)$$

Minimum determinants according to GCV standards

$$GCV = \frac{1}{n} \frac{\sum_{i=1}^n (y_i - \hat{f}(x_i, \alpha))^2}{1 - (\tilde{c}(\alpha)/n)^2} \quad (8)$$

The addition of the basis function is still being done in order to ensure that the maximum value of M_{max} represents the basis for the K function.

2) *Backward Stepwise*: The backward stepwise step in MARS is used to simplify models with overlapping regions by removing the basis function and producing a model with continuous derivatives. Using the recursion partition regression algorithm (RPR) on a set of basis functions $J^* = \{1, 2, \dots, M_{max-1}\}$ the sum of the basis functions from the previous step forward stepwise, removing the basis function on MARS does not result in a hole in the predictor variable space (as long as the constant basis is not removed). The following is a list of the backward stepwise steps involved in getting rid of the basis function:

Initials of $J^* = \{1, 2, \dots, M_{max-1}\}$; $K^* \leftarrow K$. Lack of fit (LOF) will be assigned to non-conforming functional bases.

$$lof \leftarrow \min_{\{a_j | j \in J^*\}} LOF \left[\sum_{j \in J^*} \alpha_k B_k(x) \right] \quad (9)$$

Each iteration outside the for loop causes the elimination of one basis function, while each iteration inside the for loop selects a basis function. The base constant $B_k(x) =$ will not be eliminated during the backward stepwise elimination process. This algorithm can produce up to $B_k(x) =$ model lines. Each succeeding sequence has one fewer basis function than its predecessor.

D. MARS Model Estimation And GCV

The MARS model will select a sub-model to minimize the prediction of residual estimation (chosen based on optimal function basis) according to the generalized cross-validation (GCV) criteria in equation (8). $\hat{\alpha}$ is the parameter to be estimated via the penalized residual sum of squares problem (PRSS). The following is a PRSS model with M_{max} Basis Functions (BFs) utilizing the MARS method:

$$PRSS \approx (y_i - B(\tilde{d})\theta)^2 + \sum_{m=1}^{M_{max} \sum_{i=1}^{(N+1)K_m} L_{im}^2 \theta_{im}^2} \alpha_m \quad (10)$$

Where,

The $(N \times (M_{max} + 1))$ - matrix is denoted by $B(\tilde{d}) = (B(\tilde{d}_1), \dots, B(\tilde{d}_N))^T$, the Euclidean form is indicated by $\|\cdot\|_2$, and the number L_{im} is what defines the roots.

For the probability model based on the equation below:

$$P(Y = 1 | X = x) = \pi(x) = \frac{e^{g(x)}}{1 + e^{g(x)}} \quad (11)$$

probability transformation of the MARS model

$$\ln \left[\frac{\pi(x)}{1 - \pi(x)} \right] = a_0 + \sum_{m=1}^M a_m \prod_{k=1}^{K_m} \left[S_{km} \cdot \left(x_{vN(k,m)} - t_{km} \right) \right] \varepsilon_i \quad (12)$$

III. RESULTS AND DISCUSSION

This research was carried out to develop a predictive model by employing a regression analytic strategy with the MARS model and applying it to a collection of uncertain sound feature data. In addition to allowing for greater flexibility in data analysis regression problems, splines are also developed to accommodate local data and exhibit distinct behavior in each sub-interval. Because spline is a piecewise polynomial, i.e., polynomials with segmented properties, this indicates that the spline regression approach that we propose in the field of speech emotion recognition with high data dimensions is ideally suited for the problem of predicting specific forms of emotion. This segmented property offers greater flexibility than conventional polynomials, allowing for more effective adaptation to the characteristics of a function or database.

A descriptive analysis of the initial phases of data exploration to gain an overview of the employed data. This study employs the RAVDESS dataset consisting of 120 WAV-format sound files along with sound feature extraction

and selection techniques employing Mel Frequency Cepstral Coefficients (MFCC) to generate 180 sound features $\{x_1, x_2, \dots, x_n; x_n = x_{180}\}$. This leads to two forms of emotion, 'angry' = 1 and not angry 'neutral' = 2, the sound feature data produced is not normally distributed, so a nonparametric regression analysis approach is highly appropriate.

The next step is to determine the Basis Function (BF), Maximum Interaction (MI), and Minimum Observation (MO) values after determining the shape of the data distribution through data exploration. For values of BF = 36, MI, and MO in this study using values 1, 2, and 3, more than three results in a model that is extremely complex and less accurate [36]. The stages involved in determining the value of BF, MI, and MO are shown in the table below.

TABLE I
MI AND MO DETERMINATION

BF	MI	MO	GCV	MSE	R2
36	1	None	0.0172	0.0079	0.9643
36	1	0	0.0164	0.0062	0.9720
36	1	1	0.0173	0.0061	0.9723
36	1	2	0.0130	0.0062	0.9721
36	1	3	0.0161	0.0065	0.9706
36	2	None	0.0172	0.0079	0.9643
36	2	0	0.0164	0.0062	0.9720
36	2	1	0.0173	0.0061	0.9723
36	2	2	0.0130	0.0062	0.9721
36	2	3	0.0161	0.0065	0.9706
36	3	None	0.0172	0.0079	0.9643
36	3	0	0.0164	0.0062	0.9720
36	3	1	0.0173	0.0061	0.9723
36	3	2	0.0130	0.0062	0.9721
36	3	3	0.0161	0.0065	0.9706

Table 1 demonstrates that the minimum observation significantly influences the 36 basis functions in determining the minimum GCV value. In contrast, the maximum value of interaction does not affect the formation of speech emotion prediction models, so MI = 1, MO = 2 with BF = 36 function basis can be used.

MARS modeling's development prediction model employs Google Colab and the Python 3.8 programming language. As shown in Fig. 1, the MARS regression of the training data, with the intercept value and the maximum variable coefficient for each predictor variable for the response variable and the maximum variable coefficient for each predictor variable.

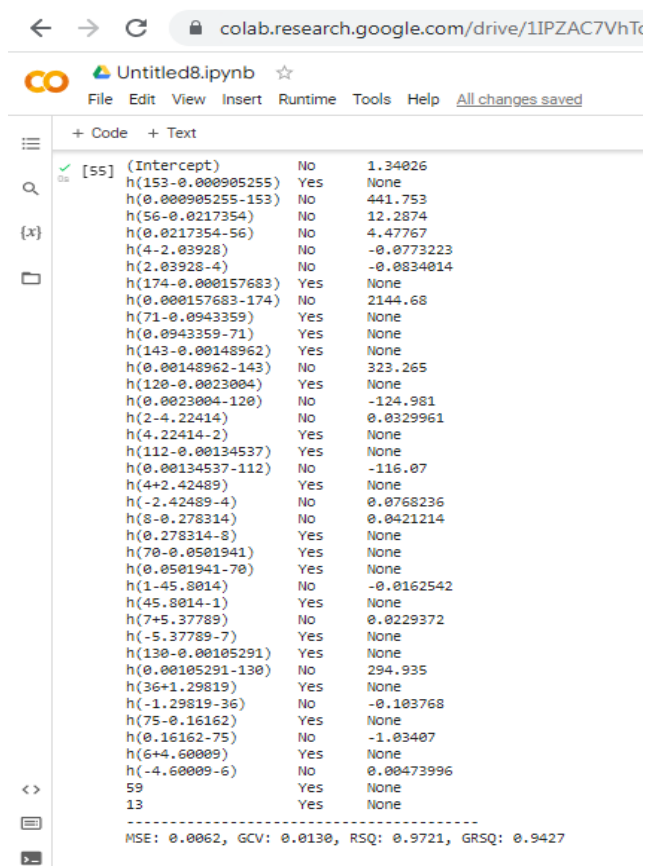


Fig. 1 MARS regression training data

Based on the forward and backward stepwise, the MSE value of 0.0062 is obtained for the sought optimal model formation function. With a minimum GCV of 0.0130, RSQ of 0.9721, and GRSQ of 0.9427, the estimation results are as follows:

$$\begin{aligned}
 \hat{f}(\underline{x}) = & 1.34026 + 2144.68(0.00157683 - X174) \\
 & + 441.753(0.000905255 - X153) \\
 & + 323.265(0.00148962 - X143) \\
 & + 294.935(0.00105291 - X130) \\
 & + 12.2874(X56 - 0.0217354) \\
 & + 4.47767(0.0217354 - X56) \\
 & + 0.0768236(2.03928 - X4) \\
 & + 0.0421214(X8 - 0.278314) \\
 & + 0.0329961(-2.42489 - X4) \\
 & + 0.0229372(X7 + 5.37789) \\
 & + 0.00473996(-4.60009 - X6) \\
 & - 0.0162542(X1 - 45.8014) \\
 & - 0.0773223(X4 - 2.03928) \\
 & - 0.0834014(X2 - 4.22414) \\
 & - 0.103768(-1.29819 - X36) \\
 & - 1.03407(0.16162 - X75) \\
 & - 116.07(0.00134537 - X112) \\
 & - 124.981(0.0023004 - X120)
 \end{aligned}$$

Then, the results of the optimal estimation of the accommodating weight can be interpreted using equation (11), an example of estimation/interpretation of the optimal estimation of weight:

Approximate example:
Maximum coefficient value = 2144.68 with a base function
B8 = (0.000157683-X174)

$$\pi(x) = \frac{\exp(2144.68 + 1.34026)}{1 + \exp(2144.68 + 1.34026)} = 0.9995$$

Assuming that the other independent variables remain constant, the emotion of anger is determined if the added value of the feature less than 1 ($X174 < 1$) has the potential to affect the emotional form of 0.9995, and the coefficient B8 (function 8th basis) increases the effect on changes in the emotional form of anger by 2144.86. In contrast, if the value of the added feature is greater than 1 ($X174 > 1$), the B8 coefficient (8th function basis) is not significant, and its value is 0. The optimal function basis estimate results for estimating the probability of emotional shape variables are presented in the table below.

TABLE II
FUNCTIONAL BASIS FOR ESTIMATING THE PROBABILITY OF VARIABLES OF EMOTIONAL SHAPE

Basis Function	Anger Emotional Possibility $\pi(x)$	Not Anger Emotional Possibility (neutral) $1 + \pi(x)$
B2 = (0.000905255-X153)	0.9977	0.0023
B3 = (X56-0.0217354)	0.9316	0.0684
B4 = (0.0217354-X56)	0.8533	0.1467
B5 = (X4-2.03928)	0.5581	0.4419
B6 = (2.03928-X4)	0.5569	0.4431
B8 = (0.000157683-X174)	0.9995	0.0005
B12 = (0.00148962-X143)	0.9969	0.0031
B14 = (0.0023004-X120)	1.0089	-0.0089
B15 = (X2-4.22414)	0.5786	0.4214
B18 = (0.00134537-X112)	1.0088	-0.0088
B20 = (-2.42489-X4)	0.5863	0.4137
B21 = (X8-0.278314)	0.5803	0.4197
B25 = (X1-45.8014)	0.5697	0.4303
B27 = (X7+5.37789)	0.5768	0.4232
B30 = (0.00105291-X130)	0.9966	0.0034
B32 = (-1.29819-X36)	0.5529	0.4471
B34 = (0.16162-X75)	0.2344	0.7656
B36 = (-4.60009-X6)	0.5718	0.4282

From the estimated results in Table 2 the learning process or learning of the input variables or variable xi. This study produces a speech emotion recognition prediction model with a number of variables that are recognized as variables that influence changes in emotional form as much as 15 of 180 voice features Mel Frequency Cepstral Coefficient (MFCC) with an accuracy rate of 97.21%. The outcomes of learning test data and training data from predictive models were constructed utilizing the multivariate additive regression spline (MARS) regression approach, acquiring four prediction errors and 116 accurate predictions, as shown in Table 3.

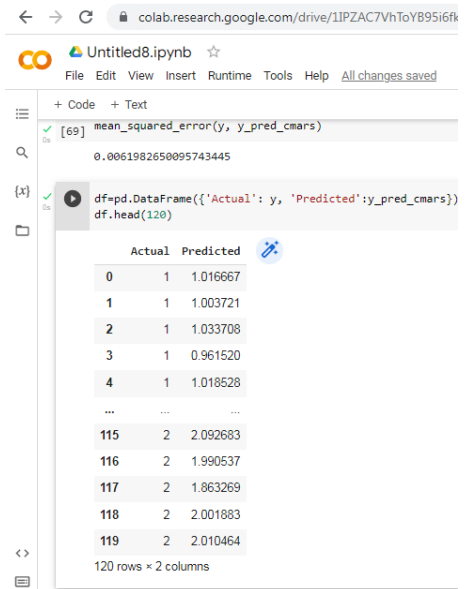


Fig. 2 Prediction Results of Actual Emotional Data

TABLE III
ACCURACY LEVEL MEASUREMENT

		Actual Value	
		TRUE	FALSE
Predicted Value	POSITIVE	70	1
	NEGATIVE	46	3

$$precision = \frac{TP}{TP+FP} \times 100 = \frac{70}{70+1} \times 100 = 99\%$$

$$recall = \frac{TP}{TP+FN} \times 100 = \frac{70}{70+3} \times 100 = 96\%$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 = \frac{70+46}{70+46+1+3} \times 100 = 97\%$$

The accuracy test for the predictive model yields 97% with 99% precision and 96% recall. The prediction model was created for speech emotion recognition using a nonparametric regression analysis approach, and the best model accurately predicts the presence of potential angry, non-angry, or neutral emotions.

IV. CONCLUSION

In this study, we devised a method using nonparametric regression analysis to develop a predictive model for emotion recognition in speech. Generally, sound feature data are coefficient values and lack a data distribution; therefore, nonparametric regression is the appropriate method. Developing a prediction model using the MARS model to examine the relationship between predictors and responses through the basis function is one method that can be used to solve problems in SER. By determining the optimal estimation of the basis function, it is possible to reduce sound features that influence emotional form changes. For future studies, we can extend the nonparametric regression analytic

approach to sound feature data types containing noise or spontaneous sound data under various conditions.

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