Application of Gaussian Process Regression Function for Predict Tool Wear

Nguyen Duc Luan

Abstract— **This paper presents a cutting tool estimation technique based on the Gaussian process regression (GPR) function for predict of tool wear (flank wear width). Tool wear prediction parameters and corresponding confidence intervals are provided by the GPR model. In addition, the GPR model provides better performance than artificial neural networks (ANN) and assistive vector machines (SVM) on the predicted accuracy due to Gaussian noise can be quantitatively modeled in the GPR model. Experimental settings were conducted to evaluate the effectiveness of the proposed tool wear predictive model. Experimental results show that the flank wear width of the cutting tool can be accurately monitored using the robust tool wear assessment technique presented in many cutting conditions. This study lays the foundations for monitoring tool wear in true industrial environments.**

I. INTRODUCTION

Monitoring tool wear is one of the important factors to ensure the reliability and stability of the production system because when the cutting tool is worn out excessively, it will increase the cutting force and even machine tool sound. In addition, tool errors lead to 20% downtime in modern production systems, reducing machining productivity [1,2]. To solve the above problems, an effective monitoring system to timely and accurately assess the wear status of the cutting tools and propose maintenance methods. Nowadays, as modern manufacturing systems become more complex, the need for stable and reliable operation also requires a monitoring system that can give early warning about tool wear. This is also the problem studied in this paper.

There has been much research to develop and improve the tool wear monitoring model, which mainly includes signal acquisition, feature extraction and system identification [3,4]. An integrated tool wear monitoring system is illustrated in Fig. 1. The scope of monitoring the wear of a cutting tool during machining primarily covers the width, area, state of wear and broken. Frequently used signals and corresponding sensors have been shown to be feasible for monitoring tool wear considered in [5], including cutting force [6], vibration [7], acoustic emission sensor [8] electric current or spindle power [9]. For identification systems, artificial neural networks (ANN) [10] and support vector machines (SVM) [11] are artificial intelligence models that are most widely used to monitor flank wear of cutting tools. Ghosh et al. [12] developed a model combining sensors based on ANN to predict tool wear and found that the composite parameters from multiple sensors improved predictive accuracy compared to their single sensors. By combining cutting forces, torque, cutting conditions and cutting times, Kaya et al. [13] developed a powerful base on flank wear monitoring system for milling Inconel 718 materials. Salgado et al. [14] realized the tool wear prediction using minimal squared support vector machines (LS-SVM) and found that the based on LS-SVM model outperformed the based on ANN model in predictive accuracy. This works solved the problem of monitoring flank wear of cutting tools in specific areas [15]. However, they cannot provide uncertainty of the predicted results. Uncertainty analysis and quantification are of great importance for improving product quality and efficiency and can be integrated into modern production systems.

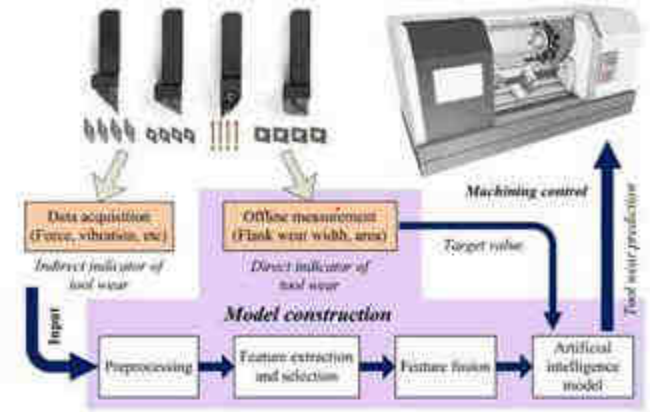


Fig. 1 Diagram of the integrated cutting tool wear monitoring system

In order to implement and overcome these characteristics, in this work, the Gaussian Process Regression (GPR) [16] function is used to build an effective tool wear forecasting model by the signal features obtained and the flank wear of the cutting tool. The GPR model is a powerful and flexible tool that can provide both predictive results and confidence intervals (uncertainty estimates) that help quantify predictive ability. The GPR model has been widely used in data-based modeling for various systems. From here the article was made for the purpose of timely and accurate monitoring of flank wear during turning using experimental processes combined with the GPR model.

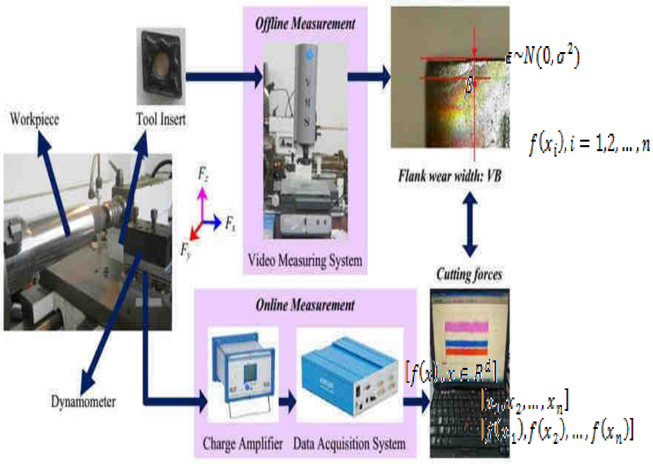
II. EXPERIMENTAL METHODOLOGY

1. Experimental setup and data collection

The cutting tests of dry turning normal steel (50#) that have been standardized by inserting cemented carbide tools are conducted to confirm the effectiveness of the tool wear assessment technique presented. A three-component force sensor is used during machining to monitor the tool width of the tool flank wear. A schematic diagram of a test set to monitor tool wear is illustrated in Fig. 2. Machining parameters in cutting test sets are listed in Table 1. The cutting force signals are initially collected at a sampling rate of 20 kHz using a dynamometer. In addition, the flank wear width (VB) of the inserts is measured and recorded after each cutting process (at set intervals) using the Video Measuring System (VMS) until the tool break (VB > 0.5 mm).

Manuscript received Dec 10, 2020

Nguyen Duc Luan, Ha Noi University of Industry, Viet Nam



$K(x,x^*)$ $M(x)$ $[f(x), x \in R^d]$

Fig. 2 Experimental design

Table 1. Experimental parameters

Experiment No.	Cutting speed (m/min)	Feed rate (mm/r)	Cutting deep (mm)	Replications
1	350	0.15	0.75	2
2	350	0.15	1.5	2
3	350	0.25	0.75	2
4	350	0.25	1.5	2
5	350	0.35	0.75	1
6	350	0.35	1.5	1

The flank wear widths (VB) of inserts were used as the object of study in this study. A total of 215 data files were collected and recorded in the ten cutting test sets as shown in Table 1. One data file corresponds to some cases. Moreover, it is necessary to perform fusion to eliminate noise and weaken its negative effects. The extracted signal features or merged features and the corresponding machining parameters constitute the feature vectors used as input base on the GPR tool wear forecasting model. A total of 430 unique vector samples were taken and divided equally for the training and test data sets that did not overlap. Also note that the extracted signal features need to be standardized before the feature consolidation, given by

$$x' = \frac{x - \overline{x}}{\sigma_x} \quad (1)$$

where $\overline{x}$ is the mean value, σ_x is the standard deviation.

2. Gaussian Process Regression Model

Gausian process regression (GPR) model [16,17] is a non-parametric probabilistic model based on the kernel. The trained data set is monitored: $[(x_i, y_i); i = 1,2,\ldots,n]$, where $x_i \in R^d$ $y_i \in R$ are taken from an unknown distribution function. The GPR model solves the problems in predicting the value of a ynew response variable on the basis of the given value of the new input vector xnew and the trained data. The model of a linear regression function is expressed as:

$$y = x^T.\beta + \varepsilon \quad \ldots..(2)$$

Where , is the error variable, is the coefficient predicted from the dataset. The responsiveness of the GPR model is constructed by giving hidden variables from the Gaussian process (GP) with the explicit basis functions *H*. The covariance function of the latent variables aimed to produce the smoothness for basic functions and response functions corresponding to the input attributes *x* from the p-dimensional attribute space.

A GP model is a set of random variables where any finite element of theirs has a Gaussian distribution. If is a GP model then there are n observation parameters and generally distributed random variables are also Gaussian functions. A GP model is defined by the covariance function and average function

That is, if is a GP then $E[f(x)] = M(x)$

And $Cov[f(x), f(x^*)] = E\{[f(x) - M(x)][f(x^*) - M(x^*)]\} = K(x, x^*)$ (3)

Then, the models are surveyed as follows:

$$H(x)^T.\beta + f(x) \quad (4)$$

Where $f(x) \sim GP[0, K(x,x^*)]$ with $f(x)$ as an average GP model without covariance function $K(x,x^*)$. $H(x)$ is a set of basic functions that are converted from the vector of original characteristic *x* in R^d to the attribute vector *H(x)* in R^P. β is a fundamental function factor of a vector defined by *P*. This described model is the GPR model. A response y can be modeled as follows:

$$P[y_i | f(x_i), x_i] \sim N[y_i | H(x_i).\beta, \sigma^2] \quad (5)$$

Thus the GPR model is a nonparametric probability model with a latent variable $f(x_i)$ given for each observation x_i. This vector model is defined to be equivalent to:

$$P[(y_i|F), X] \sim N[(y_i|H.\beta + F), \sigma^2] \quad (6)$$

where: $X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_n^T \end{bmatrix}$; $Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$; $H = \begin{bmatrix} H(x_1)^T \\ H(x_2)^T \\ \vdots \\ H(x_n)^T \end{bmatrix}$;

$$F = \begin{bmatrix} f(x_1) \\ f(x_2) \\ \vdots \\ f(x_n) \end{bmatrix} \quad (7)$$

In the GPR model the latent variables $[f(x_1), f(x_2), \ldots, f(x_n)]$ are distributed as follows:

$$P(F|X) \sim N[F|0, G(X,X)] \quad (8)$$

The Model is similar to the linear regression model, where *G(X,X)* is determined as follows:

$$G(X,X) = \begin{bmatrix} K(x_1,x_1) & K(x_1,x_2) & \ldots & K(x_1,x_n) \\ K(x_2,x_1) & K(x_2,x_2) & \ldots & K(x_2,x_n) \\ \vdots & \vdots & \vdots & \vdots \\ K(x_n,x_1) & K(x_n,x_2) & \ldots & K(x_n,x_n) \end{bmatrix} \quad (9)$$

The covariance functions $K(x, x^*)$ are usually parameterized by the kernel parameters or hyperparameters and and usually written in the form of $K[(x, x^*)|\theta]$ to clearly indicate the dependence on $^{-}$.

3. Experimental results and analysis

This work aims at real-timely and accurately monitoring the tool wear in machining process by utilizing the proposed experiment and the GPR model. The GPR-based tool wear predictive model is constructed by fitting the target value and the fused features as illustrated in Fig. 1. In general, the prediction accuracy of the GPR model is almost unaffected by Gaussian noises since they can be modeled quantitatively as given by Eq. 6. Therefore, GPR performs better than other data-driven methods, such as artificial neural networks (ANN) and support vector machines (SVM).

In this study, v-SVR [17], LS-SVM [18], BPNN [19] and Elman [20] are also used to implement the tool wear prediction process. The feature vectors include 48 extracted features (without aggregate features) and the corresponding machining parameters are inserted directly into the tool wear predictive models to show the advantages of GPR compared to the remaining predictive models.

The predictive results of the five predictive tool wear models (GPR, v-SVR, LS-SVM, BPNN and Elman) are shown in Fig. 3. Errors indicate the absolute value of the difference between predictive and measurement tool wear. It can be seen that GPR, v-SVR and LS-SVM can effectively follow the tool wear path. Meanwhile, the predictability of BPNN and Elman is not very good. To compare the performance of the five model predictive tool wear, four types of evaluation indicators were given by

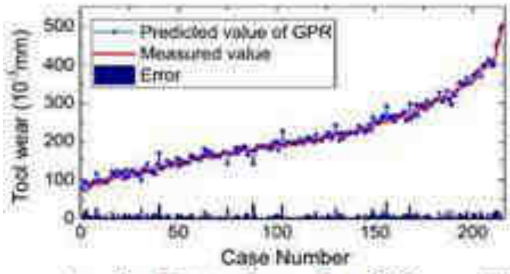
$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - f_i\right| \tag{10}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - f_i\right)^2} \tag{11}$$

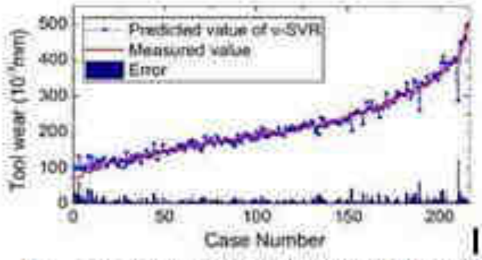
$$MAE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|y_i - f_i\right|}{y_i}\times 100\% \tag{12}$$

$$PCC = \frac{\sum_{i=1}^{N}(y_i - \bar{y})\left(f_i - \bar{f}\right)}{\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2\left(f_i - \bar{f}\right)^2}} \tag{13}$$

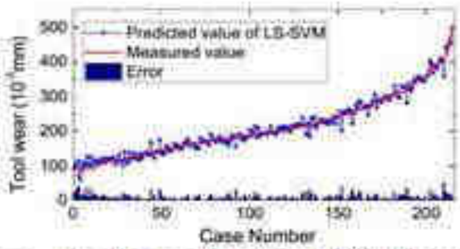
Where yi is the flank wear width of the tool measured by the VMS, fi is the predictive value of a tool wear prediction model at the xi test point as the corresponding feature vector of yi. MAE is the mean absolute error, RMSE is the root mean square error, MAPE is the mean absolute percentage error, PCC is the Pearson correlation coefficient. Note that larger PCC means better performance of the model prediction tool wear. Comparing the performance of the five tool wear forecast models according to the different evaluation indicators is shown in Fig. 4. The number in the column in each sub-configuration represents the value of the rating. It was found that the GPR had the minimum MAE/RMSE/MAPE value and the maximum PCC value among the models predicting wear of the five tools. Therefore, it can be concluded that GPR has better predictability than the remaining models.



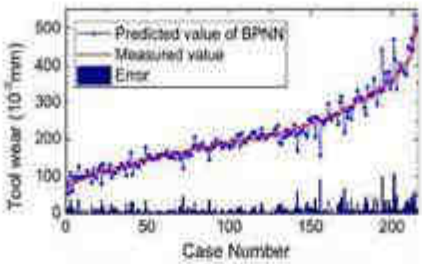
a) Predict tool wear by GPR model



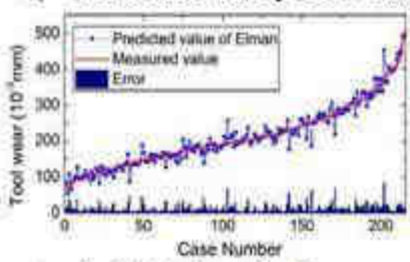
b) Predict tool wear by v-SVR model



c) Predict tool wear by LS-SVM model

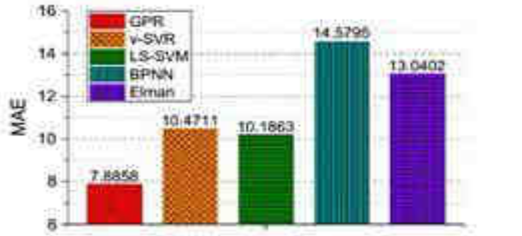


d) Predict tool wear by BPNN model

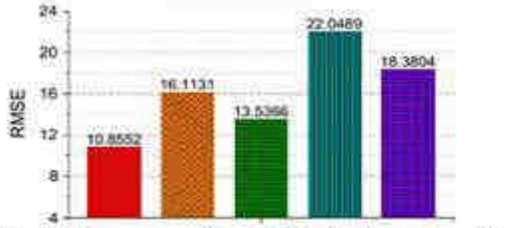


e) Predict tool wear by Elman model

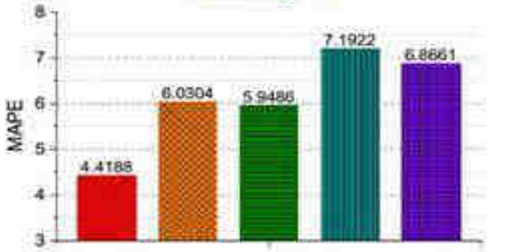
Fig. 3 Predictive results with different tool wear predictive models



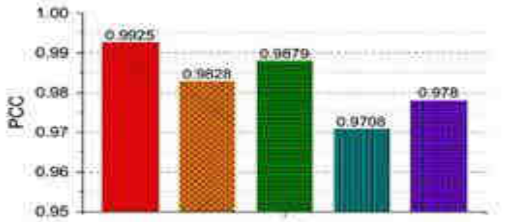
a) Performance of predictive tool wear models according to MAE



b) Performance of predictive tool wear models according to RMSE

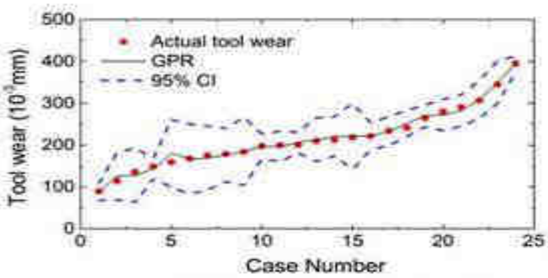


c) Performance of predictive tool wear models according to MAPE

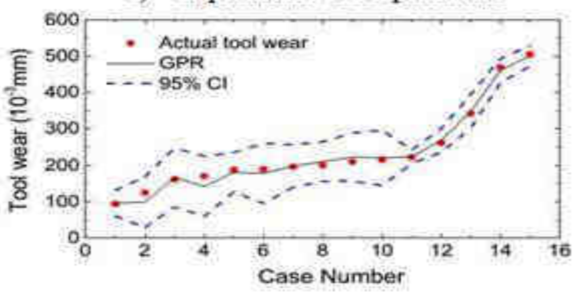


d) Performance of predictive tool wear models according to PCC

Fig. 4 The performance of models for predicting tool wear according to MAE, RMSE, MAPE, PCC.



a) Experiment No. 2 replication 2



b) Experiment No. 4 replication 1

Fig. 5 The GPR predicted results of the tool wear

The confidence interval (CI) of the predictive results can also be provided by the GPR model. In this work, a 95% CI analysis of the sample of the predicted results of the GPR was also performed. The upper and lower limits of 95% CI are given by $\bar{f_*}+2\times\sqrt{\cos(f_*)}$ and $\bar{f_*}+2\times\sqrt{\cos(f_*)}$, respectively. The predictive results of the GPR-based tool wear model are shown in Fig. 5.

CONCLUSIONS

In this study, a new method predicts tool wear based on the proposed GPR model was developed for accurately online monitoring for flank wear of tool insertion. The main tasks are summarized as follows:

- Analysis and experimental results show that the GPR model works better than ANN and SVM in terms of predictive accuracy. In addition, the GPR model can also provide confidence intervals of predictive results.
- Experimental results show that the flank wear width of the cutting tool can be accurately monitored using the robust tool wear assessment technique presented in many cutting conditions.
- Less computational efforts for model construction and comparable testing time make the GPR model an attractive option for on-line tool wear monitoring.

These research results provide important assurance to accurately monitoring the tool wear in the machining process.

REFERENCES

1. Lins, R.G., de Araujo, P.R.M., Corazzim, M.: In-process machine vision monitoring of tool wear for Cyber-Physical Production Systems. Robotics and Computer-Integrated Manufacturing 61, 101859 (2020). doi:https://doi.org/10.1016/j.rcim.2019.101859
2. Li, Z., Liu, R., Wu, D.: Data-driven smart manufacturing: Tool wear monitoring with audio signals and machine learning. Journal of Manufacturing Processes 48, 66-76 (2019). doi:https://doi.org/10.1016/j.jmapro.2019.10.020
3. Niu, B., Sun, J., Yang, B.: Multisensory based tool wear monitoring for practical applications in milling of titanium alloy. Materials Today: Proceedings 22, 1209-1217 (2020). doi:https://doi.org/10.1016/j.matpr.2019.12.126
4. Klaic, M., Murat, Z., Staroveski, T., Brezak, D.: Tool wear monitoring in rock drilling applications using vibration signals. Wear 408-409, 222-227 (2018). doi:https://doi.org/10.1016/j.wear.2018.05.012
5. avikumar, S., Ramachandran, K.I.: Tool Wear Monitoring of Multipoint Cutting Tool using Sound Signal Features Signals with Machine Learning Techniques. Materials Today: Proceedings 5(11, Part 3), 25720-25729(2018). doi:https://doi.org/10.1016/j.matpr.2018.11.014
6. Sanchez, Y., Trujillo, F.J., Sevilla, L., Marcos, M.: Indirect Monitoring Method of Tool Wear using the Analysis of Cutting Force during Dry Machining of Ti Alloys. Procedia Manufacturing 13, 623-630 (2017). doi:https://doi.org/10.1016/j.promfg.2017.09.127
7. Móricz, L., Viharos, Z.J., Németh, A., Szépligeti, A., Büki, M.: Off-line geometrical and microscopic & on-line vibration based cutting tool wear analysis for micro- milling of ceramics. Measurement 163, 108025 (2020). doi:https://doi.org/10.1016/j.measurement.2020.108025
8. Bhuiyan, M.S.H., Choudhury, I.A., Dahari, M., Nukman, Y., Dawal, S.Z.: Application of acoustic emission sensor to investigate the frequency of tool wear and plastic

deformation in tool condition monitoring. Measurement 92, 208-217 (2016). doi:https://doi.org/10.1016/j.measurement.2016.06.006

9. Corne, R., Nath, C., El Mansori, M., Kurfess, T.: Study of spindle power data with neural network for predicting real-time tool wear/breakage during inconel drilling. Journal of Manufacturing Systems 43, 287-295 (2017). doi:https://doi.org/10.1016/j.jmsy.2017.01.004
10. Balan, G.C., Epureanu, A.: - The monitoring of the turning tool wear process using an artificial neural network. In: Pham, D.T., Eldukhri, E.E., Soroka, A.J. (eds.) Intelligent Production Machines and Systems. pp. 20-25. Elsevier Science Ltd, Oxford (2006)
11. Kong, D., Chen, Y., Li, N., Duan, C., Lu, L., Chen, D.: Relevance vector machine for tool wear prediction. Mechanical Systems and Signal Processing 127, 573-594 (2019). doi:https://doi.org/10.1016/j.ymssp.2019.03.023
12. Ghosh, N., Ravi, Y.B., Patra, A., Mukhopadhyay, S., Paul, S., Mohanty, A.R., Chattopadhyay, A.B.: Estimation of tool wear during CNC milling using neural network- based sensor fusion. Mechanical Systems and Signal Processing 21(1), 466-479 (2007). doi:https://doi.org/10.1016/j.ymssp.2005.10.010
13. Kaya, B., Oysu, C., Ertunc, H.M.: Force-torque based on-line tool wear estimation system for CNC milling of Inconel 718 using neural networks. Advances in Engineering Software 42(3), 76-84 (2011). doi:https://doi.org/10.1016/j.advengsoft.2010.12.002
14. Salgado, D.R., Alonso, F.J.: An approach based on current and sound signals for in-process tool wear monitoring. International Journal of Machine Tools and Manufacture 47(14), 2140-2152 (2007). doi:https://doi.org/10.1016/j.ijmachtools.2007.04.013
15. Obikawa, T., Shinozuka, J.: Monitoring of flank wear of coated tools in high speed machining with a neural network ART2. International Journal of Machine Tools and Manufacture 44(12), 1311-1318 (2004). doi:https://doi.org/10.1016/j.ijmachtools.2004.04.021
16. Nguyen, D., Yin, S., Tang, Q., Son, P.X., Duc, L.A.: Online monitoring of surface roughness and grinding wheel wear when grinding Ti-6Al-4V titanium alloy using ANFIS-GPR hybrid algorithm and Taguchi analysis. Precision Engineering 55, 275-292 (2019). doi:https://doi.org/10.1016/j.precisioneng.2018.09.018
17. Kong, D., Chen, Y., Li, N.: Gaussian process regression for tool wear prediction. Mechanical Systems and Signal Processing 104, 556-574 (2018). doi:10.1016/j.ymssp.2017.11.021
18. Al-Hadeethi, H., Abdulla, S., Diykh, M., Deo, R.C., Green, J.H.: Adaptive boost LS-SVM classification approach for time-series signal classification in epileptic seizure diagnosis applications. Expert Systems with Applications 161, 113676 (2020). doi:https://doi.org/10.1016/j.eswa.2020.113676
19. Xu, J., Yamada, K., Seikiya, K., Tanaka, R., Yamane, Y.: Effect of different features to drill-wear prediction with back propagation neural network. Precision Engineering 38(4), 791-798 (2014). doi:https://doi.org/10.1016/j.precisioneng.2014.04.007 [20] Krishnan, S., Lokesh, S., Ramya Devi, M.: An efficient
20. Elman neural network classifier with cloud supported internet of things structure for health monitoring system. Computer Networks 151, 201-210 (2019). doi:https://doi.org/10.1016/j.comnet.2019.01.034