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Technology Forecasting Using Deep Learning Neural Network: Taking the Case of Robotics

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ABSTRACT Technology forecasting not only helps business managers to make the right decisions but also helps researchers to grasp the direction of technology development. Technology forecasting, which facilitates the identification of the development technologies with high potential, can be an effective tool to support the management and plan for the future research activities. For this purpose, this paper firstly constructs Multi-modal input based on deep learning (MIDL) text classification model to extract relevant SCI papers from Web of Science database from 1996 to 2019 for topic classification, and then apply the Ensemble Empirical Mode Decomposition (EEMD) and Long Short-Term Memory (LSTM) neural networks to build an EEMD-LSTM technology forecasting model to predict the future development of each research field. Besides, we verify the validity of the method by taking robotics as an example in this paper. The results show that the accuracy, recall and F1 of MIDL text classification model are 0.826, 0.822 and 0.824 respectively. As compared with the optimal results of other classification models, the accuracy, recall and F1 are improved by 4.1%, 3.5%, and 3.8% respectively. The mean MAPE of the EEMD-LSTM model is 7%, which is 11% lower than ARIMA, 8% lower than LSTM, and 10% lower than 2-layer-LSTM.

INDEX TERMS Technology forecasting, deep learning, artificial intelligence technology, EEMD, robotics.

I. INTRODUCTION

Nowadays, the development of a country is more and more dependent on technological innovation, and it has become a core concern for governments and enterprises to analyze and predict the development trajectory of technology and find the most promising technology areas [1]. Scientific predictive analysis of technologies can effectively address this issue. Technology forecasting is becoming an important driver of the direction of industry and technology development [2]. With the accelerated development of globalization, as the industrial paradigm undergoes significant changes and high technologies emerge, technology forecasting has received more attention from governments and business communities [3], [4]. Technology forecasting refers to the analysis of the conditions and potential of technological development within a specific framework, a continuous observational study of the current status and development of technologies, which leads to a preliminary determination of their future fields of application and prospects and an assessment of their potential. Technology forecasting not only assists science and technology strategy makers in making scientific decisions, but also

helps researchers to grasp the direction of technology development and is an effective tool to support the management and planning of future research activities.

In the early stage of the study, scholars often used the method of expert opinion for technical forecasting [5], [6]. The method is based on expert experience. Its process relies mainly on expert experience and domain knowledge for technology identification and forecasting [7], [8]. There is methodological technocratic dependence [9], and its objectivity, consistency, validity, and comprehensiveness are increasingly challenged [10]–[12]. Since quantitative analysis methods are continuously applied to technology forecasting [13], [14], existing studies have attempted to improve the reliability and validity of technology forecasting using paper and patent data [15]. These methods can help to some extent to solve the problem of subjective bias of experts [16], [17]. Latent Dirichlet Allocation (LDA) and Subject-Action-Object (SAO) methods are used to mine papers and patent topics. Technology evolution paths are identified thereby enabling technology forecasting [18]. However, SAO is more of a solution for key information extraction, and it is difficult to carry out deep content mining and scale processing of massive data at this stage. The topic model of LDA is able to identify hidden topics from massive text information

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in a targeted manner by quantifying massive text through probabilistic models [19], and predict technical topic trends through its probability distribution [20].

Patents and papers are the carriers of technical information. In recent years, scholars have started to make technology forecasts in terms of the number of publications of papers and patents [21]. Technology forecasting through analysis of the number of papers and patents is a time series forecasting (TSF) problem. At present, the common methods for TSF are regressions, machine learning and deep learning [22]. Regressions commonly use the methods including multiple linear regression, autoregressive moving average (ARMA) [23], and autoregressive integrated moving average (ARIMA) [24]. Machine learning such as Support Vector Machine (SVM) [25], [26], Decision Tree (DT) [27], Random Forest (RF) [28] and artificial neural networks (ANNs) have been applied to TSF. In recent years the use of deep learning methods to construct TSF models is a relatively popular research topic. Deep learning has a deeper and broader network structure than machine learning, which can significantly improve prediction accuracy [29]. Mudassir, *et al.* [30] used Long-Short Term Memory (LSTM) network for forecasting bitcoin price fluctuations. Cai, *et al.* [31] used generalized regression neural network (GRNN) for wind power prediction, and the results showed that the deep learning approach has higher forecasting accuracy.

In order to further improve the prediction accuracy, some scholars have used decompose time series [32] and matrix profile [33] to process the time series data. The processed data are constructed into TSF models and then predicted to obtain more accurate prediction results. Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD) are effective tools to decompose time series and they have been applied in previous researches. The EMD method is an adaptive time-decomposition time series method, which does not require a predetermined number of decomposition layers and basis functions, but rather decomposes the data according to its own complex fluctuation characteristics. Kong, *et al.* [32] constructed an EMD-CNN-LSTM prediction model to achieve short-term load forecasting for electricity, and the results showed that the model has a higher prediction accuracy. In EMD decomposition, when there are outliers in the signal, it will affect the selection of the extreme points, thus making the distribution of the extreme points uneven and generating the phenomenon of mode mixing [34]. To deal with this situation Wu and Huang [35] proposed the EEMD method to compensate for the shortcomings of the EMD method. Jiang, *et al.* [36] combined EEMD and online least square support vector machine (OLSSVM) to achieve electricity demand forecasting with much higher prediction accuracy than traditional machine learning algorithms.

As mentioned above, current scholars have conducted in-depth research on technology forecasting, while for technology forecasting methods are slightly inadequate. Many scholars still use the method of expert opinion for technical forecasting, and the method sometimes suffers from

objectivity challenges in forecasting results due to the over-reliance on the subjective judgment of experts. Deep learning has been widely used in various prediction fields because of its advantages, such as high prediction accuracy and applicability, but few scholars have applied deep learning to technology forecasting. In addition, the different types of literature characterize the different stages of technological development. SCI papers can reflect the basic stage of technological research, and patent data characterize the stage of technological research experimental development [37]. Suitable data should be selected for analysis in the research process according to the actual research purpose. Therefore, this paper proposes a technology prediction method that incorporates deep learning and signal decomposition. Using robotics as a research example, we select data from SCI papers to predict the development of basic research stages of robotics and then verify the validity of the model. The main contributions of this paper are summarized as follows:

- Multi-modal input based on deep learning (MIDL) text classification model is proposed, which reduces the training parameters and time by using pre-training method. LDA topic extraction feature words and paper titles are used as input data for text classification to further improve the accuracy of prediction results.
- A technical forecasting method containing a time series data decomposition layer and a forecasting layer is proposed. In the data decomposition layer, the EEMD method is first used to decompose the time series data published in the paper, and the decomposed results are separately predicted by LSTM, and finally the prediction results are combined to obtain the final prediction results.
- In this paper, we use robotics as a research example and select SCI papers to forecast the development of basic research stages in robotics. The text classification aspect is compared with DT, SVM, Native Bayes (BN), Bagging and Xgboost algorithms. The results show that the prediction accuracy, recall and F1 value of the MIDL text classification model are optimal. The technical forecasting aspects are compared with LSTM, ARIMA, and 2-Layer LSTM models. The results show that the EEMD-LSTM proposed in this paper has better performance in each metrics.

The remainder of this paper is organized as follows, and the next section describes the research methodology of this paper in detail. The third section shows the experimental procedure and analyzes the results. Finally, a discussion is presented and conclusions are given.

II. METHODOLOGY

The technology forecasting model constructed in this paper consists of the following three main parts. Firstly, data collection and pre-processing. Secondly, constructing the MIDL paper classification model to identify the research topics of each paper. Thirdly, constructing the EEMD-LSTM technology forecasting model to predict the

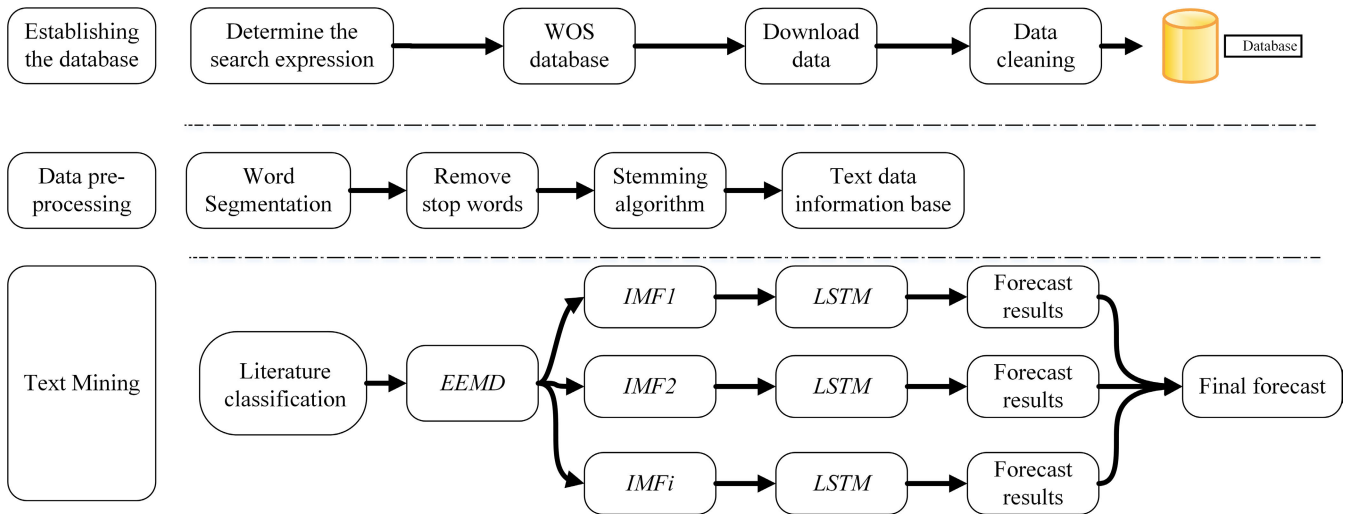


FIGURE 1. Research framework.

future development of each research area. The specific steps are shown in Figure 1.

A. CONSTRUCTION OF TRAINING AND TEST SETS

The data of all papers on robotics is retrieved from the Web of Science database. Subsequently, all information fields of all retrieved papers are downloaded in bulk from the Web of Science database. The textual data is pre-processed in Python to exclude data from papers that lacks keywords and abstracts. It is difficult and time-consuming to screen the raw data by manual screening because of the large raw data. Therefore, in this paper, we combine the initial screening of feature words with manual labeling to screen the training samples, as shown in Figure 2. Firstly, we identify the main research areas of robotics based on the Clarivate Analytics study [38]. The 2-3 feature words in each area of research were identified by consulting experts After that, python is used to match the abstract text data with feature words, and the data that do not contain feature words in the abstract is excluded to obtain the initial data set. Then two independent back-to-back data tagging method is used to label the category of the paper by reading the summary and title of the primary data sample, and the noise samples which are not related to the category are eliminated. Data samples from each study area are eventually obtained, and according to the ratio of 8:2, randomly selected literature as training data and test data.

Text data is an unstructured data. In order to make the machine understand and process textual information, it is necessary to transform text into a structured data which is easy to understand and process by computer. The LDA topic model is widely used in text clustering, topic mining, and similarity computation, and has the advantage of strong generalization ability and poor over fitting compared to other topic analysis models [39]. It uses an unsupervised machine learning model, and the analysis can be automatically trained and obtained for topic and feature word probabilities using only training data input, without the need for manual data labeling.

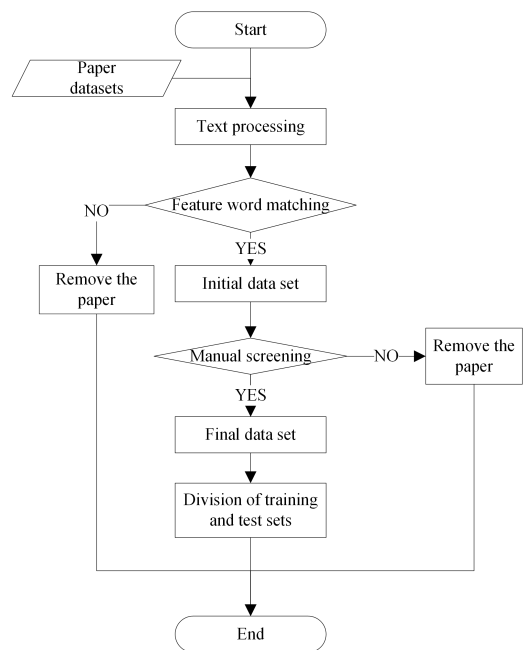


FIGURE 2. Flowchart of training set and test set selection.

Previous scholars have often analyzed article abstracts through word frequency statistics, an approach that often fails to yield more accurate results [40]. In this paper, the LDA topic model is used to extract the themes of the abstracts, which can be used to uncover potential themes and relevant feature words in the dataset.

B. MIDL TEXT CLASSIFICATION MODEL

In this paper, the MIDL paper classification model is constructed to classify the literature research topics, and the model framework is shown in Figure 3.

In order to apply machine learning to textual data, it is necessary to convert the textual data into a digital feature vector. In natural language processing field, word embedding

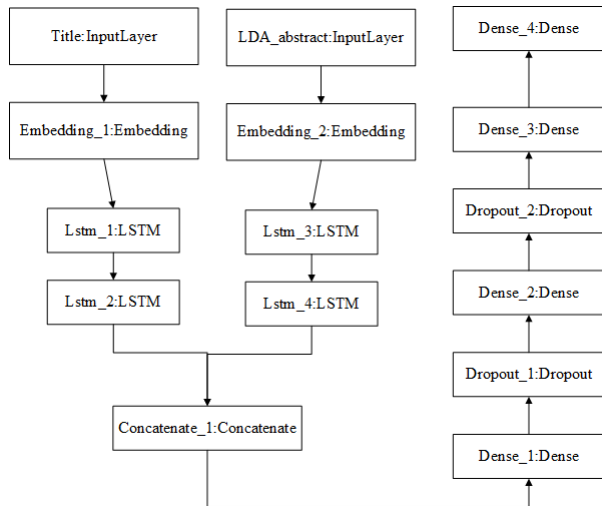


FIGURE 3. MIDL paper classification model framework.

is normally used to transform text data into digital feature vectors. The commonly use word embedding algorithms are word2vec, GloVe and FastText. FastText is a text classification tool proposed by Facebook in 2016 as an efficient shallow network. FastText model architecture and Word2Vec in the CBOW model is very similar, the difference is that the CBOW input is the target word context. FastText input is a number of words and their N-gram features, these features are used to represent a single document. Studies have shown that FastText performs better than word2vec [41]. Therefore, this paper builds MIDL text classification model using FastText word embedding algorithm for text data. The detailed process is as follows:

1) DATA PRE-PROCESSING

The paper title and the LDA-extracted paper abstract feature words are processed by word separation. To ensure the uniformity of the model input data, the “pad_sequences” function in the Keras library is used to preprocess the word separation results of the paper title and feature words, respectively.

2) PREPARING THE WORD EMBEDDING MATRIX

Download FastText word embedding data, this paper uses the crawl-300d-2M file for word embedding training, the file contains 300-dimensional embedding vectors of two million words. Then write a program in Python to parse the FastText file and construct the word embedding matrix (embedding matrix).

3) DEFINING THE MODEL

The parameter settings for each layer of the MIDL text classification model constructed in this paper are shown in appendix A.

4) FastText EMBEDDING

Load the FastText word embedding matrix into the embedding layer of the MIDL text classification model and freeze the embedding layer training.

5) SETTING PARAMETERS

Setting training set and test set for training. Select “RMSProp” for the model optimizer, set “batch size” to 64 and “categorical_crossentropy” for the loss function.

C. EEMD

Empirical Mode Decomposition (EMD) performs layer-by-layer decomposition based on different time scales in the signal [34]. It can be decomposed into a set of independent Intrinsic Mode Functions (IMFs) with steady-state features from the original time series based on the local feature scale of the data itself. The analysis of the IMFs allows the extraction of the characteristic information contained in the raw data. Each IMFs must meet two conditions: on the one hand, the number of extremes and cross-zero points in the entire data series is equal or differs by a maximum of 1. On the other hand, at any moment, the mean of the upper envelope consisting of local maxima and the lower envelope consisting of local minima is zero, that is, the upper and lower envelopes are locally symmetric with respect to the time axis. The decomposition result is shown in (1). Set the original signal as $x(t)$ and obtain a series of IMFs through EMD.

$$x(t) = \sum_{i=1}^n imf_i(t) + r(t) \quad (1)$$

where $imf_i(t)$ denotes the i -th IMF and $r(t)$ is the decomposition residual term. IMFs obtained are listed in descending order of frequency [42].

In EMD decomposition, when there are outliers in the signal, it will affect the selection of the extreme points, which will be unevenly distributed. The case where the obtained envelope line is a combination of the local envelope and the real signal envelope with anomalous values will result in pattern overlap [34]. To compensate for the shortcomings of the EMD method, Wu and Huang [35] proposed an EEMD decomposition method using white noise as an adjunct. The EEMD decomposition adds white noise to the signal to be decomposed to smooth out anomalous events, and makes use of the uniform distribution of white noise spectrum to automatically distribute signals of different scales to a suitable reference scale. Using the zero-mean characteristic of white noise, the noise is averaged many times so that it cancels each other out, thus suppressing the effects of noise. The EEMD process is as follows:

A white Gaussian noise with M times mean 0 and constant amplitude standard deviation is added to the original signal $x(t)$.

$$x_i(t) = x(t) + n_i(t) \quad (2)$$

where $n_i(t)$ is white Gaussian noise, $M > 1$, $i = 1 \sim M$. Perform EMD decomposition on $x_i(t)$ separately. The K IMFs are obtained as $c_{ij}(t)$ ($j = 1 \sim K$) and the remainder as $r_i(t)$. The obtained IMFs are averaged to eliminate the effect of adding white noise multiple times on the true IMFs, which

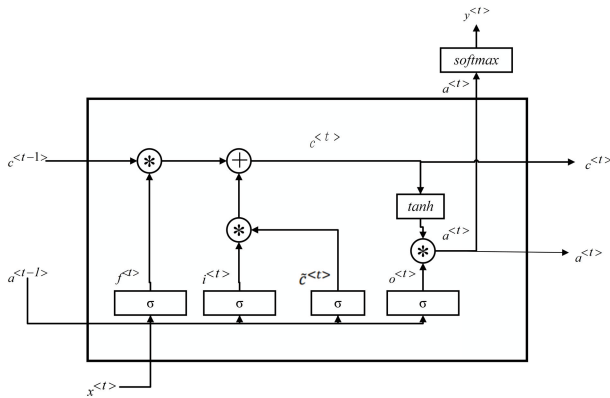


FIGURE 4. STM.

are obtained by EEMD decomposition as follows:

$$c_j(t) = \frac{1}{M} \sum_{i=1}^M c_{ij}(t) \quad (3)$$

where $c_j(t)$ denotes the j -th IMFs obtained after EEMD decomposition of the original signal.

D. LSTM

LSTM is essentially a deformation of Recurrent Neural Network (RNN). The model resembles a standard recurrent neural network with hidden layers, but with nodes in each common layer replaced by storage units. The LSTM model adds input gates, output gates, and forgot gates to the neuronal portion of the RNN. This design structure is an effective solution to the problem of disappearing gradients, making LSTM well suited to deal with long-term dependency problems. The detailed schematic diagram of the structural unit of the LSTM neural network is shown in Figure 4.

At moment t , the inputs of LSTM neural network are $x^{<t>}$, $c^{<t-1>}$, and $a^{<t-1>}$, and the outputs are $c^{<t>}$ and $a^{<t>}$, where $x^{<t>}$ is the t moment sequence input value, $c^{<t-1>}$ is the LSTM neural network $t-1$ moment gate control unit state, and $a^{<t-1>}$ is the LSTM neural network $t-1$ moment output value. $a^{<t>}$ and $c^{<t>}$ are the values of the LSTM neural network at time t and the state of the gate control unit at time t . In the LSTM neural network, the input gate controls the degree of influence of $x^{<t>}$ on $c^{<t>}$, the forgot gate controls the degree of influence of $c^{<t-1>}$ on $c^{<t>}$, and the output gate controls the degree of influence of $c^{<t>}$ on $a^{<t>}$.

$$\Gamma_f = \sigma \left(W_f \left[a^{<t-1>}, x^t \right] + b_f \right) \quad (4)$$

$$\Gamma_i = \sigma \left(W_i \left[a^{<t-1>}, x^t \right] + b_i \right) \quad (5)$$

$$\Gamma_o = \sigma \left(W_o \left[a^{<t-1>}, x^t \right] + b_o \right) \quad (6)$$

where Γ_f , Γ_i , and Γ_o are the state of the forget gate, input gate, and output gate. W_f , W_i , and W_o denote the weight matrix of forgot gates, input gates, and output gates. b_f , b_i , and b_o are the forgot gate, input gate, and output gate biases. The final result of the LSTM neural network is determined by the

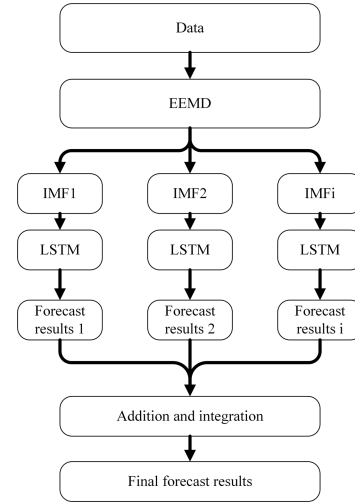


FIGURE 5. EEMD-LSTM.

output gates and unit states in the network.

$$\tilde{c}^{(t)} = \tan \left(W_c \left[a^{<t-1>}, x^t \right] + b_c \right) \quad (7)$$

$$c^{(t)} = \Gamma_i * \tilde{c}^{(t)} + \Gamma_f * c^{<t-1>} \quad (8)$$

$$a^{(t)} = \Gamma_o * \tanh \left(c^{(t)} \right) \quad (9)$$

where $c^{(t)}$ is the input unit state of the LSTM neural network at time t , W_c is the input unit state weight matrix, b_c is the input unit state bias term, and finally the output of the LSTM neural network at time t is obtained as $a^{(t)}$ and $c^{(t)}$.

E. EEMD-LSTM

The time series data fluctuations by EEMD decomposition are relatively simple, creating favorable conditions for further construction of high-precision prediction models. Therefore, this paper combines both EEMD and LSTM methods to construct a new technology forecasting method. Figure 5 shows the flow of EEMD-LSTM. Firstly, the EEMD decomposition is used to obtain the high-frequency and low-frequency components and trend items for each research area by taking the year-by-year time series data of the number of papers in each research area as input data. Secondly, establishing corresponding LSTM forecasting models for the high-frequency and low-frequency components. Finally, the prediction values for each sequence are obtained from the LSTM prediction model for each component, and the final prediction results are obtained by summing.

In this paper, Python is used to write the EEMD-LSTM model. Keras is used to build the model, and the background is “Tensorflow”. The parameters are shown in Table 1.

III. ANALYSIS RESULTS

A. DATA COLLECTION AND PRE-PROCESSING

1) DATA COLLECTION

This paper collects SCI paper data from the Web of Science database. The search is conducted on the subject with robot as the keyword and the search date is October 21, 2020. The time

TABLE 1. Model parameter.

Parameter	2-layer LSTM	LSTM
Units	32	32
LSTM	2	1
Batch_size	1	1
Lr	0.001	0.001
Dropout	0.1	-
Activation	Tanh	Tanh

period is chosen from 1996 to 2019, and the document type is “Article”. A total of 28,831 papers are obtained, eliminating the literature with missing abstracts and keywords, and finally 28,632 papers are obtained as the primary data for this study.

2) PRE-PROCESSING

Data pre-processing is a fundamental part of text mining and topic recognition. The pre-processing of abstract data is used to standardize and structure the abstract data so that it can be used as input data for natural language processing. The quality of the data pre-processing directly affects the quality of thematic analysis and text classification. This is why abstract data pre-processing is very important. In this paper, we use Python language to divide the abstracts of papers, remove stop words and extract stemming text pre-processing, and then ensure the quality of model results.

B. CONSTRUCTION OF TRAINING SET AND TEST SET

The data from the paper on robotics is selected for this experiment to verify the method validity. According to a report on robotics published by Clarivate Analytics in 2018 [38], the current phase of robotics research is focused on Machine Learning, Machine Control, Man-Machine Interface, Medical Application, and Control Algorithm. Therefore, this paper selects eight key research areas of robotics based on this research report and expert opinion: Intelligent Robot(IR), Parallel Robots(PR), Humanoid Robot Human-Computer Interaction(HR), Social Robots(SR), Robot Adaptive Control System(RACS), Mobile Robot Path Planning(MRPP), Medical Surgical Robot(MSR) and Medical Rehabilitation Robot(MRR) to conduct experiments on the MIDL text classification model. In order to accurately screen the experimental training set and the test set, the feature words for each research area are selected based on the area of expertise of each robotics technology. The feature terms for each research area are shown in Table 2.

In this paper, a 2-person independent back-to-back data labeling method is used to classify the primary data into categories, in order to ensure the accuracy of the identification results. The excluded irrelevant noise files are added to other research areas for training. Details of the data samples, training and test sets for each research area are shown in the Table 3.

This paper uses the LDA topic model for topic extraction of abstracts. The core of the model is the estimation of the parameters θ and ϕ , the approximate estimation of which is usually done using a special case of Gibbs sampling in the Markov chain Monte Carlo algorithm.

TABLE 2. Characteristics of key research areas.

Research Areas	Key Research Areas	Characteristic Word
Machine Learning	Intelligent Robot	autonomous robot intelligent robot
Machine Control	Parallel Robots	parallel robots parallel manipulator
Man-Machine Interface	Humanoid Robot Human-Computer Interaction	human-robot interaction humanoid robot
	Social Robots	social robots human-robot interaction
Control Algorithm	Robot Adaptive Control System	adaptive control robot manipulators robot control
	Mobile Robot Path Planning	robot path planning mobile robot
Medical Application	Medical Surgical Robot	medical robot surgical robot
	Medical Rehabilitation Robot	rehabilitation robot assistive robot

TABLE 3. Sample data, training data, test data.

Key Research Areas	Sample	Train	Test
Intelligent Robot	340	272	68
Parallel Robots	593	473	120
Humanoid Robot Human-Computer Interaction	379	303	76
Social Robots	701	561	140
Robot Adaptive Control System	638	509	129
Mobile Robot Path Planning	562	450	112
Medical Surgical Robot	474	379	95
Medical Rehabilitation Robot	548	438	110
Other	970	693	277
Total	5205	4078	1127

Approximate estimation of the parameters of the LDA thematic model using Gibbs sampling method requires determining the best values for three variables in the model: the prior parameters α , β and the number of themes K .

In order to determine the number of topics K for the LDA topic model, this paper first calculates the degree of perplexity for different numbers of topics, and the detailed results are shown in Figure 6. Figure 6 shows that as the number of topics increases, the model perplexity gradually decreases, but there is no “breaking point” where the exact number of topics can be obtained. Then, we calculate and plot the relationship between the number of topics and the model consistency score as shown in Figure 6, which shows that the model has the highest score when the number of topics is 2, indicating that the model works optimally when the number of topics is 2 [43]. The final number of themes $K = 2$ of the LDA theme model is determined, and the two themes and 20 feature words under the corresponding themes of each literature abstract are extracted to form the feature words of each literature. In addition, the priori parameters are set to empirical values $\alpha = 50/K$ and $\beta = 0.1$ [44].

C. COMPARATIVE ANALYSIS OF CLASSIFICATION RESULTS

The common models for text classification are DT, SVM, NB, Bagging and Xgboost algorithm. To compare and analyze the effectiveness of the MIDL classification, the natural language processing TF-IDF algorithm is used to quantify the word vectors of abstracts and LDA topic model-based abstract feature words, which constitute the feature vectors of each classification model. Decision Trees, Support

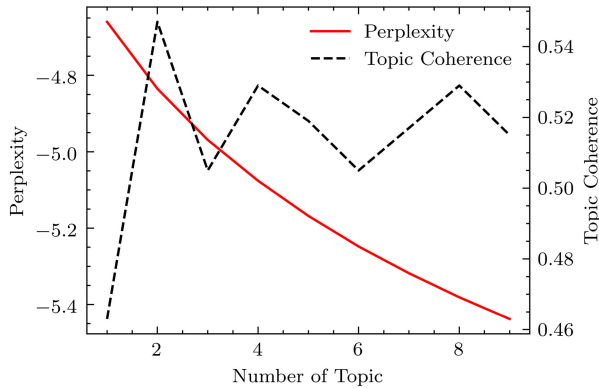


FIGURE 6. Graph of topic perplexity and consistency scores.

TABLE 4. Average accuracy, average recall, and average F1 values for text classification models.

Model	Accuracy	Recall	F1
LDA-DT	0.639	0.641	0.640
LDA-NB	0.645	0.713	0.677
LDA-SVM	0.726	0.722	0.724
LDA-Bagging	0.650	0.657	0.653
LDA-Xgboost	0.743	0.747	0.745
MIDL	0.826	0.822	0.824
DT	0.717	0.711	0.714
NB	0.639	0.697	0.667
SVM	0.721	0.723	0.727
Bagging	0.630	0.646	0.638
Xgboost	0.785	0.787	0.786

TABLE 5. Number of papers and ARIMA optimal parameters by research area.

Research Areas	Number	ARIMA
Intelligent Robot	1242	0,1,1
Parallel Robots	986	0,1,1
Humanoid Robot Human-Computer Interaction	2654	1,1,1
Social Robots	1784	2,1,2
Robot Adaptive Control System	5523	0,1,2
Mobile Robot Path Planning	3154	1,2,2
Medical Surgical Robot	2402	0,2,1
Medical Rehabilitation Robot	1245	1,1,1
Other	9642	

Vector Machines, Bayesian, Bagging and Xgboost algorithms are selected to construct text classification models. Then, the classification results of each text classification model are evaluated. This paper compares the classification results of each model using accuracy, recall and F1 values. The accuracy, recall, and F1 values for each model are shown in Table 4.

According to Table 4, the proposed MIDL text classification model is better than other text classification models in terms of accuracy, recall rate and F1 value. The results show that the MIDL text classification model can significantly improve the classification accuracy and can be applied to the literature classification field in the future. Subsequently, the MIDL text classification model is applied to identify the topics of all the SCI literature on robotics, and then we obtain the distribution of articles in the eight main research fields of robotics, and the statistical results are shown in Table 5.

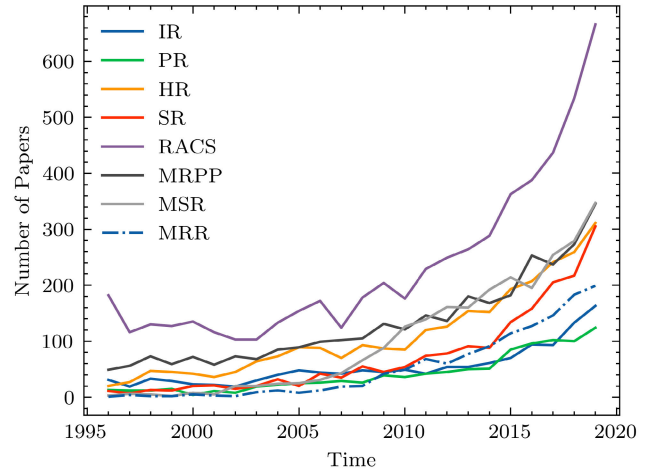


FIGURE 7. Time series of number of papers by research area.

D. ANALYSIS OF FORECAST RESULTS BASED ON EEMD-LSTM

Based on the number of papers published in each research field from 1996 to 2019, a time series plotting the number of papers published year by year in each research field is shown in Figure 7. As can be seen in the figure, the number of articles issued in all research areas shows an upward trend from 1996 to 2019, but the growth rate of time series data varies by research area, and some research areas show a decline in some years.

1) ANALYSIS OF EEMD RESULTS

In order to better present the EEMD decomposition results, this paper performs EEMD decomposition on the time series data of Robot Adaptive Control System, and the results are shown in Figure 8. Three IMFs are obtained in total. Figure 8 shows that the high-frequency component of the year-by-year number of papers published is separated from the low-frequency component by EEMD. The components IMF1, IMF2, and IMF3 represent the high-frequency to low-frequency components of the Robot Adaptive Control System, with IMF1 being the most high-frequency component. IMF3 represents the general trend of change in the number of papers published year by year for the Robot Adaptive Control System, which shows an upward trend.

2) COMPARATIVE ANALYSIS

Since the Web of Science database of robotics-related literature dates back to 1996, this paper selects the 1996-2016 paper publication data as the training set, and the number of publications from 2017 to 2019 as the test set for the construction of an EEMD-LSTM-based time series forecasting model. In order to compare and analyze the predictions of the EEMD-LSTM model, this paper uses the LSTM neural network, optimal ARIMA and 2-layer LSTM neural network models to construct a time series prediction model for the experimental data. Predictions are measured using root mean square error (RMSE) and mean absolute percent error (MAPE). ARIMA is a classical method of time series

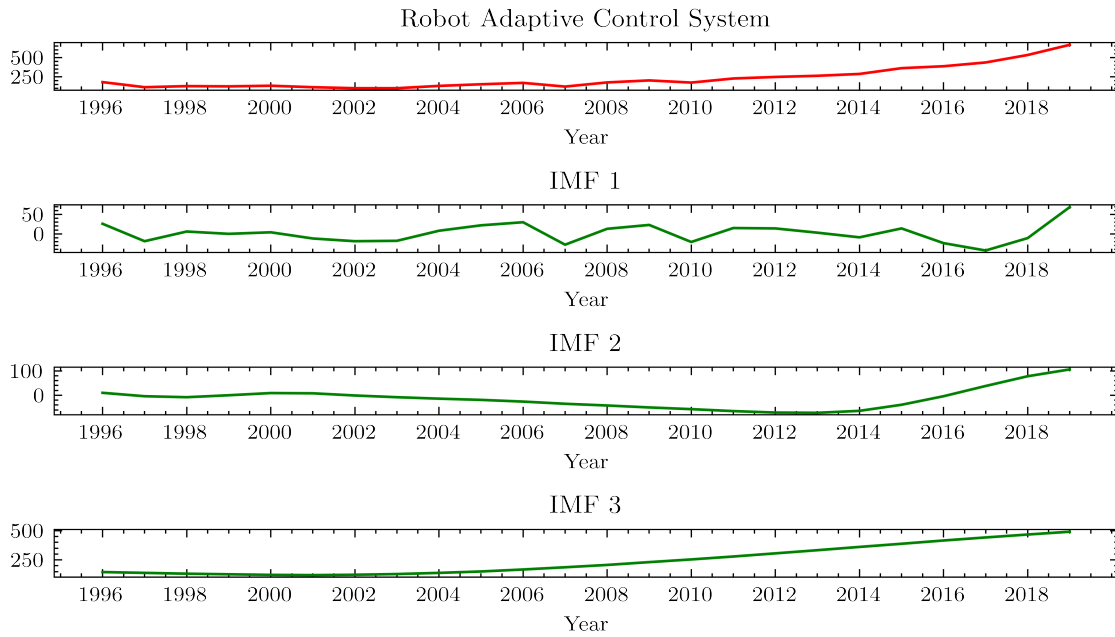


FIGURE 8. Robot Adaptive Control System time series EEMD diagram.

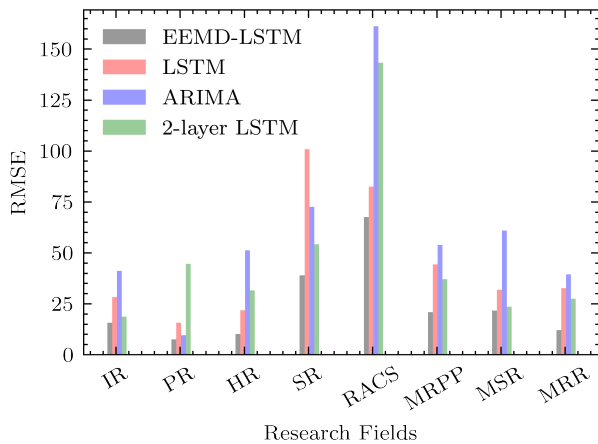


FIGURE 9. Predictive model RMSE comparison chart.

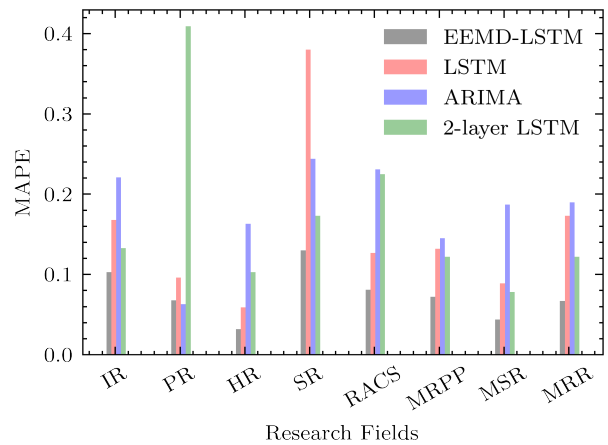


FIGURE 10. Predictive model MAPE comparison chart.

analysis, which can be expressed as ARIMA (p, d, q). In this paper, BIC values are used to determine the optimal parameters of autoregressive coefficient (p), the number of differences (d) and the moving average term (q). The detailed results are shown in Table 5. The year-by-year published data in each research area passed the smoothness test (ADP) and the residual white noise test, and the optimal ARIMA model all passed the residual test. The various parameters of the LSTM neural network prediction model are identical to EEMD-LSTM, and the parameter settings are detailed in Table 1.

Figure 9 shows the RMSE values predicted by the four prediction models for the test data. It can be seen that the prediction results of the EEMD-LSTM model are basically better than other prediction models, especially when predicting areas with large data fluctuations, the prediction accuracy is greatly improved.

Figure 10 shows the MAPE values for the four prediction model experiments, with predictions similar to RMSE. The EEMD-LSTM time series prediction model outperformed the remaining three models in many areas, and the prediction errors in many study areas were substantially smaller than the three prediction models in the control experiment. The MAPE of the EEMD-LSTM prediction model is essentially less than 10%, which indicates that the model predictions are closer to reality.

Table 6 shows the variance and mean of the prediction errors of the four prediction models. It reflects that the mean and variance of RMSE and MAPE for the EEMD-LSTM predictions are much lower than for the control prediction model. The results show that the EEMD-LSTM model can not only improve the prediction accuracy, but also has higher stability.

TABLE 6. Variance and mean of the four prediction models RMSE and MAPE.

Model	RMSE		MAPE	
	Variance	Mean	Variance	Mean
ARIMA	1726.825	61.26	0.003	0.18
2-layer-LSTM	1424.126	47.59	0.01	0.17
EEMD-LSTM	349.883	24.356	0.001	0.07
LSTM	815.747	44.75	0.009	0.15

TABLE 7. Trend in the number of papers by field of study.

Key Research Areas	2020	2021	2022	2023
Intelligent Robot	133	146	155	186
Parallel Robots	122	110	125	132
Humanoid Robot				
Human-Computer Interaction	294	330	334	343
Social Robots	234	254	276	293
Robot Adaptive Control System	532	592	621	591
Mobile Robot Path Planning	292	294	310	326
Medical Surgical Robot	302	316	320	347
Medical Rehabilitation Robot	196	182	202	206

E. FORECAST RESULTS

The EEMD-LSTM model is used to predict the number of papers in each research area of robotics from 2020 to 2023, and the predictions are shown in Table 7.

Table 7 shows that the state of development of the robotics research field can be divided into four categories based on the number of papers and future trends.

The first category, this field is characterized by a large and growing number of annual publications. These research areas are at the core of robotics research and will attract a large number of scholars for continued exploration and research in the future. Medical Surgical Robot, Social Robots and Humanoid Robot Human-Computer Interaction are exactly this type of technology, and these research areas will be ongoing research interests in the future. For these research areas, the government can increase investment in research and development, and innovative research institutes and enterprises should be fostered to carry out technological research and development. Efforts should be made to overcome key core technologies and promote the deep integration of industry, universities and research, so as to occupy the technological high point and form an asymmetrical advantage in technological innovation.

The second category, the field shows a large number of future publications but stagnant growth. These research areas are still the hotspots of today's academic research, but future development may enter a "bottleneck" period. The core technologies in these areas require systemic breakthroughs that will lead to continued development of research areas. Robot Adaptive Control System, Mobile Robot Path Planning falls into this category. For these research areas, the country should combine core technologies and research foundations and concentrate resources to build a number of key national science and technology research teams, deploying a number of targeted research projects on core technologies and conducting scientific research, accelerate the development

of core technologies, and enhance independent innovation capacity and competitiveness in scientific and technological innovation.

The third category, which has a relatively small amount of relevant research literature, but has significantly increased its impact in recent years. It is a frontier area of robotics with rapid future growth. These research areas have already attracted a large number of researchers worldwide in a short period of time, such as Intelligent Robot. For this type of research, the government should encourage enterprises and research institutes to work closely together, actively participate, collaborate and innovate to promote the all-round development of frontier technologies, thus moving towards more advanced research fields.

The fourth category, these areas are characterized by a small number of future publications and slow growth. These research areas are emerging areas of robotics with high potential for future development, such as Medical Rehabilitation Robot and Parallel Robots. Government can consider giving priority support to science, technology and innovation funding for these research areas, encourage and support young innovators to explore and innovate in the new fields, wide interdisciplinary research and multidisciplinary convergence, and then promote innovation and development in these fields.

IV. CONCLUSION

In this paper, we construct a MIDL text classification model, and the input data use the abstract subject terms and paper titles to improve the classification accuracy. A new time series forecasting model is proposed. The time series data are separated from high frequency to low frequency by EEMD, and the decomposition results are put into the LSTM model for training, and the prediction results of each series are summed to obtain the final prediction results. This paper verifies the effectiveness of the method by using robotics as an example. The conclusions are summarized as follows:

The prediction accuracy of the MIDL text classification model proposed in this paper is 0.826, the recall is 0.822, and the F1 value is 0.824. The analysis is found by comparing with DT, NB, SVM, Bagging and Xgboost algorithms. The F1 value of the MIDL model is significantly improved by 15.41% for DT, 23.53% for NB, 13.34% for SVM, 29.15% for Bagging, and 4.83% for Xgboost.

In terms of time series prediction. The use of deep learning methods can significantly improve the prediction performance, which indicates that deep learning models can better achieve technical forecasting. The time series model combining EEMD and LSTM proposed in this paper has better performance. The mean RMSE of the EEMD-LSTM model is 24.35, which is much lower than that of ARIMA, LSTM and 2-layer-LSTM. The mean MAPE of EEMD-LSTM is 7%, and this result is improved by 11% compared to ARIMA, 10% for 2-layer-LSTM, and 8% for LSTM. In addition, the RMSE and MAPE variance of the EEMD-LSTM prediction model are much lower than those of the LSTM,

Layer	Name	Parameter Names	Parameter Settings
Input Layer	Title	character size	30
Input Layer	LDA_abstract	character size	40
Embedding	Embedding_1	dimension	300
Embedding	Embedding_2	dimension	300
LSTM	Lstm_1	dropout	0.1
		recurrent_dropout	0.5
		units	64
LSTM	Lstm_2	units	32
LSTM	Lstm_3	dropout	0.1
		recurrent_dropout	0.5
		units	64
LSTM	Lstm_4	units	32
Dense	Dense_1	units	512
		activation	relu
		regularization	L2
		lr	0.001
Dropout	Dropout_1	dropout	0.5
Dense	Dense_2	units	256
		activation	relu
		regularization	L2
		lr	0.001
Dropout	Dropout_2	dropout	0.5
Dense	Dense_4	units	128
		activation	relu
		regularization	L2
		lr	0.001
Dense	Dense_5	Units	9
		activation	softmax

ARIMA and 2-layer LSTM, which indicates that the EEMD-LSTM model has high stability while ensuring prediction accuracy.

The technical prediction method proposed in this paper is applied to predict future SCI publications in robotics, and thus to understand the future trends of robotics. Medical Surgical Robot, Social Robots and Humanoid Robot Human-Computer Interaction are the core areas of robotics research at this stage. For these research areas, the country can increase its R&D investment and focus on conquering key core technologies to seize the technological high ground to form asymmetric advantages in science and technology innovation.

Rapid identification of technology trends for technology researchers is the main purpose of this paper. The identification of research topics in SCI papers enables a quicker understanding of the current state of technology development. In addition, deep learning applied to technology prediction can more accurately predict the future development trend of technology. It provides effective data support for enterprise technology layout. It also provides new solution ideas and methods for technology prediction.

In addition, there are some limitations in this study that will be the focus of subsequent research. For instance, this paper only uses a single dimension of information for technology prediction, so the research results can only reflect the actual situation of the basic research stage represented by SCI papers. Therefore, future research studies will consider combining patents and other relevant data to achieve technology prediction, and further improve the accuracy of prediction results.

APPENDIX I. MIDL TEXT CLASSIFICATION MODEL PARAMETER SETTINGS FOR EACH LAYER REFERENCES

- [1] I. Miles, "The development of technology foresight: A review," *Technol. Forecasting Social Change*, vol. 77, no. 9, pp. 1448–1456, Nov. 2010.
- [2] A. K. Firat, W. L. Woon, and S. Madnick, *Technological Forecasting—A Review*. Cambridge, MA, USA: Composite Information Systems Laboratory (CISL), Massachusetts Institute of Technology, 2008.
- [3] H. Grupp and H. A. Linstone, "National technology foresight activities around the globe - Resurrection and new paradigms," *Technol Forecast Soc*, vol. 60, no. 1, pp. 85–94, Jan. 1999.
- [4] C. Pietrobelli and F. Puppato, "Technology foresight and industrial strategy," *Technol. Forecasting Social Change*, vol. 110, pp. 117–125, Sep. 2016.
- [5] T. Lintonen, A. Konu, S. Rönkä, and E. Kotovirta, "Drugs foresight 2020: A Delphi expert panel study," *Substance Abuse Treatment, Prevention, Policy*, vol. 9, no. 1, p. 18, May 2014.
- [6] M. Esmailian, M. Tavana, D. Di Caprio, and R. Ansari, "A multiple correspondence analysis model for evaluating technology foresight methods," *Technol. Forecasting Social Change*, vol. 125, pp. 188–205, Dec. 2017.
- [7] B. R. Martin, "Technology Foresight: A review of recent government exercises," *Sci., Technol., Ind. Rev.*, vol. 17, pp. 15–50, 1996.
- [8] T. Shin, "Delphi study at the multi-country level: Gains and limitations," in *Proc. Int. Conf. Technol. Foresight, Approach Potential New Technol. Foresight. Nat. Inst. Sci. Technol. Policy*, 2001, pp. 161–172.
- [9] S. Y. Liu and Y. C. Wang, "A study of applying fuzzy theory in simulation-based education," *Appl. Sci.*, vol. 9, no. 10, p. 1989, May 2019.
- [10] G. Tichy, "The over-optimism among experts in assessment and foresight," *Technol. Forecasting Social Change*, vol. 71, no. 4, pp. 341–363, May 2004.
- [11] H. Liu, J. Yu, J. Xu, Y. Fan, and X. Bao, "Identification of key oil refining technologies for China national petroleum Co. (CNPC)," *Energy Policy*, vol. 35, no. 4, pp. 2635–2647, Apr. 2007.
- [12] B. Förster and H. von der Gracht, "Assessing Delphi panel composition for strategic foresight—A comparison of panels based on company-internal and external participants," *Technol. Forecasting Social Change*, vol. 84, pp. 215–229, May 2014.
- [13] Y. Cho, S.-P. Yoon, and K.-S. Kim, "An industrial technology roadmap for supporting public R&D planning," *Technol. Forecasting Social Change*, vol. 107, pp. 1–12, Jun. 2016.
- [14] S. J. Barnes and J. Mattsson, "Understanding current and future issues in collaborative consumption: A four-stage Delphi study," *Technol. Forecasting Social Change*, vol. 104, pp. 200–211, Mar. 2016.
- [15] J. Yoon and K. Kim, "Identifying rapidly evolving technological trends for R&D planning using SAO-based semantic patent networks," *Scientometrics*, vol. 88, no. 1, pp. 213–228, Jul. 2011.
- [16] W. Yeo, S. Kim, H. Park, and J. Kang, "A bibliometric method for measuring the degree of technological innovation," *Technol. Forecasting Social Change*, vol. 95, pp. 152–162, Jun. 2015.
- [17] S. Jun, "A forecasting model for technological trend using unsupervised learning," in *Database Theory and Application, Bio-Science and Bio-Technology*. Berlin, Germany: Springer, 2011, pp. 51–60.
- [18] Y. Huang, D. Zhu, Y. Qian, Y. Zhang, A. L. Porter, Y. Liu, and Y. Guo, "A hybrid method to trace technology evolution pathways: A case study of 3D printing," *Scientometrics*, vol. 111, no. 1, pp. 185–204, Apr. 2017.
- [19] Y. Wang, J. Liu, J. Qu, Y. Huang, J. Chen, and X. Feng, "Hashtag graph based topic model for tweet mining," in *Proc. IEEE Int. Conf. Data Mining*, Dec. 2014, pp. 1025–1030.
- [20] V. J. Duriau, R. K. Reger, and M. D. Pfarrer, "A content analysis of the content analysis literature in organization studies: Research themes, data sources, and methodological refinements," *Organizational Res. Methods*, vol. 10, no. 1, pp. 5–34, Jan. 2007.
- [21] T. Furukawa, K. Mori, K. Arino, K. Hayashi, and N. Shirakawa, "Identifying the evolutionary process of emerging technologies: A chronological network analysis of world wide Web conference sessions," *Technol. Forecasting Social Change*, vol. 91, pp. 280–294, Feb. 2015.
- [22] Y. Chen, P. B. Luh, C. Guan, Y. Zhao, L. D. Michel, M. A. Coolbeth, P. B. Friedland, and S. J. Rourke, "Short-term load forecasting: Similar day-based wavelet neural networks," *IEEE Trans. Power Syst.*, vol. 25, no. 1, pp. 322–330, Feb. 2010.

- [23] A. Hosovsky, J. Pitel, M. Adamek, J. Mizakova, and K. Zidek, "Comparative study of week-ahead forecasting of daily gas consumption in buildings using regression ARMA/SARMA and genetic-algorithm-optimized regression wavelet neural network models," *J. Build. Eng.*, vol. 34, Feb. 2021, Art. no. 101955.
- [24] C. Katris, "A time series-based statistical approach for outbreak spread forecasting: Application of COVID-19 in Greece," *Expert Syst. Appl.*, vol. 166, Mar. 2021, Art. no. 114077.
- [25] B. Liu, M. Lai, J.-L. Wu, C. Fu, and A. Binaykia, "Patent analysis and classification prediction of biomedicine industry: SOM-KPCA-SVM model," *Multimedia Tools Appl.*, vol. 79, nos. 15–16, pp. 10177–10197, Apr. 2020.
- [26] D. Gupta, M. Pratama, Z. Y. Ma, J. Li, and M. Prasad, "Financial time series forecasting using twin support vector regression," *PLoS ONE*, vol. 14, no. 3, pp. 1–27, Mar. 13 2019.
- [27] J. D. Wang, P. Li, R. Ran, Y. B. Che, and Y. Zhou, "A short-term photovoltaic power prediction model based on the gradient boost decision tree," *Appl. Sci.*, vol. 8, no. 5, p. 689, May 2018.
- [28] J. J. Wang, X. Sun, Q. Cheng, and Q. Cui, "An innovative random forest-based nonlinear ensemble paradigm of improved feature extraction and deep learning for carbon price forecasting," *Sci. Total Environ.*, vol. 762, Mar. 2021, Art. no. 143099.
- [29] M. Zhou, B. Wang, S. Guo, and J. Watada, "Multi-objective prediction intervals for wind power forecast based on deep neural networks," *Inf. Sci.*, vol. 550, pp. 207–220, Mar. 2021.
- [30] M. Mudassir, S. Bennbaia, D. Unal, and M. Hammoudeh, "Time-series forecasting of bitcoin prices using high-dimensional features: A machine learning approach," *Neural Comput. Appl.*, pp. 1–15, Jul. 2020, doi: 10.1007/s00521-020-05129-6.
- [31] H. Cai, Z. Wu, C. Huang, and D. Huang, "Wind power forecasting based on ensemble empirical mode decomposition with generalized regression neural network based on cross-validated method," *J. Electr. Eng. Technol.*, vol. 14, no. 5, pp. 1823–1829, Sep. 2019.
- [32] Z. Kong, C. Zhang, H. Lv, F. Xiong, and Z. Fu, "Multimodal feature extraction and fusion deep neural networks for short-term load forecasting," *IEEE Access*, vol. 8, pp. 185373–185383, 2020.
- [33] C.-C.-M. Yeh, N. Kavantzias, and E. Keogh, "Matrix profile IV: Using weakly labeled time series to predict outcomes," *Proc. VLDB Endowment*, vol. 10, no. 12, pp. 1802–1812, Aug. 2017.
- [34] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N.-C. Yen, C. C. Tung, and H. H. Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. Roy. Soc. London. Ser. A, Math., Phys. Eng. Sci.*, vol. 454, no. 1971, pp. 903–995, Mar. 1998.
- [35] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," *Adv. Adapt. Data Anal.*, vol. 1, no. 1, pp. 1–41, Jan. 2009.
- [36] P. Jiang, R. Li, H. Lu, and X. Zhang, "Modeling of electricity demand forecast for power system," *Neural Comput. Appl.*, vol. 32, no. 11, pp. 6857–6875, Jun. 2020.
- [37] J. P. Martino, "A review of selected recent advances in technological forecasting," *Technol. Forecasting Social Change*, vol. 70, no. 8, pp. 719–733, Oct. 2003.
- [38] J. Kim (2018), *Robotics Development and Patent Analysis*. [Online]. Available: <http://info.clarivate.com/robotic>
- [39] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Mar. 2003.
- [40] K.-L. Nguyen, B.-J. Shin, and S. Joon Yoo, "Hot topic detection and technology trend tracking for patents utilizing term frequency and proportional document frequency and semantic information," in *Proc. Int. Conf. Big Data Smart Comput. (BigComp)*, Jan. 2016, pp. 223–230.
- [41] P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "Enriching word vectors with subword information," *Trans. Assoc. Comput. Linguistics*, vol. 5, pp. 135–146, Dec. 2017.
- [42] J. Huang, M. Korolkiewicz, M. Agrawal, and J. Boland, "Forecasting solar radiation on an hourly time scale using a coupled AutoRegressive and dynamical system (CARDS) model," *Sol. Energy*, vol. 87, pp. 136–149, Jan. 2013.
- [43] K. Stevens, P. Kegelmeyer, D. Andrzejewski, and D. Butcher, "Exploring topic coherence over many models and many topics," presented at the Empirical Methods Natural Lang. Process., Jul. 2012.
- [44] Y. Sun and S. Kirtonia, "Identifying regional characteristics of transportation research with transport research international documentation (TRID) data," *Transp. Res. A, Policy Pract.*, vol. 137, pp. 111–130, Jul. 2020.



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