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Deep learning in economics: a systematic and critical review

Yuanhang Zheng[1] · **Zeshui Xu**[2] · **Anran Xiao**[2]

Abstract
From the perspective of historical review, the methodology of economics develops from qualitative to quantitative, from a small sampling of data to a vast amount of data. Because of the superiority in learning inherent law and representative level, deep learning models assist in realizing intelligent decision-making in economics. After presenting some statistical results of relevant researches, this paper systematically investigates deep learning in economics, including a survey of frequently-used deep learning models in economics, several applications of deep learning models used in economics. Then, some critical reviews of deep learning in economics are provided, including models and applications, why and how to implement deep learning in economics, research gap and future challenges, respectively. It is obvious that several deep learning models and their variants have been widely applied in different subfields of economics, e.g., financial economics, macroeconomics and monetary economics, agricultural and natural resource economics, industrial organization, urban, rural, regional, real estate and transportation economics, health, education and welfare, business administration and microeconomics, etc. We are very confident that decision-making in economics will be more intelligent with the development of deep learning, because the research of deep learning in economics has become a hot and important topic recently.

Keywords Deep learning · Economics · Critical review · Intelligent decision-making

✉ Zeshui Xu
xuzeshui@263.net

Yuanhang Zheng
yuanhang_zheng@foxmail.com

Anran Xiao
xiaoanran_ubby@163.com

[1] College of Computer Science, Sichuan University, 610064 Chengdu, PR China

[2] Business School, Sichuan University, 610064 Chengdu, PR China

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1 Introduction

Economics is a significant subject that studies various economic activities and corresponding economic relations of human society, aiming to help people discover economic regulation, instruct economic practice and forecast economic behavior (Marshall, 1992). In order to study the concepts, theories and basic reasoning principle of economics, economic methodology were constructed (Blaug, 1981). The development of economic methodology has gone through the following five stages: (1) Before 1790s, possible economic laws were concluded through complicated history and statistical data of economic and social phenomena, represented by a book "An Inquiry Into the Nature and Causes of the Wealth of Nations" (Smith, 1976); (2) Between Mid-17th to Mid-19th century, that was the period of classical economics, researchers adopted reasoning mode that takes deduction as the leading actor and induction as the supplementary; (3) From late 19th century to early 20th century, Marshall founded the neoclassical school, which provides economic community with tools such as static method, local analysis and general equilibrium analysis, etc. Then, he began to pay attention to the statistical supplement of economic theory (Marshall, 1992); (4) At 1930, the publication of Keynes's General Theory broke the neoclassical harmony between individual and social interests, reintroducing moral issues and dynamic changes into economics. So that from 1930 to 1960 s, Positivism and falsificationism disputed each other and this period became the golden age of the development of economic methodology (Keynes, 1936); (5) After 1960s, with the rapid development of econometrics, statistics, econometric methods and tools became the main research weapons adopted by mainstream economics. Positivism dominated the upper hand (Ahelegbey, 2016; Lee, 2020).

As far as we know, the methodology of economics develops from qualitative to quantitative, and mathematic models play important roles (Lindenlaub & Prummer, 2021; Page & Clemen, 2013; Tsakas et al., 2021). But it is undeniable that the criticism and reflection on this methodology system has never stopped (Cerniglia and Fabozzi, 2020; Rattinger, 1976). Especially with the emergence of many "black swan events" such as the financial crisis and epidemic disease, the interpretation and prediction ability of Positivist Economics has been greatly challenged, and the effectiveness of the policy measures proposed by it has been seriously questioned. Without strict premise of hypothesis and mathematic models, machine learning has been adopted to handle a large amount of data or the economic problem cannot be described by mathematic models (Hugo et al., 2019; Ozgur & Akkoc, 2021).

However, if the amount of data in economic field is extremely huge and the information is buried in meaningless features, the feature learning efficiency of machine learning algorithms will largely decrease and its performance will be severely affected. Deep learning aims at mining the relationships and regulations hidden in the data by constructing the representation hierarchy of data, for performing downstream tasks, such as classification and decision-making. Hence, it can also improve the intelligent decision-making in economic fields. Because it can deal with a larger amount of higher dimensional data and mine the potential information and rules in the data, deep learning models usually perform better than traditional machine learning models. Combined with other models, deep learning variants solve many practical problems in economics. Therefore, deep learning has greatly improved the development of economics research. A comprehensive literature review and critical comments on deep learning in economics, not only provide economists with new ideas and methods to solve economic problems, but also expand the application scenarios for machine learning community.

As special type of machine learning, deep learning models are representation-learning methods with multiple simple but non-linear modules, constructed in the form of multi-layer neural network (LeCun et al., 2015). It has strong expression ability and can perform sufficiently complex functions for fitting features. Its concept came into people's sight when deep belief network (DBN) was proposed by Hinton and Salakhutdinov (2006). Since then, deep learning has become an important driving force for scientific research and application in the field of artificial intelligence. Some several deep learning models, e.g., Deep Neural Network (DNN), Restricted Boltzmann Machine (RBM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Autoencoder (AE), or hybrid techniques, like Deep Reinforcement Learning (DRL), have been developed rapidly and widely applied in pattern recognition (Salakhutdinov & Hinton, 2012), speech recognition (Arisoy et al., 2015), computer vision (Guo et al., 2020), auto-controlling (Roopaei et al., 2017), mechanical equipment (Wu et al., 2019), medical system (Xu et al., 2020), financial field (Huang et al., 2020) and other fields. The main differences between these deep learning models are discussed in Table 1.

Although the application of deep learning in the economic field started late, it has developed very rapidly. Searched from Web of Science, Scopus and DBLP dataset, the first three published papers about the topic of deep learning and economics were collected at 2014. Then, the number of relevant articles increases every year in the average speed of 222.4% from 2015, until 631 published papers in 2021. Comprehensive review of advanced machine learning and deep learning methods (Nosratabadi et al., 2020) has summarized four data science methods in economics, including deep learning models, hybrid deep learning, hybrid machine learning, and ensemble models. The findings show that the development trends of hybrid models will outperform other learning algorithms. Moreover, a bibliometric analysis on deep learning (Li et al., 2020b) provides researchers with a statistical perspective on the development of the field. A state-of-the-art survey about fusing deep learning and fuzzy systems (Zheng et al., 2021) gives a systematic analysis on the fusion effect of fuzzy technology and deep learning.

In this paper, we try to investigate and present answers to the following research questions:

1) Which deep learning models are preferred (and more successful) in economics? What are the characteristics of different deep learning algorithms in the economic field?
2) What economic application areas are of interest to deep learning community? What are the differences when execute deep learning models against traditional soft computing/machine learning techniques?
3) What are the drawbacks of the current applications of deep learning in economics?
4) What are the future directions of researches about deep learning in economics?

Therefore, this paper systematically investigates the frequently used deep learning models in economics and several applications of deep learning in economics, aiming to provide a comprehensive cognition of deep learning in economics and seek a new path or new ideas for its development. The main insights of the paper are in the following aspects: (1) Introducing deep learning into economics community and making a survey of frequently-used deep learning models in economic applications, including DNN, RBM, DBN, CNN, RNN, AE, Transformer and DRL (The main differences between these deep learning models are shown in Table 1); (2) Exhibiting applications of deep learning in economics, in which the applications are classified based on Journal of Economic Literature (JEL) classification system. It is a standard method of classifying scholarly literature in the field of economics ("Jel classification system,"); (3) Providing some critical review of deep learning in economics, and offering some possible trends and opportunities of the further fusion.

The rest of the paper is constructed as follows: Sect. 2 presents some statistical results of literature about deep learning in economics. Then, Sect. 3 introduces eight frequently-used deep learning methods and their applications in economics and Sect. 4 analyzes the most common applications of using deep learning in economics. Section 5 offers some critical review of deep learning in economics, including critical review on models and applications, models and applications, why and how to implement deep learning in economics, research gap and future challenges. Finally, the answers to our initially stated research questions and some conclusions are exhibited in Sect. 6.

2 Statistical results

In order to collect as many relevant published documents as possible, broader search strings were initially identified, i.e., Web of Science: TS = (economics OR economy) AND TS = "deep learning", and search span is set from 2006 to 2021 (because the concept of deep learning coming into people's sight was in 2006 when DBN was proposed). Then, till Dec. 31th, 2021, 548 articles matched the constraints. Scopus: (TITLE-ABS-KEY (economics) OR TITLE-ABS-KEY (economy) AND TITLE-ABS-KEY ("deep learning")) AND PUBYEAR > 2005 AND PUBYEAR < 2022. Then, till Dec. 31th, 2021, 1,384 articles matched the constraints. DBLP: searching from "economy, deep learning" OR "economics, deep learning", 6 articles matched the constraints. After combining all articles searched from different databases and removing duplicates, 1,468 articles are retained for further consideration. To ensure that final search results are as accurate as possible, a total of 1,414 articles are collected after purely peer-reviewed academic journal articles finally. These articles are ranked according to the published time and analyzed from the number of articles by year.

As shown in Fig. 1, the earliest three relevant articles published in 2014, after the concept of deep learning emerged (Hinton and Salakhutdinov, 2006). From 2014 to 2015, only some researchers paid attention to this topic. But starting from 2016, the number of articles kept increasing year by year, till 631 articles in 2021. Meanwhile, it is easy to see that more and more scholars have been devoted to the research field of deep learning and economics.

3 Frequently-used deep learning models in economics applications

3.1 Deep neural network (DNN) in economics

DNN is one of fundamental models of deep learning (Hinton et al., 2012) and it can be thought of as a neural network with many hidden layers. As we can see in Fig. 2, DNN is made of three types of network layer. The first layer is the input layer, the last layer is the output layer, and the layers in middle are both the hidden layers. Layers to layers are fully

Table 1 Main differences between the deep learning models

	Features	Advantages	Disadvantages	Main variants
DNN	a. Can be regarded as a neural network with many hidden layers, which are fully connected; b. Use forward propagation and back propagation algorithms to tune parameters.	a. Can be used in wide range of applications; b. Network structure is simple.	a. The number of parameters is easy to be inflated; b. Need a lot of computation.	DNN-HMM, DNN-CTC
RBM	a. Be a stochastic generated neural network that can learn probabilistic distribution from an input data set; b. Be the building block of DBN.	a. Flexible and efficient computation; b. Easy to reason.	a. Only suitable for working on binary-valued data; b. Model is relatively simple so that expression ability is not good enough.	Conditional RBM, Point-wise Gated RBM, Temporal RBM
DBN	a. Can be regarded as either a generation model or a discriminant model; b. Can be used for both unsupervised and supervised learning.	a. The generation model learns the joint probability density distribution, so it can represent the distribution of data from a statistical point of view and reflect the similarity of similar data; b. The generative model can restore the conditional probability distribution, which is equivalent to the discriminant model.	a. The classification accuracy of the generative model is not as high as the discriminant model when it is used for classification problems; b. Because the generation model learns the joint distribution of data, the learning problem is more complex; c. The input data are required to be labeled for training.	Convolution DBN
CNN	a. Effectively reduce the dimension of large data images to small data (without affecting the results); b. Can retain the characteristics of the picture, similar to the principle of human vision.	a. The weight sharing strategy reduces the parameters that need to be trained, making the generalization ability of the trained model stronger; b. Pooling operation can reduce the spatial resolution of the network, so that the translation invariance of the input data is not required.	Depth models are prone to gradient dissipation.	GoogleNet, VGG, Deep Residual Learning
RNN	a. Long-term information can be effectively retained; b. Select important information to keep, and select "forget" for less important information.	The model is a depth model in time dimension, which can model the sequence content.	a. There are many parameters that need to be trained, which are prone to gradient dissipation or gradient explosion; b. Without feature learning ability.	LSTM, GRU

Table 1 (continued)

	Features	Advantages	Disadvantages	Main variants
AE	a. Data dependent; b. Learn automatically from data samples.	a. Strong generalization; b. Can be used for dimension reduction; c. Can be used for feature detectors; d. Can be used for generation model.	a. Information is somewhat lost in the process of encoding and decoding; b. The compression ability only applies to samples similar to training samples.	Denoising AE, Stack AE, Undercomplete AE, Regular AE
Transformer	a. Self-attention mechanism; b. Focus on global information.	a. Enables to model more long-distance dependencies; b. Parallel computing.	a. High program complexity; b. Not Turing complete; c. Compute resource input average.	Linear Transformer, Sparse Transformer, Reformer, Set Transformer, Transformer-XL
DRL	a. Combine deep learning with reinforcement learning; b. End-to-End training.	a. Learn control strategies directly from high-dimensional raw data; b. Large numbers of samples can be produced for supervised study.	a. Difficult to achieve continuous motion control; b. Overestimation, that is, the estimated value function is larger than the true value function.	QR-DQN, Rainbow DQN

Fig. 1 The number of articles by year

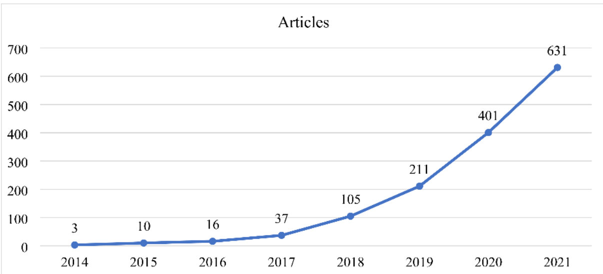
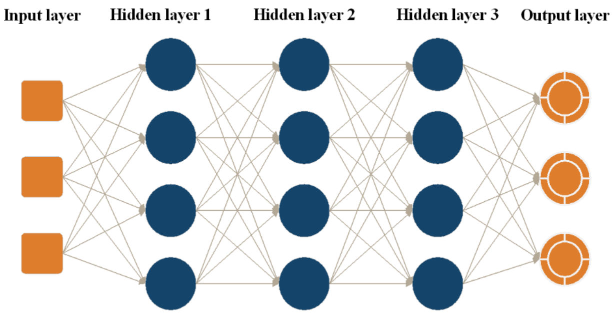


Fig. 2 Architecture of DNN model



connected and each layer performs specific effect of sorting and ordering in a process that some are called as "representation hierarchy".

As one of the fundamental methods of deep learning, DNNs have been applied in various research fields of economics, e.g., financial economics, macroeconomics and mone-

Table 2 DNN in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Zhong & Enke, 2019)	Predict the daily return direction of the SPDR S&P 500 ETF	DNN, ANN	Single DNN or single ANN	Significantly higher classification accuracy
(Chatzis et al., 2018)	Forecast stock market crisis events	MXNET DNN	LOGIT, CART, RF, SVM, NN, XGBoost	Higher discriminatory power and superior predictive accuracy
(He et al., 2019)	Forecast financial time series	DNN, LSTM	Five strategies	Outperforms others in MAPE, RMSE, R^2
(Kremsner et al., 2020)	Compute risk measure	DNN	Classical methods in references	Can solve problems with high dimension
(Alaminos et al., 2019)	Predict currency crisis event	DNN, DNDT	LOGIT, MLP, SVM, AdaBoost	Higher levels of accuracy
(Galeshchuk & Mukherjee, 2017)	Predict exchange rate	DNN, LSTM	Shallow neural network	Significantly higher predictive accuracy
(Lukman et al., 2020)	Predict the amount of salvage and waste materials	DNN	The component based neural network model	Higher and more steady prediction accuracy
(Bazan-Krzywoszanska & Bereta, 2018)	Forecast real estate value	DNN	Linear regression	Perform better in test data according to prediction criteria MAE, MRE
(Ding et al., 2019)	Estimate socioeconomic status	S2S models containing DNN and LSTM	Random Guess, STL, GBDT	Outperform other models in precision, recall, and F1-score
(Yuan & Lee, 2020)	Forecast intelligent sales volume	DNN, grey analysis, LSSVR	GA-ANN, GA-LSSVR, and PSO- LSSVR	Superior performance in Google Index
(Feng et al., 2018)	Recognize pattern and make classification	DNN	Traditional auction	Better performance when the number of SUs exceeds a certain value
(Frey et al., 2019)	Predict for investment decisions	DNN, Gradient Boosting, RF	GLM	Higher prediction accuracy
(Tan et al., 2020)	Estimate poverty	Deep ResNet, FPN	Linear regression model with night-time light data, linear regression model with both night-time light data and spectral index data	Outperform other models with the Pearson correlation coefficient

Note: ANN (Artificial Neural Network), LOGIT (Logistic Regression), MXNET (Deep Learning Techniques), CART (Classification and Regression Trees), RF (Random Forest), SVM (Support Vector Machine), NN (Neural Network), XGBoost (Extreme Gradient Boosting), DNDT (Deep Neural Decision Tree), MLP (Multilayer Perceptron), LSTM (Long Short-Term Memory), RMSE (Root Mean Square Error), STL (Standard Template Library), GBDT (Gradient Boosting Decision Tree), LSSVR (Least-Square Support Vector Regression), GA (Genetic Algorithm), PSO (Particle Swarm Optimization), GLM (Generalized Linear Models), FPN (Feature Pyramid Network), ResNet (Residual neural Network)

tary economics, urban, rural, regional, real estate, and transportation economics, industrial organization, etc. Some of applications are shown in Table 2. Not only single DNN model

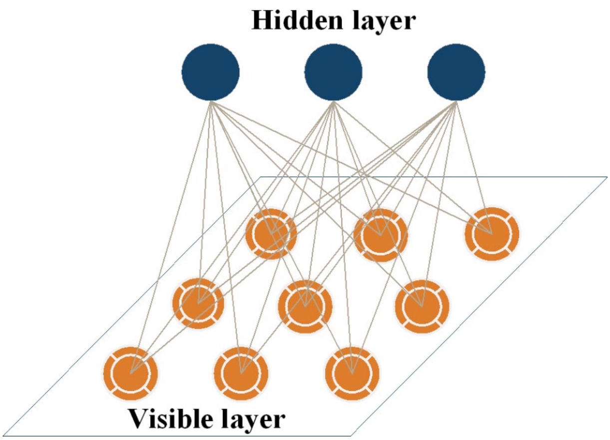


Fig. 3 Architecture of RBM model

(Bazan-Krzywoszanska & Bereta, 2018; Feng et al., 2018; Kremsner et al., 2020; Lukman et al., 2020), but also hybrid models (Chatzis et al., 2018; Ding et al., 2019; Frey et al. 2019; Galeshchuk & Mukherjee, 2017; He et al., 2019; Tan et al., 2020; Yuan & Lee, 2020; Zhong & Enke, 2019), often achieve higher classification or prediction accuracy than other benchmark methods.

3.2 Restricted Boltzmann Machine (RBM) in economics

Inspired by energy function of statistical physics, RBM is a randomly generated neural network that can learn probability distributions from input data sets (Le Roux & Bengio, 2008). As a special topology structure of Boltzmann Machine (BM), RBM has two layers: a visible layer and a hidden layer. Unlike convolutional BM (Krefl et al., 2020), there are connections between all units of different layers while there is no connection between units in the same layer in RBM. The architecture of RBM is exhibited in Fig. 3. Because of the advantages of strong representation and easy reasoning, RBM is successfully applied to recommendation system (Chen et al., 2020), image segmentation (Li & Wang, 2020), natural language processing (Tsutsui & Hagiwara, 2019), etc.

RBM model can better maintain the intrinsic characteristics of the original data because the error of feature reconstruction is lower in the process of feature learning (Mittelman et al., 2014). These intrinsic characteristics enable RBM to learn more reconfigurable features and build a wonderful prediction model. In the field of economics, RBM has been applied in several subfields, like macroeconomics and monetary economics (Galeshchuk, 2017), urban, rural, regional, real estate, and transportation economics (Rafiei & Adeli, 2016), agricultural and natural resource economics (Li et al., 2017; Pei et al., 2020), etc. Please refer to Table 3 for more details. The approaches have also been proven effectively in economic predictions and performed better than the compared method.

3.3 Deep Belief Network (DBN) in economics

DBN is a kind of probabilistic generation model (Hinton et al., 2006), which is used for statistical modeling and representing abstract features or statistical distributions of things. As is shown in Fig. 4, DBN' s graph structure is composed of multiple nodes. There is no

Table 3 RBM in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Galeshchuk, 2017)	Predict exchange rate	RBM, AE	Multilayer perceptron, Autoregressive integrated moving average model, Random walk model	Higher accuracy
(Rafiei & Adeli, 2016)	Estimate the sale prices of real estate units	Deep RBM, nonmating genetic algorithm	Standard genetic search, best first, linear forward selection, and correlation-based feature subset	The superiority of the new method is substantiated in accuracy of classifier
(Pei et al., 2020)	Forecast vehicle velocity	RBM, bidirectional LSTM	RBF-NN, BP-NN, EV, 5MC, RBF-WT	Performs better in RMSE
(Li et al., 2017)	Time series forecasting	RBM, BSASA	BP, Elman, RBMBP, BSABP, DEBP	Superior capability in preventing the search result from falling into the minimum

Note: BSASA (Backtracking Search Algorithm with Simulated Annealing), BP (Back Propagation), RBF-NN (Radial Basis Function Neural Network), BP-NN (Back Propagation Neural Network), EV (Exponentially Varying prediction method), 5MC (5-stageMarkov chain prediction method), WT (a novel velocity predicted method based on Wavelet Transform), RBMBP (Restricted Boltzmann Machine Back Propagation), BSABP (Backtracking Search Algorithm Back Propagation), DEBP (Differential Evolution Back Propagation)

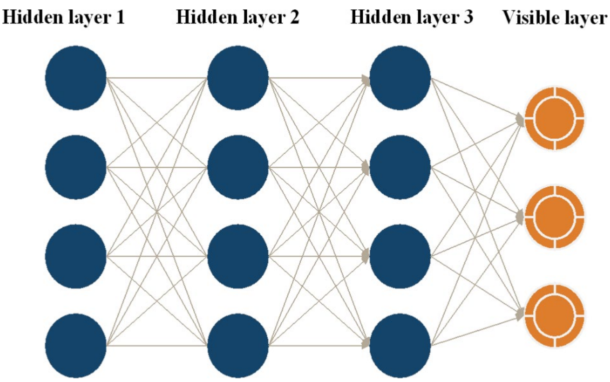


Fig. 4 Architecture of DBN model

internal connection between nodes of the same layer, and there are full connections between nodes of two adjacent layers. The lowest layer of the network is the observable variable, and all nodes of other layers are the hidden variables.

DBN has been utilized for solar power forecasting (Gensler et al., 2016), short-term load forecasting of integrated energy (Huan et al., 2020), and very short-term bus load forecasting (Shi et al., 2019). It is also helpful for fault signal recognition in power distribution sys-

Table 4 DBN in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Gensler et al., 2016)	Forecast the energy output of solar power plants	DBN, AE, LSTM	Multilayer perceptrons, physical models	Superior forecasting performance
(Cui et al., 2020)	Predictive control for ultrasupercritical power plant	DBN, Economic model predictive control	Subspace model identification	Performs better in terms of economic performance and tracking performance
(Rao et al., 2020)	Detect and classify the fault signal in power distribution system	DBN	SVM, quadratic SVM, RBF SVM, polynomial SVM, MLP SVM, LM-NN, GD-NN	Effectively detects and classifies the fault signal
(Huan et al., 2020)	Forecast short-term load of integrated energy systems	DBN, BP, multitask regression layer	SVR, ARIMA, BPNN	Learns better features and improves the forecasting accuracy
(Shi et al., 2019)	Forecast very short-term bus load	Phase space reconstruction, DBN	PSR-NN, DBN, ARIMA, NN, LSTM, PSR-DBN (no tuning)	Higher prediction accuracy and better adaptability

Note: LM-NN (Levenberg-Marquardt Neural Network), GD-NN (Gradient Descent Neural Network), BPNN (Back Propagation Neural Network), SVR (Support Vector Regression), ARIMA (Autoregressive Integrated Moving Average Model,), PSR-NN (Phase Space Reconstruction Neural Network), PSR-DBN (Phase Space Reconstruction Deep Belief Network)

tem (Rao et al., 2020) and power plant control (Cui et al., 2020) (For detailed information, please see Table 4). When compared with other machine learning algorithms or benchmark methods, DBN performs better and gets more accurate results. As researchers have found that DBN has excellent nonlinear fitting ability to fit the moving point trajectory and provide prediction of the trajectory (Shi et al., 2019). DBN also can extract abstract high-level features and analyze the correlation of multiple features, so that it can learn better features and improve the forecasting accuracy (Huan et al., 2020). Moreover, DBN is regarded as one of advanced artificial intelligence techniques in the construction of robust methods of computer vision applied to precision agriculture from the results of the systematic review (Patricio & Rieder, 2018).

3.4 Convolutional neural network (CNN) in economics

Convolutional neural network (CNN) is one of the representative algorithms in deep learning, composed of three types of layers: convolution layer, pooling layer and fully connected layer (Goodfellow et al., 2016; Gu et al., 2018) (Inquire Fig. 5 for its architecture). Compared with other neural network structures, CNN requires relatively few parameters, which enable it to be widely used and obtain higher computation efficiency (Fujita & Cimr, 2019).

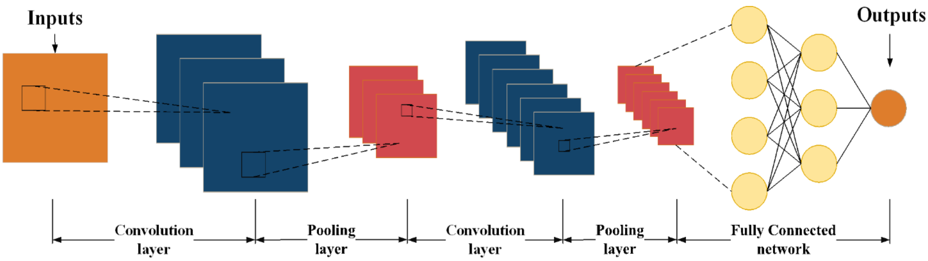


Fig. 5 Architecture of CNN model

Developed by LeCun and his team, CNN has successfully solved the handwriting digit classification problem (Lecun et al., 1998), so that it comes into the sights of computer vision researchers rapidly (Abdalla et al., 2019; Kheradpisheh et al., 2018; Selim et al., 2016; Zhang et al., 2020b). In other fields, CNN has been generally applied to natural language processing (Gu et al., 2018), recommendation systems (Zhang & Yang, 2019), remote sensing science (Zhang et al., 2018), etc., which also obtains excellent achievements.

CNN has been widely applied to solve problems in macroeconomics and monetary economics (Chen et al., 2019; Galeshchuk and Demazeau, 2017; Yasir et al., 2019; Yu et al., 2020a), industrial organization (Adebowale et al., 2020; Guo, 2020; Ullah et al., 2019; Wang & Zeng, 2020), financial economics (Liu et al., 2020; Liu et al., 2018), agricultural and natural resource economics (Conte et al., 2019; Gadekallu et al., 2020), urban, rural, regional, real estate (Ajami et al., 2019; Yao et al., 2018), business administration and business economics (Lan et al., 2018), health, education, and welfare (Yeh et al., 2020). Shown in Table 5, cooperated with other machine learning approaches or deep learning algorithms, CNN and its variants usually perform better or improve the estimation and classification accuracy than baseline methods. Among other deep learning models, CNN is great for financial forecasting and economic assessment because of two main causes: Firstly, noise filters and dimensionality reduction approaches help to select crafted input features (Yasir et al., 2019); Secondly, information mining through visual images provides unique and complementary perspective for higher economic prediction performance (Galeshchuk & Demazeau, 2017).

3.5 Recurrent neural network (RNN) in economics

Proposed from the idea that the cognition of people towards all things is coming from memory and experience, Recurrent neural network (RNN) is a class of recursive neural networks that takes sequence data as input (Goodfellow et al., 2016). Distinguished from other neural networks, RNN not only considers the input of previous moment, but also endows the network a "memory" function to handle the situation that the decision of current state is dependent on previous state. Starting from Jordan network in 1986 (Jordan, 1986) and Elman network in 1990 (Elman, 1990), RNN has occupied an important position in deep learning algorithms and been successfully applied to natural language processing, like speech recognition (Wang, 2020), language modeling (Noaman et al., 2018) and machine translation (Mahata et al., 2019), and also been used in various time series forecasting (Waheeb & Ghazali, 2020), music recommendation (Kim et al., 2019), commodity recommendation

Table 5 CNN in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Yasir et al., 2019)	Forecast foreign exchange rate	CNN	Linear regression, SVR	Perform better than other methods in prediction accuracy
(Chen et al., 2019)	Forecast interaction of exchange rates	CNN, fixed-length binary Strings, a binary component	A random selection rule method, a trend rule method	Higher prediction performance
(Galeshchuk & Demazeau, 2017)	Predict exchange rates	CNN	RW, ARIMA, Shallow neural networks	Outperform the baseline methods in prediction
(Yu et al., 2020a)	Estimate economy	CNN	Luminosity product	Improve the estimation accuracy
(Guo, 2020)	Encode image features and select the image features of commodities	CNN, attention mechanism	Analyze different impact of different situations with the assistance of CNN	Successfully extract the most important image feature corresponding to the decoding time
(Ullah et al., 2019)	Detect cyber security threats	CNN, DNN	GIST-SVM, LBP-SVM, CLGM-SVM	Outperform when measuring the cyber-security threats
(Wang & Zeng, 2020)	Select typical economic indicators	CNN	Deep confidence network, Multilayer trestle automatic coder	Improve the classification accuracy and adaptability
(Adebowale et al., 2020)	Detect intelligent phishing	CNN, LSTM	Single CNN, single LSTM	Higher classifier prediction performance and less training time
(Liu et al., 2020)	Forecast stock price	CNN, GBoost	WSAEs-LSTM	More accurate prediction
(Liu et al., 2018)	Predict stock price movement from financial news	TransE Model, CNN, LSTM	T-SVM, J-SVM, C-SVM, C-LSTM, J-LSTM	Predict better
(Conte et al., 2019)	Estimate catfish density	CNN, Aerial images ainalysis	-	-
(Gadekallu et al., 2020)	Classify tomato plant diseases	CNN, Whale optimization algorithm	DNN without Dimensionality Reduction, DNN with Dimensionality Reduction using PCA	Higher accuracy and low rate, lesser time for training and testing of the data
(Ajami et al., 2019)	Predict data-driven index of multiple deprivation	CNN	Principal component regression model combining hand-crafted and GIS features, ensemble model	Outperform than others in terms of R^2, RMSE, BIAS
(Yao et al., 2018)	Map fine-scale urban housing prices	UMCNN and RF	CNN (HSR), PCA-CNN (HSR), SD, CNN (HSR & SD), PCA-CNN (HSR & SD), CNN (HSR) & SD, PCA-CNN (HSR) & SD, CNN (SD), CNN (HSR) & CNN (SD)	The highest housing price simulation accuracy

Table 5 (continued)

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Lan et al., 2018)	Extract features of trademark images	CNN, Constraint theory	LBP, SIFT, HOG, CNN-original, CNN-LBP, CNN-Siamese	Best comprehensive retrieval ability
(Yeh et al., 2020)	Predict asset wealth	Deep CNN	Simpler KNN, scalar NL	Meets or exceeds published performance

Note: RW (Random walk without a drift), GIST (Generalized Search Tree),T-SVM (Tf-idf algorithm feature extraction and SVM prediction model), J-SVM (Joint learning feature extraction and SVM prediction model), C-SVM (CNN feature extraction and SVM prediction model), C-LSTM (CNN feature extraction and LSTM prediction model), J-LSTM (Joint learning and LSTM prediction model), PCA (Principle Component Analysis), GIS (Geographic Information System), UMCNN (Convolutional Neural Network for United Mining), HSR (High Spatial Resolution), PCA (Principal Component Analysis), SD (Spatial Data), LBP (Local Binary Pattern), SIFT (Scale Invariant Feature Transform), HOG (Histogram of Oriented Gradients), KNN (K-Nearest Neighbor), NL (Nighlights)

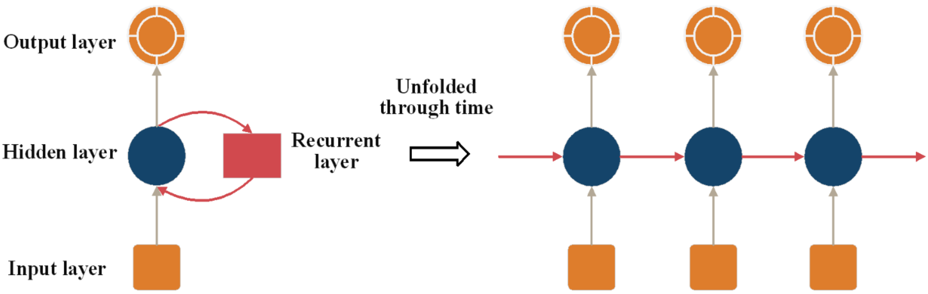


Fig. 6 Architecture of RNN and its unfolded framework through time

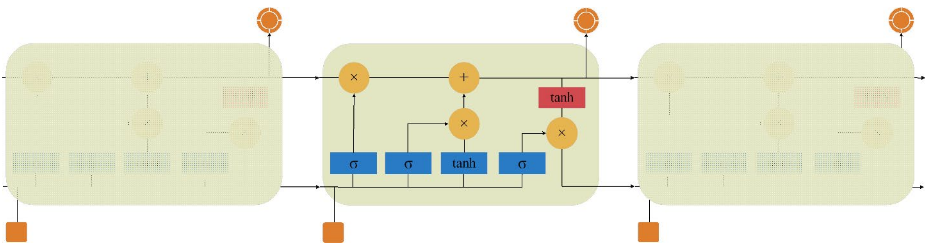


Fig. 7 Architecture of LSTM model

(Chen et al., 2021), etc. The architecture of RNN and its unfolded framework through time is shown in Fig. 6.

Then, Hochreiter and Schmidhuber (1997) proposed a RNN variant called Long Short-Term Memory (LSTM), which can tackle issues mentioned by Bengio et al. (1994) and learn long-term dependency relations. Its structure is exhibited in Fig. 7, composed of special units: blocks and gates.

RNN can still be seen in industrial organization, macroeconomics and monetary economics, agricultural and natural resource economics, financial economics. Collaborated with other machine learning algorithms such as logistic regression, encoder-decoder and attention mechanism, RNN and its variants (Alsmadi et al., 2020; Andrijasa, 2019; Becerra-Vicario et al., 2020; Mishev et al., 2020; Zhang et al., 2020a) show superiority in prediction or evaluation than the compared methods, e.g., SVM, neural network. As one of typical deep learning models, RNN is believed to be more suitable to simulate the sequence dynamical data and capture contextual information than regular feedforward neural networks (Alsmadi et al., 2020; Anbazhagan & Kumarappan, 2013). More importantly, for timeseries like electricity price or exchange rate, they present high periodicity patterns and multiple time steps prediction, so that RNN is acted as an ideal option. (Andrijasa, 2019; Zhang et al., 2020a). As a variant of RNN, the essence of LSTM is to introduce the concept of cellular state. Unlike RNN which only considers the most recent state, the cellular state of LSTM determines which states should be left behind and which states should be forgotten. Hence, LSTM plays an important role in many fields of economic research. In comparison with other benchmark methods, the authors design some measurement indicators and the results show that the proposed methods combining LSTM present high reliability and good capability of forecasting, estimating and detection. Table 6 exhibits some typical applications of RNN in economics.

3.6 Autoencoder (AE) in economics

Proposed by LeCun (1987), AE is a kind of artificial neural network used in semi-supervised learning or unsupervised learning, for representation learning of input information by taking input information as learning target (Bengio et al., 2013; Goodfellow et al., 2016). As shown in Fig. 8, AE is built by encoder and decoder, which is helpful for dimensionality reduction of data (Chen et al., 2018), feature extraction (Meng et al., 2017) and anomaly detection (Han et al., 2020). It also has some variants like undercomplete autoencoder (Buongiorno et al., 2019), regularized autoencoder (Hong et al., 2020) and variational autoencoder (Che et al., 2020).

In the economic field, AE is usually employed to automatically learn features from the high dimensional data (Long et al., 2020; Ranjan et al., 2021) and for self-adaptive feature reduction (Li et al., 2020). In order to force AE to learn useful information, noises are often added to the input data (Vincent et al., 2008), and then the network is trained to express the original data without noise. Meanwhile, sparse penalty is added to the encoding layer so that the active neurons of encoding layer are limited and the original data can be replaced with discovery features (Li et al., 2020; Xu et al., 2016). In addition, the merit of AE is the interpretability of the model (Suimon et al., 2020), which is largely superior to most of deep learning models in tackling with economic issues. Shown in Table 7, compared with some prediction technologies and other deep learning models, AE also performs well and gets more accurate prediction results, requiring less trainable parameters and training time.

3.7 Transformer in economics

Transformer model proposed by Google in 2017 is a well-known architecture for deep learning, which performs well on a variety of natural language processing tasks (He et al., 2021). Transformer is based on the self-attention mechanism dispensing with recurrence and convolutions entirely (Vaswani et al., 2017). Moreover, Transformer is composed of two parts, including encoder and decoder (Fan et al., 2022). Encoder codes the input and decoder decodes the encoded information, and finally get the decoded output, its structure is shown

Table 6 RNN in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Alsmadi et al., 2020)	Predict helpful reviews	RCNN	Fasttext, SVM, Bi-LSTM, (3 Layers) CNN	Outperform conventional as well as deep learning-based models in classification accuracy
(Becerra-Vicario et al., 2020)	Predict bankruptcy	DRCNN, LOGIT	Single DRCNN, single LOGIT, neural network	Predict well
(Ebrahimi et al., 2020)	Identify semi-supervised cyber threat	Transductive SVMs, LSTM	k-NN, LOGI, RF, SVM, CNN, LSTM, Transductive SVM	State-of-the-art classification performance
(Agarwal et al., 2021)	Detect Fraudulent resource consumption attack	LSTM	DTC, RFC, LR, SVM, KNN, ANN	Perform best in effectively and accurately detecting FRC attacks
(Arkhangelski et al., 2020)	Evaluate the economic benefits	LSTM	MILP, fuzzy logic, or another linear optimization technique	More prediction accuracy
(Haytamy & Omara, 2020)	Predict the Cloud QoS provisioned values	LSTM, PSO	MQPM	Outperforms the existing MQPM model in terms of RMSE
(Andrijasa, 2019)	Predict exchange currency rates	Encoder-decoder RNN	-	-
(Tang et al., 2020)	Forecast economic recession through Share Price	LSTM	MA, KNN, ARIMA, Prophet	LSTM outperforms the other models in prediction
(Zhang et al., 2020a)	Forecast day-ahead electricity price	DRNN	Single SVM, hybrid SVM network	Outperform in terms of simulating the relationships between external factors and the electricity price
(Zhang et al., 2019)	Promote the accuracy of wind prediction	LSTM, multi-objective PSO	Grey Model	Numeric results demonstrate that LSTM is superior to the traditional grey model in terms of prediction accuracy, robustness, and computational efficiency
(Zhou et al., 2019)	Forecast electricity price	LSTM, SMBO	SVR, BPNN, GTB, DTR, LSTM series models include shallow LSTM, stacked LSTM, EEMD-LSTM and EEMD-LSTM-SMBO	Much better than that of the general LSTM model and traditional models in accuracy and stability
(Abdel-Nasser & Mahmoud, 2019)	Forecast photovoltaic power	LSTM-RNN	MLR, BRT, and neural networks	Further reduction in the forecasting error
(Guo et al., 2018)	Forecast short-term power load	Integrating several LSTM networks	LSTM, ARIMA, SVR, MLP	Improve the forecasting performance

Table 6 (continued)

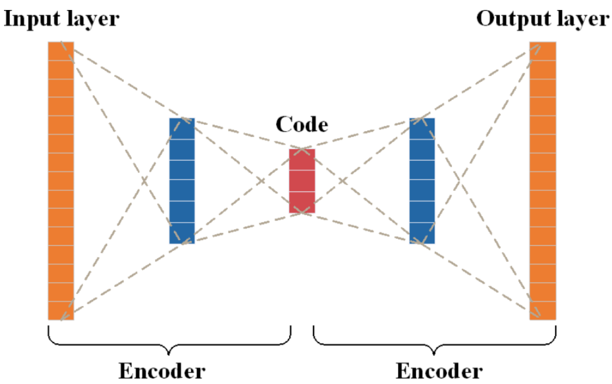
Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Mishev et al., 2020)	Analyze sentiment in finance	RNN, RNN-Attention, CNN, Dense Network	SVC, XGB, Dense, CNN, RNN	Better performance in several criteria
(Ji et al., 2021)	Forecast stock indices	IPSO and LSTM	Support-vector regression, LSTM and PSO-LSTM	High reliability and good forecasting capability
(Jin et al., 2020)	Predict stock closing price	LSTM, sentiment analysis, attention mechanism, empirical modal decomposition	LS_RF, S_LSTM, The LSTM model that considers the S_AM_LSTM	The highest accuracy, the lowest time offset and the closest predictive value when predicting the stock market
(Nikou et al., 2019)	Predict stock price	LSTM	ANN, RF, SVM	Better in prediction of the close price of iShares MSCI United Kingdom than the other methods
(Niu et al., 2020)	Predict stock price index	VMD-LSTM	PNN, ELM, CNN, and LSTM, and the hybrid models EMD-BPNN, EMD-ELM, EMD-CNN, EMD-LSTM, VMD-BPNN, VMD-ELM, and VMD-CNN	The hybrid models perform significantly better than the single models
(Sharaf et al., 2021)	Predict stock price	LSTM, CNN, Stacked-LSTM, and Bidirectional-LSTM	SVM, Linear Regression, LOGIT, K-Neighbors, Decision Tree, RF	Outperform the other models based on several evaluation metrics
(Katayama et al., 2019)	Identify sentiment polarity in financial news	LSTM, Convolution model	Common polarity dictionary	Captures more news sentiment
(Tao et al., 2020)	Evaluate the impact of the Northridge Earthquake	LSTM, NAR neural network	Single LSTM, single NAR	Perform better based on some criteria
(He, 2021)	Predict investment benefits and national economic attributes	EEMD-LSTM	BP model, EEMD-BP model, LSTM model, and ARMA	Highest prediction accuracy
(Wu et al., 2018)	Estimate remaining useful life of complex engineered systems	Vanilla LSTM	RNN, GRU	Significance of performance improvement

Table 6 (continued)

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Sehovac & Grolinger, 2020)	Forecast electrical load	S2S RNN	Vanilla RNN, LSTM, and GRU	Outperform other models
(Li et al., 2021)	Predict the price of gold	VMD-ICSS-BiGRU	SVR, LR, ANN, LSTM	Consistently reduce the forecasting error and improve the fitting performance effectively

Note: RCNN (Recurrent Convolutional Neural Network), Bi-LSTM (Bidirectional-LSTM), DRCNN (Deep Recurrent Convolutional Neural Network), DRNN (Deep Recurrent Neural Network), SVC (Support Vector Classifier), XGB (Extreme Gradient Boosting), IPSO (Improved Particle Swarm Optimization), LS_RF (Random Rorest estimates using LSboost), S_LSTM (The LSTM model considering the sentiment index), S_AM_LSTM (The LSTM model that considers the sentiment index and attention mechanism), EMD (Empirical Modal Decomposition), NAR (Nonlinear Autoregressive), DTC (Decision Tree Classifier), RFC (Random Forest Classifier), MINLP (Mixed-Integer Nonlinear Programming), MQPM (Multivariate Quality of service Prediction Model), SMBO (Sequence Model-Based Optimization), GTB (Gradient Boosting Regressor), DTR (Decision tree regressor), EEMD (Ensemble Empirical Mode Decomposition), MLR (Multiple Linear Regression), BRT (Bagged Regression Trees), MA (Moving Average), ARMA (Autoregressive Moving Average), S2S RNN (Sequence to Sequence Recurrent Neural Network), ICSS (Iterated Cumulative Sums of Squares), BiGRU (Bidirectional Gated Recurrent Unit), GRU (Gated Recurrent Unit), LR (Linear Regression)

Fig. 8 Architecture of AE model



in Fig. 9. Besides natural language processing, it has also been successfully applied to image classification, object detection, and segmentation tasks (Bazi et al., 2021; Yu et al., 2020b). It has some variants like Vision Transformer (ViT) (Fisichella and Garolla, 2021), Data efficient image Transformers (DeiT) (Touvron et al., 2020), Convolutional vision Transformer (CvT) (Wu et al., 2021), and Swin-Transformer (Liu et al., 2021).

In the field of economy, Transformer takes advantage of performing well on a variety of natural language processing tasks by treating a sentence as a sequence of words and proposing a self-attentive layer structure (Liao et al., 2021). In addition, Bidirectional Encoder Representation from Transformer (BERT) (Devlin et al., 2018) is used to pre-train deep bidirectional representation (Wang & Li, 2022; Yue et al., 2020), and ViT applied directly to sequences of image patches can perform very well on image classification tasks (Fisichella & Garolla, 2021). Therefore, compared with some prediction technologies and conventional

Table 7 AE in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Wang et al., 2020a)	Forecast long-term time series in industrial production	SSAEN, SAEGN	BPNN, DLSTM, GrC-based long-term prediction model	Significantly improve the long-term time series prediction accuracy
(Long et al., 2020)	Learn features and recognize fault of Delta 3-D printers	SAE, ESN	ESN, SAE-Softmax, DBN-ESN	Best forecasting performance
(Heaton et al., 2017)	Predict and classify financial market	Stacked auto-encoders, DL	-	-
(Li et al., 2020a)	Detect feed-water heater performance	SDSAE	PCA(T^2), PCA(SPE), GA-ELM, PCA-BPNN	Achieves the best performance according to detection threshold, computation accuracy, Acc_{normal}, Acc_{fault}
(Suimon et al., 2020)	Represent the Japanese yield curve	AE	LSTM, VAR	Effective, and interpretable
(Ranjan et al., 2021)	Analyze and predict large-scale road network congestion	Convolutional AE	ConvLSTM, PredNet	More accurate prediction result, less trainable parameter and training time

Note: SSAEN (Stacked Sparse Auto-Encoders Network), SAEGN (Sparse Auto-Encoder Granulation Network), DLSTM (Deep Long Short-Term Memory), SAE (Sparse Autoencoder), ESN (Echo State Network), SDSAE (Sacked Denoising Sparse Autoencoder), SPE (Squared Prediction Error), GA-ELM (Genetic Algorithm based Extreme Learning Machine), VAR (Vector Autoregression), ConvLSTM (Convolution Long Short-Term memory), PredNet (Prediction Network)

deep learning methods, Transformer performs well on higher accuracy in prediction, more efficient and robust training process, and less accumulation of errors (Shown in Table 8).

3.8 Deep reinforcement learning (DRL) in economics

DRL is a brand new technique that combines deep learning with reinforcement learning to realize end-to-end learning from perception to action. Although so many people had the same idea, the publication "Playing Atari with Deep Reinforcement Learning" brought DRL into researcher's vision (Mnih et al., 2013). Then, DeepMind improved DQN, Hinton, Bengio and Lecun took DRL as one of important development directions of deep learning in the future (LeCun et al., 2015). It is used to describe and solve problems in which agents adopt learning strategy to maximize the return or realize some specific targets in the process of interacting with environment. The architecture of DRL is constructed in Fig. 10.

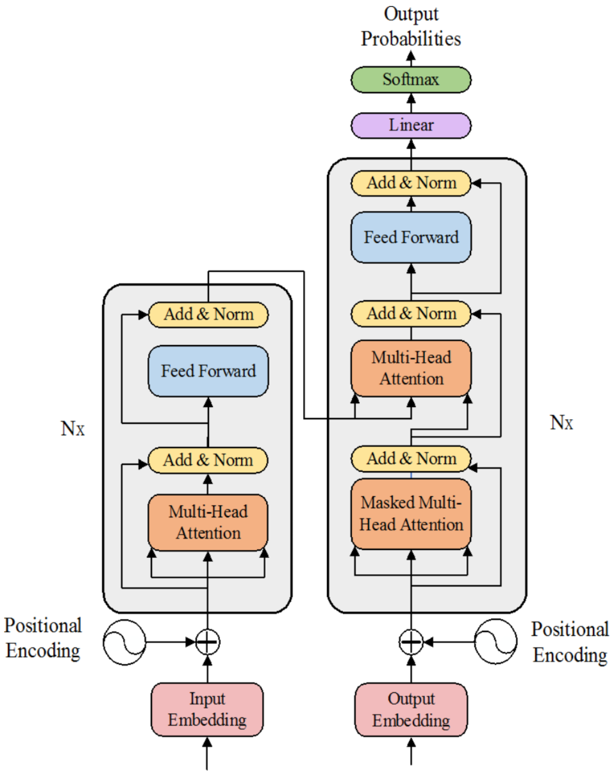


Fig. 9 Architecture of Transformer model

DRL is widely applied in economics to help people make intelligent and reliable decisions (Table 9). Comprehensive review (Mosavi et al., 2020) has discussed the development of DRL methods and applications in economics. For example, in the field of financial economics, Chakole and Kurhekar (2020) proposed an algorithm using deep Q-learning techniques to make trading decisions. In terms of agricultural and natural resource economics, a state-of-the-art proximal policy optimization (PPO) algorithm was adopted to derive alternating current optimal power flow solutions with operational constraints (Zhou et al., 2020b), and a novel DRL method combining deep deterministic policy gradient (DDPG) principles with a prioritized experience replay (PER) strategy was developed to solve the examined electric vehicle pricing problem (Qiu et al., 2020). From the aspect of macroeconomics and monetary economics, health, education, and welfare, deep neural model of DRL, DQN and DDPG are used to recommend cryptocurrency trading points (Sattarov et al., 2020) and learn optimal policy for COVID-19 prevention (Uddin et al., 2020). Furthermore, some comparisons between DRL and other conventional methods present the best performance of the proposed DRL. That is because DRL can not only statistically forecast the change trend direction, but also capture the discrete nature of environmental state, so that it greatly assists human in making rapid and effective decisions.

Table 8 Transformer in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Wang & Li, 2022)	Detect renewable energy incidents from news articles containing accidents in various renewable energy systems	PTM word2vec, BERT, TCNN, TRNN	BERT-TCNNs BERT-TRNNs word2vec-TCNNs word2vec-TRNNs TCNNs, TRNNs	Effective and robust in detecting renewable energy incidents from large-scale textual materials
(Liao et al., 2021)	Predict multistep-ahead location marginal price	Transformer, with seq2seq architecture	LSTM, Bi-LSTM, GRU, Bi-GRU, and TCN	Avoid the error accumulation of the results, higher accuracy
(Yue et al., 2020)	Predict accurate energy and classify simultaneous status	BERT	GRU, LSTM, CNN	More stable and precise, higher prediction consistency
(Fisichella & Garolla, 2021)	Develop a complete trading system with a combination of trading rules on Forex time series data	ViT	ResNet50	Fewer computational resources to train

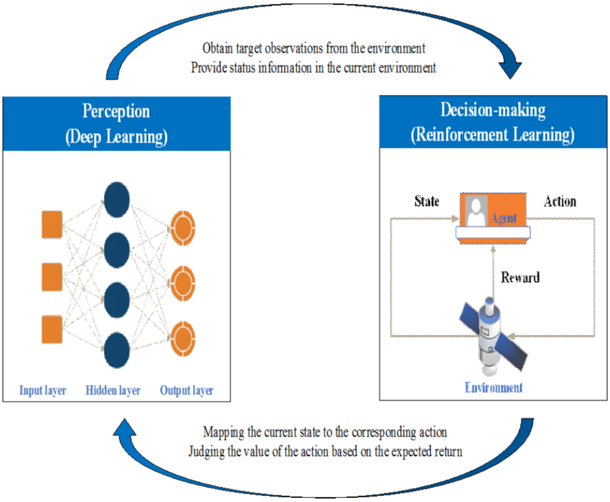
Note: PTM (Pre-Trained Model), BERT (Bidirectional Encoder Representation from Transformer), TRNN (Text Recursive Neural Network), TCNN (Text Convolution Neural Network), seq2seq (sequence to sequence), GRU (Gated Recurrent Unit), Bi-GRU (Bi-directional Gated Recurrent Unit), TCN (Train Communication Network), Vision Transformer (ViT).

4 Applications of deep learning in economics

4.1 Financial economics

Financial economics covers studies about issues related to various sub-fields: general financial markets dealing with securities (stocks, bonds, and commodity and other futures), financial institutions and services, and corporate finance and governance ("Jel classification system,"). From Table 10, we know that the selected data come from relevant database, websites or references, and time span of data is usually several years. In this field, various deep learning models like AE, RNN, CNN, DNN, LSTM, DRL and their variants, have been utilized to predict and classify financial market, forecast stock price, evaluate and analyze supply chain financial credit level, etc. In particular, many scholars are interested in exploiting different deep learning models to make effective and accurate predictions for stock market (Chatzis et al., 2018; Katayama et al., 2019; Nikou et al., 2019; Sharaf et al., 2021; Tao et al., 2020; Zhong & Enke, 2019). But for different aims or facing different types

Fig. 10 Architecture of DRL



of data, deep learning models play a variety of roles in the field of financial economics. For example, if we consider the effect of time or long-term information, RNN or LSTM models are popular to forecast the stock price; if image information is involved during the estimation process, CNN may be an ideal option; if we need to make trading decisions or decide the change trend, DRL and its variants stand out.

4.2 Macroeconomics and monetary economics

Macroeconomics and monetary economics mainly include researches about the aggregate performance of an economy: output, employment, prices, and interest rates and their determinants ("Jel classification system,"). This field concentrates on the law of economic operation of an economic field with the help of national income, overall economic investment and consumption and other overall statistical concepts. It is easy to find that the data are mainly obtained from bank websites or government office, and most of long-term data, such as more than ten years, are taken into consideration. That is because macroeconomics and monetary economics issues need to be addressed by observing and exploring long-term data. As shown in Table 11, various deep learning models including DNN, LSTM, CNN, RNN, AE and RBM, are utilized to predict currency crisis event (Alaminos et al., 2019), forecast exchange rate (Andrijasa, 2019; Galeshchuk, 2017; Galeshchuk & Mukherjee, 2017; Yasir et al., 2019), or estimate economy condition (Tang et al., 2020; Yu et al., 2020a). Among these deep learning models, DNN seems to be one of the most popular models to handle forecasting problems with large amount of data, CNN is good at reducing dimensionality of high-dimensional data and fusing image information. Similarly, RNN and LSTM are both suitable to deal with short-term or long-term dependencies problems in macroeconomics and monetary economics.

Table 9 DRL in economics

Article	Aim of study	Specific approach	Benchmark methods for comparison	Superiority of the proposed method
(Chakole & Kurhekar, 2020)	Make trading decisions	Deep Q-learning	Decision Tree strategy, Buy-and-Hold strategy	Outperforms in terms of some economic indicators: Accumulated Return, Maximum Drawdown, Average daily return, average annual return, Skewness, Kurtosis, Sharpe ratio, and Standard Deviation
(Zhou et al., 2020b)	Derive optimal power flow	DRL, PPO with IL	IL, PPO	Perform better in accuracy and running time
(Qiu et al., 2020)	Pricing electric vehicles	PDDPG	Q-learning, DQN, DDPG	Better performance in standard deviation, learning pace, flexibility and computational time
(Sattarov et al., 2020)	Recommend cryptocurrency trading points	Deep Neural Model of DRL	Double cross strategy, swing trading, scalping trading	Best performance in number of actions and quality of Trading
(Uddin et al., 2020)	Estimate impact of COVID-19 on the spread of the infection, personal satisfaction or quality of life, resource use and economy	DQN, DDPG	Random, Q-Learning, SARSA	Perform better in terms of best rewards and best policy

Note: IL (Imitation Learning), PDDPG (Prioritized Deep Deterministic Policy Gradient), DQN (Deep Q Network), DDPG (Deep Deterministic Policy Gradient), SARSA (State-Action-Reward-State-Action).

4.3 Agricultural and natural resource economics

Agricultural and natural resource economics mainly discuss economic issues pertaining to two closely related fields: agriculture and natural resources ("Jel classification system,"). Table 12 demonstrates some examples of applying deep learning for agricultural and natural resource economics. In terms of the features of problems and the selected data, CNN is used

Table 10 Applications of deep learning for financial economics

Application subfield	Article	Aim of study	Data set	Date size	Time span	Used models
Financial market	(Heaton et al., 2017)	Predict and classify financial market	Component stocks of the biotechnology IBB index	Weekly returns data	2012–2016	Stacked AE
	(Mishev et al., 2020)	Analyze sentiment in finance	Financial Phrase-Bank dataset, SemEval-2017 task dataset	4,845 English sentences, 2,510 news headlines	-	RNN, RNN, Attention, CNN, Dense Network
Stock market	(Zhong & Enke, 2019)	Forecast daily stock return	SPDR S&P 500 ETF (ticker symbol: SPY)	60 factors over 2,518 trading days	2003–2013	DNN, ANN
	(Chatzis et al., 2018)	Forecast crisis events	FRED and the SNL	More than 5,000 records	1996–2017	MXNET, DNN
	(Nikou et al., 2019)	Predict stock price	iShares MSCI United Kingdom exchange	869 data	2015–2018	LSTM
	(Sharaf et al., 2021)	Predict stock price	Quandl dataset	-	2000–2019	LSTM, CNN, Stacked-LSTM, Bi-LSTM
	(Tao et al., 2020)	Evaluate the impact of the Northridge Earthquake	http://finance.yahoo.com/	616 listed companies	1992–1994	LSTM, NAR neural network
	(Katayama et al., 2019)	Identify sentiment polarity in financial news	Economy Watchers Survey	234,626 samples	2000–2018	LSTM, Convolution model
	(Ji et al., 2021)	Forecast stock indices	Australian stock market index	2,523 records	2010–2020	LSTM-IPSO
	(Jin et al., 2020)	Predict stock closing price	Stock of Apple from (https://stocktwits.com/)	96,903 comments	2013–2018	LSTM, sentiment analysis, attention mechanism, empirical modal decomposition
	(Liu et al., 2020)	Forecast stock price	CSMAR and WIND	-	2008–2016	CNN, Gboost
	(Xu et al., 2016)	Select feature and forecast price	Apple, S&P 500 in Yahoo Finance	6,423 financial news headlines	2011–2017	TransE Model, CNN, LSTM
	(Niu et al., 2020)	Predict stock price index	HIS, SPX, FTSE and IXIC	-	2010–2019	VMD-LSTM

Table 10 (continued)

Application subfield	Article	Aim of study	Data set	Date size	Time span	Used models
	(Sattarov et al., 2020)	Recommend cryptocurrency trading points	Bitcoin, Litecoin, and Ethereum—hourly historical data from (https://www.cryptodatadownload.com)	-	2019	DRL
	(Chakole & Kurhekar, 2020)	Make trading decisions	DJIA, NASDAQ, NIFTY and SENSEX index stocks	-	2001–2018	Deep Q-learning
Insurance mathematics	(Kremsner et al., 2020)	Compute risk measure	Dataset coming from references	-	-	DNN

Note: IPSO (Improved Particle Swarm Optimization), VMD (Variational Mode Decomposition), S&P 500 (Standard & Poor's 500 index), FRED (Federal Reserve Economic Database), SNL (S&P Global Market Intelligence), CSMAR (China Stock Market & Accounting Research Database), HIS (Daily closing prices of the Hong Kong Hang Seng Index), SPX (S&P 500 Index), FTSE (London FTSE Index) and IXIC (Nasdaq Index), DJIA (Dow Jones Industrial Average), NASDAQ (National Association of Securities Dealers Automated Quotations)

to find useful learning model from numerous images for catfish density estimation (Conte et al., 2019) and tomato plant diseases classification (Gadekallu et al., 2020), DNN is utilized to help complex investment decisions (Frey et al., 2019), RNN and LSTM is suitable for forecasting short-term power load or energy price (Abdel-Nasser & Mahmoud, 2019; Guo et al., 2018; Zhang et al., 2020a; Zhang et al., 2019; Zhou et al., 2019), DRL can derive optimal power flow (Zhou et al., 2020b) and decide the price of electric vehicles (Qiu et al., 2020). Unlike above two applications, the time period of the invested data covers different lengths. Some of them are as long as thirteen years, while others are as short as two months. And the data are selected from various channels, dataset repository, electricity market, relevant website or references, etc.

4.4 Industrial organization

There are many subcategories in industrial organization that are closely related to those in microeconomics. The studies of industry include two types: manufacturing and services ("Jel classification system,"). As shown in Table 13, in the aspect of manufacturing, Phitthayanon and Rungreunganun (2019) used deep learning technique to predict jewelry production material cost for jewelry production, Wang et al. (2020a) adopted a deep granular network with adaptive unequal-length granulation strategy to forecast long term time series for industrial enterprises, Wang and Zeng (2020) utilized multilayer CNN to select feature and estimate the influence of COVID-19 epidemic situation to sports industry. In terms of services, LSTM, CNN and their variants have been widely applied to solve problems in Internet services and restaurant industry, such as economic benefit evaluation (Arkhangelski et al., 2020), security threat detection (Adebowale et al., 2020; Ebrahimi et al., 2020; Guo, 2020; Ullah et al., 2019), reviews and bankruptcy prediction (Alsmadi et al., 2020; Becerra-

Table 11 Applications of deep learning for macroeconomics and monetary economics

Application sub field	Article	Aim of study	Data set	Data size	Time span	Models
International monetary system	(Alaminos et al., 2019)	Predict currency crisis event	IMF International Financial Statistics, World Bank Development Indicators, World Economic Outlook, and the World Bank Global Financial Database	7,708 observations	1970–2017	DNN, decision trees
Circular economy	(Lukman et al., 2020)	Predict the amount of salvage and waste materials	UK Demolition Industry	2,280 building demolition records	-	DNN
Cost efficient cardiac health monitoring	(Faust et al., 2020)	Machine classification: signal processing and make decisions	https://www.polar.com/uk-en	-	-	DL
Economic condition	(Tang et al., 2020)	Forecast economic recession through Share Price	Yahoo Finance	Six kinds of stock, and 1232 rows of data for each stock	2015–2019	LSTM
Currency exchange market	(Andrijasa, 2019)	Predict exchange currency rates	Bank Indonesia official websites	4,344 daily data series	2001–2018	Encoder-decoder RNN
	(Yasir et al., 2019)	Forecast foreign exchange rate	Daily data of exchange rate	1,304 observations	2008–2018	CNN
	(Galeshchuk, 2017)	Predict exchange rate	http://www.global-view.com/forex-trading-tools/forex-history/index.html	Each time series contains 1,304 observations	2010–2014	RBM, AE
	(Galeshchuk & Demazeau, 2017)	Forecast ungarian forint exchange rate	https://www.bloomberg.com/markets/currencies	-	2000–2017	CNN
	(Galeshchuk & Mukherjee, 2017)	Predict exchange rates	http://www.globalview.com/forex-trading-tools/forex-history/	-	2000–2015	DNN, LSTM
Macroeconomics and Monetary Economics	(Chen et al., 2019)	Forecast interaction of exchange rates	Poloniex, Kaggle, Dukascopy Bank's website	-	2016–2017	CNN, fixed-length binary Strings, a binary component

Table 11 (continued)

Application sub field	Article	Aim of study	Data set	Data size	Time span	Models
Social-economic	(Yu et al., 2020a)	Estimate economy	ImageNet data set, Landsat image dataset	-	2009	CNN
Government bonds	(Suimon et al., 2020)	Represent the Japanese yield curve	Several weekly Japanese Government Bond rates with varying maturities	-	1992–2019	AE

Note: IMF (International Monetary Fund)

Vicario et al., 2020). Meanwhile, we can see that the collected data are coming from a lot of ways: websites, industrial enterprises, references and database, which may be because of the wide coverage features of industrial organization.

4.5 Urban, rural, regional, real estate, and transportation economics

This subfield covers the research of urban, rural, and regional economics, real estate and transportation economics ("Jel classification system,"). Shown in Table 14, some data of this subfield are collected from industrial office, and others come from company and websites. In order to identify a slum's degree and predict data-driven index of multiple deprivation, CNN was utilized to capture features from 1,114 very high-resolution images (Ajami et al., 2019). In the aspect of transportation economics, various deep learning techniques, like DNN, LSTM, deep capsule network or their variants, were applied to predict transportation demand or estimate socioeconomic status (Bazan-Krzywoszanska & Bereta, 2018; Ding et al., 2019; He, 2021; Markou et al., 2020). As for real state economics, DNN was used to forecast a real estate value (Yao et al., 2018) and CNN was used to map fine-scale urban housing prices through images (Rafiei & Adeli, 2016).

4.6 Health, education, and welfare

Deep learning models have also been applied to address issues related to health, education, and welfare (Table 15). Deep residual neural networks was used to estimate poverty (Tan et al., 2020), deep CNN was applied to predict asset wealth (Yeh et al., 2020), and DRL was adopted to estimate the impact of COVID-19 on the spread of the infection, personal satisfaction or quality of life, resource use and economy (Uddin et al., 2020). We find that not only CNN, but also deep residual neural networks can handle image information. Meanwhile, DRL is still good at deciding the trend or impact.

4.7 Business administration and microeconomics

This part contains studies about business administration: production, personnel, and information technology management, new firms, corporate culture, and international business administration. Microeconomics is a branch of modern economics, mainly taking a single economic unit (a single producer, a single consumer, a single market economic activity) as a subject of analysis. As illustrated in Table 16, the method combining CNN with constraint

Table 12 Applications of deep learning for agricultural and natural resource economics

Application sub field	Article	Aim of study	Data set	Data size	Time span	Model
Food economic chain	(Conte et al., 2019)	Estimate catfish density	Aerial Images	300 images	-	CNN, Aerial Images Analysis
	(Gadekallu et al., 2020)	Classify tomato plant diseases	Plant-village dataset repository	-	-	DNN, Whale optimization algorithm
Energy market	(Frey et al., 2019)	Predict for Investment decisions	Energymap.info	1.4 million solar installations	-	DNN, gradient boosting, random forests
	(Huang & Wu, 2018)	Forecast price	5 crude oil spot prices (WTI, Brent, Forties, Dubai, and Oman), 2 financial prices (the gold prices and the U.S. exchange rate)	435 daily observations	2009–2010	DMKL, directed deep acyclic graph
	(Zhang et al., 2020a)	Forecast day-ahead electricity price	The New England electricity market, ISO launches Standard Market	-	-	DRNN
	(Zhang et al., 2019)	Promote the accuracy of wind prediction	Wind power from Hongfeng Eco-town	-	2009–2017	LSTM, multi-objective particle swarm optimization
	(Zhou et al., 2019)	Forecast electricity price	The electricity price of the Pennsylvania-New Jersey-Maryland power market	-	2018	LSTM, SMBO
	(Abdel-Nasser & Mahmoud, 2019)	Forecast photovoltaic power	Two photovoltaic datasets for locations in Aswan (Dataset1) and Cairo (Dataset2) cities, Egypt	-	1 year	LSTM-RNN
	(Guo et al. 2018)	Forecast short-term power load	https://www.torontohydro.com, http://climate.weather.gc.ca/indexe.html	-	2002–2016	Integrating several LSTM networks
	(Zhou et al., 2020b)	Derive optimal power flow	Data come from references	17,364 in data set I and 2,000 in data set II on the IEEE 14-bus system. 20,000 in data set I and 5,000 in data set II on the Illinois 200-bus system	-	DRL

Table 12 (continued)

Application sub field	Article	Aim of study	Data set	Data size	Time span	Model
Electric vehicles	(Pei et al., 2020)	Forecast vehicle velocity	Open Street Map	-	-	DBM, bi-directional LSTM
	(Qiu et al., 2020)	Pricing electric vehicles	Data come from the reference	-	-	DRL

Note: DMKL (Deep Multiple Kernel Learning), DBM (Deep restricted Boltzmann Machines)

theory was adopted to extract features of trademark images for commodity economy (Lan et al., 2018), DNN was used to assess risk for overseas investment of enterprises (Xu, 2020) and recognize pattern and make classification for multi-slot spectrum auction (Feng et al., 2018), LSTM was adopted to investigate and learn useful sentiment information from large amount of consumer review records (Luo et al., 2021).

5 Critical review of deep learning in economics

5.1 Critical reviews on deep learning models and applications in economics

Because of the excellent feature learning capability in constructing model, deep learning presents great application values in economic research. The model containing deep learning can not only handle a great amount of data in experiment, but also create an effective way to solve problems of economics. There are some comments about deep learning models and applications in economics:

1) Critical reviews of deep learning models are in terms of two points: basic models and hybrid techniques. On the one hand, different basic deep learning models play different roles in economic field. DNN, AE and RBM are the general models to construct the learning architecture because of the highly efficient computation ability when dealing with large amount of and high dimensional data. When long-term or short-term action affects the current state, or the economic problem is dynamic over time, RNN, Transformer and their variants are the most suitable options to describe the situation and construct the learning model. CNN and its variants have been widely applied to handle a large number of images in economic research, exchange rate forecast. On the other hand, hybrid deep learning has cooperated with various technologies in handling problems in economics. For example, DRL is a good way to help people make decisions and evaluate economic condition. Decision tree is one of classic decision-making methods, collaborated with DNN, they successfully predicted the currency crisis event (Alaminos et al., 2019). With the assist of attention mechanism, CNN was developed to successfully extract the most important image feature (Guo, 2020). Cooperated with logistic regression, RNN obtained better bankruptcy prediction results than single model (Becerra-Vicario et al., 2020). The combination of LSTM and sentiment analysis developed stock closing price prediction (Jin et al., 2020). Furthermore, deep learning models were successfully cooperated with other optimization technologies, e.g., improved particle swarm optimization (Ji et al., 2021), whale optimization algorithm (Gadekallu et al., 2020), multi-objective particle swarm optimization (Zhang et al., 2019),

Table 13 Applications of deep learning for industrial organization

Application sub field	Article	Aim of study	Date set	Date size	Time span	Model
Jewelry Production	(Phitthayanon & Rungreunganun, 2019)	Predict material cost	XAUUSD and XAGUSD at London Fixed market. The gold and silver price data were collected and archived by usagold.com. The diamond price data were obtained from the reference	-	2000–2018	NAR model, NARX
Industry enterprise	(Wang et al., 2020a)	Forecast long-term time series in industrial production	the Mackey–Glass time-series, the Rossler time series data, the flow of passenger on the Paris metro line 3 and 13, as well as two practical industrial datasets	-	-	SSAEN model, SAEGN model
Sports industry	(Wang & Zeng, 2020)	Select typical economic indicators	Standard economic parameter database and Yale industrial economic database	-	-	Multilayer CNN
Mart-community microgrid	(Arkhangelski et al., 2020)	Evaluate the economic benefits	A real conventional rural grid in France	-	-	LSTM
IoT (Internet of Things)	(Ullah et al., 2019)	Detect cyber security threats	GCJ	-	-	Deep CNN
Online attacks	(Adebowale et al., 2020)	Detect intelligent phishing	A data set containing 1 m URLs	-	-	CNN-LSTM
E-commerce	(Guo, 2020)	Encode image features and select the image features of commodities	MSCOCO-2015 data set	with about 160,000 product images for training, and about 80,000 product images for test and verification	-	CNN, attention mechanism
	(Alsmadi et al., 2020)	Predict helpful reviews	2014 version of the Amazon reviews dataset	around 83.7 million unique reviews	1996–2014	RCNN
Dark net marketplaces	(Ebrahimi et al., 2020)	Identify semi-supervised cyber threat	https://github.com/mohammadrezaebrahimi/JMIS-DarkNetMarketData	79k product listings	-	Transductive SVM-LSTM
Cloud services and security	(Haytamy & Omara, 2020)	Predict the Cloud QoS provisioned values	Data come from references: TimeSynth open source library and Cloud providers' dataset	-	6 months	LSTM-PSO

Table 13 (continued)

Application sub field	Article	Aim of study	Date set	Date size	Time span	Model
	(Agarwal et al., 2021)	Detect Fraudulent resource consumption attack	NASA web-server logs	-	2 months	LSTM
Restaurant industry	(Becerra-Vicario et al., 2020)	Predict bankruptcy	SABI database	460 solvent and bankrupt companies	2008–2017	DRCNN, LOGIT

Note: NARX (Nonlinear Autoregressive neural network with exogenous variables), XAUUSD (Gold Spot US Dollar), XAGUSD (Silver Spot US Dollar), GCJ (Google Code Jam)

sequence model-based optimization (Zhou et al., 2019). To sum up, basic and hybrid deep learning models accelerate the development of economic research. In the future, it is possible to use various types of deep learning models to conduct a better performance in the field of economics, and novel combinations of deep learning models and other technologies are used to tackle economic issues, such as combining deep learning with social network systems to forecast the state of economic development, or developing deep learning in multi-agent system for better economic evaluation and intelligent decision-making.

2) Critical discussions of applications in economics are unfolded from three aspects: application fields, application effects and data resources. At first, deep learning models have been widely used in various subfields of economics, up to the national economics, monetary system, financial market, stock market, down to the clothing, food, housing and transportation, which shows the generalization of deep learning models. In the future, deep learning models and their variants will be extended to other fields of economics according to the JEL classification codes guide, e.g., international economics, public economics, labor and demographic economics, economic development, innovation, technological change, and growth, law and economics, and other special topics. Extending deep learning models to supply chain finance could be interesting and gives more inspiration to scholars of economics and algorithm engineer. Secondly, deep learning models have been developed for different effects in economics, like prediction, classification, decision-making, evaluation and so on. In terms of prediction, stock price is usually the applied scene and various deep learning models have been adopted for prediction, such as DNN, LSTM, RNN, AE, etc. Fortunately, the forecast accuracy of deep learning models is frequently superior to other algorithms. As for classification, deep learning models have also been applied to image classification and text classification. Meanwhile, other deep learning models assist to make some decisions. For example, DRL helps to price electric vehicles (Qiu et al., 2020), recommend cryptocurrency trading points (Sattarov et al., 2020), and derive optimal power flow (Zhou et al., 2020b). Despite the above mentioned effects, deep learning models can be used not only in natural language processing (Khatter & Ahlawat, 2020), but also in automatic control (Zhu et al., 2020), so they can bring more and more effects and make differences in economics. Thirdly, the data of applications often come from websites, datasets, companies, references related to the research topic. To be specific, commonly used datasets of economic research are Financial Phrase-Bank dataset, World Bank Global Financial Database, ImageNet data set. Similarly, commonly used websites of economic research are Google Code Jam, Amazon reviews dataset, Yahoo financial dataset. The collection of data takes a long time, and some of them even more than ten/twenty years. The data cover an extensive range

Table 14 Applications of deep learning for urban, rural, regional, real estate, and transportation economics

Application sub field	Article	Aim of study	Data set	Data size	Time span	Model
Slums' degree of deprivation	(Ajami et al., 2019)	Predict data-driven index of multiple deprivation	1114 households living in 37 notified slums	1,114 households living	2010	CNN
Transportation system	(He, 2021)	Predict investment benefits and national economic attributes	Railway transportation industry from the National Bureau of Statistics	-	2013–2019	EEMD-LSTM
	(Ding et al., 2019)	Estimate socioeconomic status	Smart card: the dataset contains all the subway records in Shanghai; POI dataset of Shanghai is crawled based on GaoDe Map API Service2; Housing price dataset is crawled from Lianjia.com 3 website	-	2015	S2S models containing DNN and LSTM
	(Markou et al., 2020)	Time series forecasting of taxi demand	Taxi data are available by the NYC TLC.	around 600 million taxi trips after data filtering	2013–2016	A neural network architecture based on FC dense layers and a Deep Gaussian Processes architecture
Real estate market	(Bazan-Krzywoszanska & Bereta, 2018)	Forecast real estate value	the city center of Zielona Gora	163 sale and purchase transactions	2016–2017	DNN
	(Yao et al., 2018)	Map fine-scale urban housing prices	Fang.com, Tianditu.cn, several basic geographic and social media datasets	-	-	UMCNN, RF
	(Rafiei & Adeli, 2016)	Estimate the sale prices of real estate units	Tehran, Iran	360 residential condominiums (3–9 stories)	1993–2008	Deep RBM, nonmating genetic algorithm

Note: EEMD (Ensemble Empirical Mode Decomposition), FC (Fully-Connected), UMCNN (Convolutional Neural Network for United Mining), NYC TLC (New York City Taxi and Limousine Commission)

of areas, like bank, stock market, industrial, transportation, etc. Furthermore, the data could be obtained from some international or national competitions.

5.2 Critical reviews on why and how to implement deep learning in economics

Deep learning plays an important role in economics. Critical comments regarding to why and how to implement deep learning models in economics are necessary, and this will be

Table 15 Applications of deep learning for health, education, and welfare

Application sub field	Article	Aim of study	Data set	Data size	Time span	Model
Poverty	(Tan et al., 2020)	Estimate poverty	Landsat 8 images, spectral index data (NDVI, MNDWI, and NDBI), night-time light data, and statistical yearbook data	39,145 satellite images	2014–2017	Deep residual neural networks, feature pyramid networks
ttTEconomic well-being	(Yeh et al., 2020)	Predict asset wealth	Nationally representative DHS	more than 500,000 households living in 19,669 villages across 23 countries in Africa	2009–2016	Deep CNN
Policy learning	(Uddin et al., 2020)	Estimate impact of COVID-19 on the spread of the infection, personal satisfaction or quality of life, resource use and economy	Simulation data	100 episodes	-	DRL

Note: DHS (Demographic and Health Surveys)

Table 16 Applications of deep learning for business administration and microeconomics

Application sub field	Article	Aim of study	Data set	Data size	Time span	Model
Commodity economy	(Lan et al., 2018)	Extract features of trademark images	Self-built trademark training database	1,141 trademarks	-	CNN, Constraint Theory
Overseas investment of enterprises	(Xu, 2020)	Assess risk	Countries and regions that have continuity in the Fraser risk assessment learning label	the selected training samples include a total of 124 research samples containing 4,284 feature values; the selected test samples include a total of 41 research samples containing 1,426 feature values.	2018–2019	DNN
Auction market	(Feng et al., 2018)	Recognize pattern and make classification	Simulation data	-	-	DNN
Hotel management	(Luo et al., 2021)	Investigate the sentiment of hotel guests	eLong.com	363,723 reviews	2018	Bidirectional LSTM, conditional random field

useful for economists who are unfamiliar with deep learning but want to use it in their research.

1) Deep learning models usually perform better than traditional machine learning models. It can deal with a large amount of high dimensional data and mine the potential information and rules in the data. In terms of prediction, deep learning models are frequently superior to other algorithms, such as support vector machine, logistic regression, multilayer perceptron, etc., from the aspects of forecast accuracy, recall, robustness, and computational efficiency. As for classification, deep learning improves not only classification accuracy but also adaptability, because it constructs mechanism of visual perception in imitating organisms and possesses representation learning ability. Superior to conventional reinforcement learning, DRL has multiple learning layers to obtain stability and reliability during training, and get better performance. Meanwhile, deep learning models have successfully promoted the development of mathematical and quantitative methods, which play important roles in economics (Rakesh et al., 2018; Wang et al., 2020b; Wang & Li, 2020).

2) Combined with other models, deep learning variants solve more practical problems in economics. Deep Q-learning have been investigated that this model is better suited for technology stocks (Chakole & Kurhekar, 2020). The developed deep learning model can be further used to modify the inconsistent statistics during the social and economic development period (Yu et al., 2020a). Galeshchuk (2017) noticed that they wished their research effort would lead to significant improvement of the prediction accuracy in the short-and-medium term exchange rates, so that some updated versions of prediction methods can introduce a new generation of computational trading tools and change the market environment. Moreover, some researchers find that granular computing can improve deep learning model with a more efficient and transparent structure and better representation capabilities (Colace et al., 2019; Pedrycz et al., 2019). Meanwhile, granular computing can handle the interpretability and reasonability of "black box" model (Pal et al., 2020). Therefore, granular computing can also solve the same problem in economics.

3) Several requirements should be concerned if deep learning is implemented in economics. On the one hand, the samples need to be accessible and the number of samples need to be large enough. Deep learning can form sufficiently complex functions for automatically extracting and fitting features, and one of conditions is that there are as much sample data as possible. In other words, deep learning has strong expression ability based on accessible and large-scale data. On the other hand, there is a need for discrimination or classification tasks in the process of economics research. That is because deep learning is essentially learning the inherent patterns and hierarchical representation of samples, so as to execute feature extraction and classification.

5.3 Critical reviews on research gap and future challenges

Deep learning, although it is a powerful and useful technique to establish prediction model, it is often criticized as "black box" due to the difficulty to explain the solved weight coefficient and the internal mechanism of the constructed learning model. It often faces some criticisms that the computation efficiency and the result accuracy are both limited if training data are not enough or algorithm is too much complex, and if poor-quality data or unsuitable parameters tuning lead to biased and unsatisfied prediction results (please see (Groumpos, 2019; Krittanawong et al., 2019) for more criticisms regarding deep learning). In order to develop deep learning in economics, some challenges and future works are provided for further research:

1) Improve the interpretability of deep learning models in economics. Interpretability is divided into two classifications: global and local interpretability, which are detailed discussed in (Du et al., 2020) and (Guidotti et al., 2019). Global interpretability aims to understand the structure and parameters of a model from the perspective of entity. However, it requires the interpretation model to be faithful to all samples of the black box model, which is impractical (Ribeiro et al., 2016). In contrast, local interpretability only explains why individual predictions are made. The lack of local interpretability in deep learning research in economics needs more concerns, because it is important to clearly explain the reasons such as why stock price goes up or down. When applying deep learning in economics, some scholars have found that traditional machine learning performs better than deep learning in some cases. Freitas et al. (2020) discovered that decision tree performs better than DNN when predicting school dropout in IoT system. While others found some insufficiency of this topic. For example, the LSTM model needs a lot of resources and time to train, which can be a barrier for real-world applications (Ji et al., 2021). On the other hand, it is well-known that there are plenty of external factors that impact stock volatility, so that more sophisticated models that involve external factors will bring severer challenges. (Ji et al., 2021). Because of inexplicability, DNN and most of deep learning models cannot clearly interpret the theoretical and practical principles of models in economic applications such as financial market (Zhong & Enke, 2019). Similarly, just a few of research works published on behavioral finance adopt deep learning models. This may because it is full of difficulties that quantify the inputs and outputs of behavioral finance research within deep learning models (Ozbayoglu et al., 2020). Fortunately, some scholars have concerned some models or algorithms to interpret the black boxes by implementing model agnostic local interpretation methods (Du et al., 2020; Guidotti et al., 2019; Ribeiro et al., 2016).

2) Construct novel deep learning models to deal with uncertain or vague information in economics. Uncertain or vague information is quite common in economics so that one of research fields is fuzzy economics (Deng et al., 2019; Tian et al., 2019; Zhou et al., 2020a). As an emerging research direction, fuzzy economics aims to make quantitative analysis of the uncertain factors in economic relation and economic activities based on fuzzy set or fuzzy mathematics (Chang, 1976). Meanwhile, the combination of linguistic variables and economics assists to collect much natural linguistic information and reveal some undiscovered laws of economic motion (Zadeh, 1975). Deep learning can assist to acquire precise learning model from big amount of data, but previous researches about deep learning in economics leave fuzzy information out of consideration. A state-of-the-art survey about fusing deep learning and fuzzy systems (Zheng et al., 2021) have comprehensively and profoundly analyzed the fusion effect of fuzzy technology and deep learning, so it is also a good idea to combine fuzzy systems with deep learning in economics to deal with uncertain or vague information.

3) Improve the ability of deep learning to handle data issues. There are many private data in the economic field, which should be protected and kept secret. So that it is one of challenges related to data issues in deep learning applied in economics. As far as we know, Federated learning based on deep learning (Federated Machine Learning for Loan Risk Prediction) can not only protect privacy but also ensure the decent performance. The other challenge about data issues is that the data scale is not large enough, or there are not enough

labeled samples or high-quality samples, so it is not suitable to use classical deep learning models. Few-shot learning (learning from limited samples) becomes an important, fundamental and unsolved problem that machine learning community extensively concerns. self-supervised learning without labels (Wei et al., 2021), multitask learning (Zhang & Yang, 2018), embedding learning (Hou et al., 2014), learning with external memory (Graves et al., 2016) and transfer learning (Zhuang et al., 2021) has more potential to tackle various tasks.

6 Conclusion

This paper makes a comprehensive and critical review of deep learning in economics. Firstly, the research database has been explained and some statistical results have been described. Then, a survey of popular deep learning models in economics has been detailed investigated and several applications of deep learning in economics have been classified according to JEL. Finally, some critical reviews of deep learning in economics are provided, including models and applications, why and how to implement deep learning in economics, research gap and future challenges, respectively. In what follows, we are ready to give answers to our initially stated research questions.

1) Which deep learning models are preferred (and more successful) in economics? What are the characteristics of different deep learning algorithms in the economic field?

Response: DNN, RBM, DBN, CNN, RNN, AE, Transformer, DRL and their variants have been widely applied in economics. Among these, DNN, AE and RBM are the general model to construct the learning architecture due to the highly efficient computation ability. RNN, Transformer and their variants are the most suitable options to handle economic problems affected by long-term or short-term. CNN and its variants have been widely applied to control a large number of images in economic research. DRL is used to make decisions or evaluate economic condition.

2) What economic application areas are of interest to deep learning community? What are the differences when we execute deep learning models against traditional soft computing/machine learning techniques?

Response: Deep learning has been widely applied in financial economics, macroeconomics and monetary economics, agricultural and natural resource economics, industrial organization, urban, rural, regional, real estate and transportation economics, health, education and welfare, business administration and microeconomics. Compared to benchmark methods, deep learning models usually bring more accurate prediction results, better classification performance and stronger model or parameter learning capability.

3) What are the drawbacks of the current application of deep learning in economics?

Response: Sometimes, traditional soft computing or machine learning techniques perform better than certain deep learning models in some situations. Deep learning modes also need a lot of resources and time to train, which can be a barrier for real-world applications. More importantly, most of deep learning models cannot clearly interpret the theoretical and practical principles of models in economic applications, and some data issues should be taken seriously.

4) What are the future directions of researches about deep learning in economics?

Response: (i) Improve the interpretability of deep learning models in economics. (ii) Exploit different variants of deep learning models and apply them to solve more practical problems in economics. (iii) Develop the ability of deep learning models in economics to deal with uncertain or vague information. (iv) Improve the ability of deep learning to handle data issues.

We believe that with the development of deep learning, decision-making in economics will become more intelligent, and some deeper and widely researches of deep learning in economics will be an important topic for years to come.

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References

Abdalla A, Cen HY, Wan L et al (2019) Fine-tuning convolutional neural network with transfer learning for semantic segmentation of ground-level oilseed rape images in a field with high weed pressure. Comput Electron Agric 167:105091. https://doi.org/10.1016/j.compag.2019.105091

Abdel-Nasser M, Mahmoud K (2019) Accurate photovoltaic power forecasting models using deep lstm-rnn. Neural Comput Appl 31(7):2727–2740. https://doi.org/10.1007/s00521-017-3225-z

Adebowale MA, Lwin KT, Hossain MA (2020) Intelligent phishing detection scheme using deep learning algorithms. J Enterp Inform Manage. https://doi.org/10.1108/jeim-01-2020-0036

Agarwal A, Prasad A, Rustogi R et al (2021) Detection and mitigation of fraudulent resource consumption attacks in cloud using deep learning approach. J Inform Secur Appl 56:102672. https://doi.org/10.1016/j.jisa.2020.102672

Ahelegbey DF (2016) The econometrics of bayesian graphical models: A review with financial application. J Netw Theory Finance 2(2):1–33

Ajami A, Kuffer M, Persello C et al (2019) Identifying a slums' degree of deprivation from vhr images using convolutional neural networks. Remote Sens 11(11):1282. https://doi.org/10.3390/rs11111282

Alaminos D, Becerra-Vicario R, Fernandez-Gamez MA et al (2019) Currency crises prediction using deep neural decision trees. Appl Sciences-Basel 9(23):5227. https://doi.org/10.3390/app9235227

Alsmadi A, AlZu'bi S, Hawashin B et al (2020) Employing deep learning methods for predicting helpful reviews. In *2020 11th international conference on information and communication systems* (pp. 007–012). New York: Ieee

Anbazhagan S, Kumarappan N (2013) Day-ahead deregulated electricity market price forecasting using recurrent neural network. IEEE Syst J 7(4):866–872. https://doi.org/10.1109/jsyst.2012.2225733

Andrijasa MF (2019) Deep learning with encoder-decoder architecture for exchange currency rates model predictions. In A. G. Abdullah, A. B. D. Nandiyanto, I. Widiaty, A. A. Danuwijaya, & C. U. Abdullah (Eds.), *4th annual applied science and engineering conference, 2019* (Vol. 1402, pp. 066098). Bristol: Iop Publishing Ltd

Arisoy E, Sethy A, Ramabhadran B et al (2015) Bidirectional recurrent neural network language models for automatic speech recognition. In *2015 ieee international conference on acoustics, speech, and signal processing* (pp. 5421–5425). New York: Ieee

Arkhangelski J, Siano P, Mahamadou AT et al (2020) Evaluating the economic benefits of a smart-community microgrid with centralized electrical storage and photovoltaic systems. Energies 13(7):1764. https://doi.org/10.3390/en13071764

Bazan-Krzywoszanska A, Bereta M (2018) The use of urban indicators in forecasting a real estate value with the use of deep neural network. Rep Geodesy Geoinformatics 106:25–34

Bazi Y, Bashmal L, Al Rahhal MM et al (2021) Vision transformers for remote sensing image classification. Remote Sens 13(3). https://doi.org/10.3390/rs13030516

Becerra-Vicario R, Alaminos D, Aranda E et al (2020) Deep recurrent convolutional neural network for bankruptcy prediction: A case of the restaurant industry. Sustainability 12(12):5180. https://doi.org/10.3390/su12125180

Bengio Y, Courville A, Vincent P (2013) Representation learning: A review and new perspectives. IEEE Trans Pattern Anal Mach Intell 35(8):1798–1828. https://doi.org/10.1109/tpami.2013.50

Bengio, Y., Simard, P., & Frasconi, P. (1994). Learning long-term dependencies with gradient descent is difficult. IEEE Transactions on Neural Networks, 5(2), 157-166, https://doi.org/10.1109/72.279181

Blaug M (1981) The methodology of economics. Econ J 91(363):77–84

Buongiorno D, Camardella C, Cascarano GD et al (2019) An undercomplete autoencoder to extract muscle synergies for motor intention detection. In *2019 international joint conference on neural networks*. New York: Ieee

Cerniglia JA, Fabozzi FJ (2020) Selecting computational models for asset management: Financial econometrics versus machine learning—is there a conflict? J Portfolio Manage 47(1):107–118

Chakole J, Kurhekar M (2020) Trend following deep q-learning strategy for stock trading. Expert Syst 37(4):e12514. https://doi.org/10.1111/exsy.12514

Chang SSL (1976) Application of fuzzy set theory to economics. *Proceedings of the IEEE International Conference on Cybernetics and Society*, 556–558

Chatzis SP, Siakoulis V, Petropoulos A et al (2018) Forecasting stock market crisis events using deep and statistical machine learning techniques. Expert Syst Appl 112(12):353–371

Che L, Yang XP, Wang L (2020) Text feature extraction based on stacked variational autoencoder. Microprocess Microsyst 76:103063. https://doi.org/10.1016/j.micpro.2020.103063

Chen CT, Chiang LK, Huang YC et al (2019) Forecasting interaction of exchange rates between fiat currencies and cryptocurrencies based on deep relation networks. IEEE Computer Soc, Los Alamitos

Chen CY, Leu JS, Prakosa SW et al (2018) Using autoencoder to facilitate information retention for data dimension reduction. Ieee, New York

Chen HL, Wang S, Jiang N et al (2021) Trust-aware generative adversarial network with recurrent neural network for recommender systems. Int J Intell Syst 36(2):778–795. https://doi.org/10.1002/int.22320

Chen ZX, Ma WQ, Dai W et al (2020) Conditional restricted boltzmann machine for item recommendation. Neurocomputing 385:269–277. https://doi.org/10.1016/j.neucom.2019.12.088

Conte D, Gaucher P, Sansone C et al (2019) Catfish density estimation by aerial images analysis and deep learning. Assoc Computing Machinery, New York

Cui JH, Chai TY, Liu XJ (2020) Deep-neural-network-based economic model predictive control for ultrasupercritical power plant. IEEE Trans Industr Inf 16(9):5905–5913. https://doi.org/10.1109/tii.2020.2973721

Deng X, Cheng X, Gu J et al (2019) An innovative indicator system and group decision framework for assessing sustainable development enterprises. Group Decis Negot. https://doi.org/10.1007/s10726-019-09647-0

Devlin J, Chang MW, Lee K et al (2018) Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv. https://doi.org/10.48550/arXiv.1810.04805

Ding S, Huang H, Zhao T et al (2019) Estimating socioeconomic status via temporal-spatial mobility analysis - a case study of smart card data. IEEE ICCCN 2019. https://doi.org/10.1109/ICCCN.2019.8847051

Du MN, Li NH, Hu X (2020) Techniques for interpretable machine learning. Commun ACM 63(1):68–77. https://doi.org/10.1145/3359786

Ebrahimi M, Nunamaker JF, Chen HC (2020) Semi-supervised cyber threat identification in dark net markets: A transductive and deep learning approach. J Manage Inform Syst 37(3):694–722. https://doi.org/10.1080/07421222.2020.1790186

Elman JL (1990) Finding structure in time. Cogn Sci 14(2):179–211

Fan X, Feng X, Dong Y et al (2022) Covid-19 ct image recognition algorithm based on transformer and cnn. Displays 72:102150–102150. https://doi.org/10.1016/j.displa.2022.102150

Faust O, Lei NR, Chew E et al (2020) A smart service platform for cost efficient cardiac health monitoring. Int J Environ Res Public Health 17(17):6313. https://doi.org/10.3390/ijerph17176313

Feng Z, Zhang Y, Qiang W (2018) Multi-slot spectrum auction in heterogeneous networks based on deep feedforward network. Ieee Access 6:45113–45119. https://doi.org/10.1109/ACCESS.2018.2865437

Fisichella M, Garolla F (2021) Can deep learning improve technical analysis of forex data to predict future price movements? Ieee Access 9:153083–153101. https://doi.org/10.1109/access.2021.3127570

Frey UJ, Klein M, Deissenroth M (2019) Modelling complex investment decisions in germany for renewables with different machine learning algorithms. Environ Model Softw 118:61–75. 10.1016/j.envsoft.2019.03.006

Fujita H, Cimr D (2019) Computer aided detection for fibrillations and flutters using deep convolutional neural network. Inf Sci 486:231–239. https://doi.org/10.1016/j.ins.2019.02.065

Gadekallu TR, Rajput DS, Reddy MPK et al (2020) A novel pca-whale optimization-based deep neural network model for classification of tomato plant diseases using gpu. J Real-Time Image Proc. https://doi.org/10.1007/s11554-020-00987-8

Galeshchuk S (2017) Technological bias at the exchange rate market. Intell Syst Acc Finance Manage 24(1):80–86

Galeshchuk S, Demazeau Y (2017) Forecasting hungarian forint exchange rate with convolutional neural networks. Ieee, New York

Galeshchuk S, Mukherjee S (2017) *Deep learning for predictions in emerging currency markets.* Paper presented at the In Proceedings of the 9th International Conference on Agents and Artificial Intelligence

Gensler A, Henze J, Sick B et al (2016) Deep learning for solar power forecasting - an approach using autoencoder and lstm neural networks. In *2016 ieee international conference on systems, man, and cybernetics* (pp. 2858–2865). New York: IEEE

Goodfellow I, Bengio Y, Courville A (2016) Deep learning. The MIT Press

Graves A, Wayne G, Eynolds MR et al (2016) Hybrid computing using a neural network with dynamic external memory. Nature 538(7626):471–. https://doi.org/10.1038/nature20101

Groumpos PP (2019) Artificial intelligence: Issues, challenges, opportunities and threats. In: Kravets AG, Groumpos PP, Shcherbakov M, Kultsova M (eds) Creativity in intelligent technologies and data science, pt 1, vol 1083. Springer International Publishing Ag, Cham, pp 19–33

Gu JX, Wang ZH, Kuen J et al (2018) Recent advances in convolutional neural networks. Pattern Recogn 77:354–377. https://doi.org/10.1016/j.patcog.2017.10.013

Guidotti R, Monreale A, Ruggieri S et al (2019) A survey of methods for explaining black box models. ACM-CSUR 51(5):93. https://doi.org/10.1145/3236009

Guo H, Tang L, Peng Y (2018) *Ensemble deep learning method for short-term load forecasting.* Paper presented at the 2018 14th International Conference on Mobile Ad-Hoc and Sensor Networks (MSN)

Guo LN (2020) Cross-border e-commerce platform for commodity automatic pricing model based on deep learning. Electron Commer Res. https://doi.org/10.1007/s10660-020-09449-6

Guo Y, Wang H, Hu Q et al (2020) Deep learning for 3d point clouds: A survey. IEEE Trans Pattern Anal Mach Intell. https://doi.org/10.1109/tpami.2020.3005434

Han YN, Ma YY, Wang JB et al (2020) Research on ensemble model of anomaly detection based on autoencoder. Ieee, New York

Haytamy S, Omara F (2020) A deep learning based framework for optimizing cloud consumer qos-based service composition. Computing 102(5):1117–1137. https://doi.org/10.1007/s00607-019-00784-7

He J (2021) Application of deep learning model under improved emd in railway transportation investment benefits and national economic attribute analysis. J Supercomputing. https://doi.org/10.1007/s11227-020-03609-z

He QQ, Pang CI, Si YW (2019) Transfer learning for financial time series forecasting.PRICAI: Trends in Artificial Intelligence,24–36

He X, Chen YS, Lin ZH (2021) Spatial-spectral transformer for hyperspectral image classification. Remote Sens 13(3):21. https://doi.org/10.3390/rs13030498

Heaton JB, Polson NG, Witte JH (2017) Deep learning for finance: Deep portfolios. Appl Stoch Models Bus Ind 33(1):3–12. https://doi.org/10.1002/asmb.2209

Hinton G, Deng L, Yu D et al (2012) Deep neural networks for acoustic modeling in speech recognition: The shared views of four research groups. IEEE Signal Process Mag 29(6):82–97

Hinton GE, Osindero S, Teh YW (2006) A fast learning algorithm for deep belief nets. Neural Comput 18(7):1527–1554. https://doi.org/10.1162/neco.2006.18.7.1527

Hinton GE, Salakhutdinov RR (2006) Reducing the dimensionality of data with neural networks. Science 313:504–507

Hochreiter, S. & Schmidhuber, J. (1997). Long short-term memory, Neural Computing, 9(8), 1735-1780, https://doi.org/10.1162/neco.1997.9.8.1735

Hong SH, Ryu S, Lim J et al (2020) Molecular generative model based on an adversarially regularized autoencoder. J Chem Inf Model 60(1):29–36. https://doi.org/10.1021/acs.jcim.9b00694

Hou CP, Nie FP, Li XL et al (2014) Joint embedding learning and sparse regression: A framework for unsupervised feature selection. Ieee Trans Cybernetics 44(6):793–804. https://doi.org/10.1109/tcyb.2013.2272642

Huan J, Hong H, Pan X et al (2020) Short-term load forecasting of integrated energy systems based on deep learning. *2020 5th Asia Conference on Power and Electrical Engineering (ACPEE)*. https://doi.org/10.1109/ACPEE48638.2020.9136566

Huang J, Chai JY, Cho S (2020) Deep learning in finance and banking: A literature review and classification. Front Bus Res China 14(1):24. https://doi.org/10.1186/s11782-020-00082-6

Huang SC, Wu CF (2018) Energy commodity price forecasting with deep multiple kernel learning. Energies 11(11):3029. https://doi.org/10.3390/en11113029

Hugo S, Kathy B, Thomas H (2019) Machine learning in agricultural and applied economics. Eur Rev Agric Econ 47(3):1–44

Jel classification system. Retrieved from https://www.aeaweb.org/econlit/access

Ji, Y., Liew, A. W. C., & Yang, L. X. (2021). A novel improved particle swarm optimization with long-short term memory hybrid model for stock indices forecast. *Ieee Access, 9*, 23660–23671. https://doi.org/10.1109/access.2021.3056713

Jin, Z. G., Yang, Y., & Liu, Y. H. (2020). Stock closing price prediction based on sentiment analysis and lstm. *Neural Computing & Applications, 32*(13), 9713–9729. https://doi.org/10.1007/s00521-019-04504-2

Jordan, M. I. (1986). Serial order: A parallel distributed processing approach. *Institute for Cognitive Science University of California, San Diego*.

Katayama, D., Kino, Y., & Tsuda, K. (2019). A method of sentiment polarity identification in financial news using deep learning. In I. J. Rudas, C. Janos, C. Toro, J. Botzheim, R. J. Howlett, & L. C. Jain (Eds.), *Knowledge-based and intelligent information & engineering systems* (Vol. 159, pp. 1287–1294). Amsterdam: Elsevier.

Keynes, J. M. (1936). The general theory of employment, interest and money. *Foreign affairs, 7*(5).

Khatter, H., & Ahlawat, A. (2020). An intelligent personalized web blog searching technique using fuzzy-based feedback recurrent neural network. *Soft Computing, 24*(12), 9321–9333. https://doi.org/10.1007/s00500-020-04891-y

Kheradpisheh, S. R., Ganjtabesh, M., Thorpe, S. J., et al. (2018). Stdp-based spiking deep convolutional neural networks for object recognition. *Neural Networks, 99*, 56–67. https://doi.org/10.1016/j.neunet.2017.12.005

Kim, H. G., Kim, G. Y., & Kim, J. Y. (2019). Music recommendation system using human activity recognition from accelerometer data. *Ieee Transactions on Consumer Electronics, 65*(3), 349–358. https://doi.org/10.1109/tce.2019.2924177

Krefl, D., Carrazza, S., Haghighat, B., et al. (2020). Riemann-theta boltzmann machine. *Neurocomputing, 388*, 334–345. https://doi.org/10.1016/j.neucom.2020.01.011

Kremsner, S., Steinicke, A., & Szlgyenyi, M. (2020). A deep neural network algorithm for semilinear elliptic pdes with applications in insurance mathematics. *Risks, 8*(4), 136. https://doi.org/10.3390/risks8040136

Krittanawong, C., Johnson, K. W., Rosenson, R. S., et al. (2019). Deep learning for cardiovascular medicine: A practical primer. *European Heart Journal, 40*(25), 2058–2073. https://doi.org/10.1093/eurheartj/ehz056

Lan, T., Feng, X. Y., Li, L., et al. (2018). Similar trademark image retrieval based on convolutional neural network and constraint theory. In *2018 eighth international conference on image processing theory, tools and applications* (pp. 205–210). New York: IEEE.

Le Roux, N., & Bengio, Y. (2008). Representational power of restricted boltzmann machines and deep belief networks. *Neural Computation, 20*(6), 1631–1649. https://doi.org/10.1162/neco.2008.04-07-510

LeCun, Y. (1987). Modeles connexionnistes de l'apprentissage. *These De Doctorat Universite Paris, 15*(10), 1–9.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

LeCun, Y., Bottou, L., Bengio, Y., et al. (1998). Gradient-based learning applied to document recognition. *Proceedings of the Ieee, 86*(11), 2278–2324. https://doi.org/10.1109/5.726791

Lee, C. F. (2020). Financial econometrics, mathematics, statistics, and financial technology: An overall view. *Review of Quantitative Finance and Accounting, 54*(4), 1529–1578. https://doi.org/10.1007/s11156-020-00883-z

Li, H. Y., Pan, L. N., Chen, M., et al. (2017). Rbm-based back propagation neural network with bsasa optimization for time series forecasting. In *2017 ninth international conference on intelligent human-machine systems and cybernetics* (pp. 218–221). New York: Ieee.

Li, X. H., & Wang, X. L. (2020). Cv image segmentation model combining convolutional restricted boltzmann machine. *Laser & Optoelectronics Progress, 57*(4), 041018. https://doi.org/10.3788/lop57.041018

Li, X. S., Liu, J. F., Li, J. J., et al. (2020a). A stacked denoising sparse autoencoder based fault early warning method for feedwater heater performance degradation. *Energies, 13*(22), 6061. https://doi.org/10.3390/en13226061

Li, Y., Wang, S., Wei, Y., & Zhu, Q. (2021). A new hybrid VMD-ICSS-BiGRU approach for gold futures price forecasting and algorithmic trading. *IEEE Transactions on Computational Social Systems, 8*(6), 1357–1368. https://doi.org/10.1109/TCSS.2021.3084847

Li, Y., Xu, Z. S., Wang, X. X., et al. (2020b). A bibliometric analysis on deep learning during 2007–2019. *International Journal of Machine Learning and Cybernetics, 11*(12), 2807–2826. https://doi.org/10.1007/s13042-020-01152-0

Liao, S. Y., Zhuo, W., Yao, L., et al. (2021). *Locational marginal price forecasting using transformer-based deep learning network*. Paper presented at the 2021 40th Chinese Control Conference (CCC). Conference Paper retrieved from <Go to ISI>://INSPEC:21225180

Lindenlaub, I., & Prummer, A. (2021). Network structure and performance. *Economic Journal, 131*(634), 851–898. https://doi.org/10.1093/ej/ueaa072

Liu, J. L., Lin, C. M. M., & Chao, F. (2020). Gradient boost with convolution neural network for stock forecast. In Z. Ju, L. Yang, C. Yang, A. Gegov, & D. Zhou (Eds.), *Advances in computational intelligence systems* (Vol. 1043, pp. 155–165). Cham: Springer International Publishing Ag.

Liu, Y., Zeng, Q. G., Yang, H. R., et al. (2018). Stock price movement prediction from financial news with deep learning and knowledge graph embedding. In K. Yoshida & M. Lee (Eds.), *Knowledge management and acquisition for intelligent systems* (Vol. 11016, pp. 102–113). Cham: Springer International Publishing Ag.

Liu, Z., Lin, Y., Cao, Y., et al. (2021). Swin transformer: Hierarchical vision transformer using shifted windows. *arXiv*. https://doi.org/10.48550/arXiv.2103.14030

Long, J. Y., Sun, Z. Z., Li, C., et al. (2020). A novel sparse echo autoencoder network for data-driven fault diagnosis of delta 3-d printers. *Ieee Transactions on Instrumentation and Measurement, 69*(3), 683–692. https://doi.org/10.1109/tim.2019.2905752

Lukman, A. A., Ahmed, O. O., Lukumon, O. O., et al. (2020). Deep learning model for demolition waste prediction in a circular economy. *Journal of Cleaner Production, 274*(20), 122843.

Luo, J. Q., Huang, S. S., & Wang, R. W. (2021). A fine-grained sentiment analysis of online guest reviews of economy hotels in china. *Journal of Hospitality Marketing & Management, 30*(1), 71–95. https://doi.org/10.1080/19368623.2020.1772163

Mahata, S. K., Das, D., & Bandyopadhyay, S. (2019). Mtil2017: Machine translation using recurrent neural network on statistical machine translation. *Journal of Intelligent Systems, 28*(3), 447–453. https://doi.org/10.1515/jisys-2018-0016

Markou, I., Rodrigues, F., & Pereira, F. C. (2020). Is travel demand actually deep? An application in event areas using semantic information. *Ieee Transactions on Intelligent Transportation Systems, 21*(2), 641–652. https://doi.org/10.1109/tits.2019.2897341

Marshall, A. (1992). The principles of economics. *History of Economic Thought Books*.

Meng, Q. X., Catchpoole, D., Skillicorn, D., et al. (2017). Relational autoencoder for feature extraction. In *2017 international joint conference on neural networks* (pp. 364–371). New York: Ieee.

Mishev, K., Gjorgjevikj, A., Vodenska, I., et al. (2020). Evaluation of sentiment analysis in finance: From lexicons to transformers. *Ieee Access, 8*, 131662–131682. https://doi.org/10.1109/access.2020.3009626

Mittelman, R., Kuipers, B., Savarese, S., et al. (2014). *Structured recurrent temporal restricted boltzmann machines*. Paper presented at the International Conference on Machine Learning.

Mnih, V., Kavukcuoglu, K., Silver, D., et al. (2013). Playing atari with deep reinforcement learning. *Computer Science*.

Mosavi, A., Faghan, Y., Ghamisi, P., et al. (2020). Comprehensive review of deep reinforcement learning methods and applications in economics. *Mathematics, 8*(10), 42. https://doi.org/10.3390/math8101640

Nikou, M., Mansourfar, G., & Bagherzadeh, J. (2019). Stock price prediction using deep learning algorithm and its comparison with machine learning algorithms. *Intelligent Systems in Accounting Finance & Management, 26*(4), 164–174. https://doi.org/10.1002/isaf.1459

Niu, H. L., Xu, K. L., & Wang, W. Q. (2020). A hybrid stock price index forecasting model based on variational mode decomposition and lstm network. *Applied Intelligence, 50*(12), 4296–4309. https://doi.org/10.1007/s10489-020-01814-0

Noaman, H. M., Sarhan, S. S., & Rashwan, M. A. A. (2018). Enhancing recurrent neural network-based language models by word tokenization. *Human-Centric Computing and Information Sciences, 8*, 12. https://doi.org/10.1186/s13673-018-0133-x

Nosratabadi, S., Mosavi, A., Duan, P., et al. (2020). Data science in economics: Comprehensive review of advanced machine learning and deep learning methods. *Mathematics, 8*(10), 25. https://doi.org/10.3390/math8101799

Ozgur, O., & Akkoc, U. (2021). Inflation forecasting in an emerging economy: Selecting variables with machine learning algorithms. *International Journal of Emerging Markets*. https://doi.org/10.1108/ijoem-05-2020-0577

Page, L., & Clemen, R. T. (2013). Do prediction markets produce well-calibrated probability forecasts? *Economic Journal, 123*(568), 491–513. https://doi.org/10.1111/j.1468-0297.2012.02561.x

Patricio, D. I., & Rieder, R. (2018). Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review. *Computers and Electronics in Agriculture, 153*, 69–81. https://doi.org/10.1016/j.compag.2018.08.001

Pei, J. Z., Su, Y. X., Zhang, D. H., et al. (2020). Velocity forecasts using a combined deep learning model in hybrid electric vehicles with v2v and v2i communication. *Science China-Technological Sciences, 63*(1), 55–64. https://doi.org/10.1007/s11431-018-9396-0

Phitthayanon, C., & Rungreunganun, V. (2019). Material cost prediction for jewelry production using deep learning technique. *Engineering Journal-Thailand, 23*(6), 145–160. https://doi.org/10.4186/ej.2019.23.6.145

Qiu, D. W., Ye, Y. J., Papadaskalopoulos, D., et al. (2020). A deep reinforcement learning method for pricing electric vehicles with discrete charging levels. *Ieee Transactions on Industry Applications, 56*(5), 5901–5912. https://doi.org/10.1109/tia.2020.2984614

Rafiei, M. H., & Adeli, H. (2016). A novel machine learning model for estimation of sale prices of real estate units. *Journal of Construction Engineering and Management, 142*(2), 04015066.

Rakesh, V., Guo, R. C., Moraffah, R., et al. (2018). *Linked causal variational autoencoder for inferring paired spillover effects*. New York: Assoc Computing Machinery.

Ranjan, N., Bhandari, S., Khan, P., et al. (2021). Large-scale road network congestion pattern analysis and prediction using deep convolutional autoencoder. *Sustainability, 13*(9), 5108. https://doi.org/10.3390/su13095108

Rao, T. C. S., Ram, S. S. T., & Subrahmanyam, J. B. V. (2020). Fault signal recognition in power distribution system using deep belief network. *Journal of Intelligent Systems, 29*(1), 459–474. https://doi.org/10.1515/jisys-2017-0499

Rattinger, H. (1976). Econometrics and arms races - critical-review and some extensions. *European Journal of Political Research, 4*(4), 421–439. https://doi.org/10.1111/j.1475-6765.1976.tb00544.x

Ribeiro, M. T., Singh, S., Guestrin, C., et al. (2016). *"Why should i trust you?" Explaining the predictions of any classifier*. New York: Assoc Computing Machinery.

Roopaei, M., Rad, P., & Jamshidi, M. (2017). Deep learning control for complex and large scale cloud systems. *Intelligent Automation and Soft Computing, 23*(3), 389–391. https://doi.org/10.1080/10798587.2017.1329245

Salakhutdinov, R., & Hinton, G. J. N. C. (2012). An efficient learning procedure for deep boltzmann machines. *24*(8), 1967–2006.

Sattarov, O., Muminov, A., Lee, C. W., et al. (2020). Recommending cryptocurrency trading points with deep reinforcement learning approach. *Applied Sciences-Basel, 10*(4), 1506. https://doi.org/10.3390/app10041506

Sehovac, L., & Grolinger, K. (2020). Deep learning for load forecasting: Sequence to sequence recurrent neural networks with attention. *Ieee Access, 8*, 36411–36426. https://doi.org/10.1109/ACCESS.2020.2975738

Selim, A., Elgharib, M., & Doyle, L. (2016). Painting style transfer for head portraits using convolutional neural networks. *Acm Transactions on Graphics, 35*(4), 1–18. https://doi.org/10.1145/2897824.2925968

Sharaf, M., Hemdan, E. E., El-Sayed, A., et al. (2021). Stockpred: A framework for stock price prediction. *Multimedia Tools and Applications, 80*(12), 17923–17954. https://doi.org/10.1007/s11042-021-10579-8

Shi, T., Mei, F., Lu, J. X., et al. (2019). Phase space reconstruction algorithm and deep learning-based very short-term bus load forecasting. *Energies, 12*(22), 4349. https://doi.org/10.3390/en12224349

Smith, A. (1976). An inquiry into the nature and causes of the wealth of nations.

Suimon, Y., Sakaji, H., Izumi, K., et al. (2020). Autoencoder-based three-factor model for the yield curve of japanese government bonds and a trading strategy. *Journal of Risk and Financial Management, 13*(4), 82. https://doi.org/10.3390/jrfm13040082

Tan, Y. M., Wu, P., Zhou, G. H., et al. (2020). Combining residual neural networks and feature pyramid networks to estimate poverty using multisource remote sensing data. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13*, 553–565. https://doi.org/10.1109/jstars.2020.2968468

Tang, Y. M., Chau, K. Y., Li, W. Q., et al. (2020). Forecasting economic recession through share price in the logistics industry with artificial intelligence (ai). *Computation, 8*(3), 70. https://doi.org/10.3390/computation8030070

Tao, Z. R., Han, L., & Bai, K. (2020). The economic impact analysis of the 1994 northridge earthquake by deep learning tools. In J. H. Kim, Z. W. Geem, D. Jung, D. G. Yoo, & A. Yadav (Eds.), *Advances in harmony search, soft computing and applications* (Vol. 1063, pp. 111–121). Cham: Springer International Publishing Ag.

Tian, X. L., Xu, Z. S., & Gu, J. (2019). An extended todim based on cumulative prospect theory and its application in venture capital. *Informatica, 30*(2), 413–429. https://doi.org/10.15388/Informatica.2019.212

Touvron, H., Cord, M., Douze, M., et al. (2020). Training data-efficient image transformers & distillation through attention. *arXiv*. https://doi.org/10.48550/arXiv.2012.12877

Tsakas, N., Xefteris, D., & Ziros, N. (2021). Vote trading in power-sharing systems: A laboratory investigation. *Economic Journal, 131*(636), 1849–1882. https://doi.org/10.1093/ej/ueaa105

Tsutsui, Y., & Hagiwara, M. (2019). Analog value associative memory using restricted boltzmann machine. *Journal of Advanced Computational Intelligence and Intelligent Informatics, 23*(1), 60–66. https://doi.org/10.20965/jaciii.2019.p0060

Uddin, M. I., Shah, S. A. A., Al-Khasawneh, M. A., et al. (2020). Optimal policy learning for covid-19 prevention using reinforcement learning. *Journal of Information Science*. https://doi.org/10.1177/0165551520959798

Ullah, F., Naeem, H., Jabbar, S., et al. (2019). Cyber security threats detection in internet of things using deep learning approach. *Ieee Access, 7*, 124379–124389. https://doi.org/10.1109/access.2019.2937347

Vaswani, A., Shazeer, N., Parmar, N., et al. (2017, Dec 04–09). *Attention is all you need.* Paper presented at the 31st Annual Conference on Neural Information Processing Systems (NIPS), Long Beach, CA.

Vincent, P., Larochelle, H., Bengio, Y., et al. (2008). *Extracting and composing robust features with denoising autoencoders.* Paper presented at the Machine Learning, Proceedings of the Twenty-Fifth International Conference (ICML 2008), Helsinki, Finland, June 5–9, 2008.

Waheeb, W., & Ghazali, R. (2020). A novel error-output recurrent neural network model for time series forecasting. *Neural Computing & Applications, 32*(13), 9621–9647. https://doi.org/10.1007/s00521-019-04474-5

Wang, J. (2020). Speech recognition in english cultural promotion via recurrent neural network. *Personal and Ubiquitous Computing, 24*(2), 237–246. https://doi.org/10.1007/s00779-019-01293-2

Wang, Q., Chen, L., Zhao, J., et al. (2020). A deep granular network with adaptive unequal-length granulation strategy for long-term time series forecasting and its industrial applications. *Artificial Intelligence Review, 53*(7), 5353–5381. https://doi.org/10.1007/s10462-020-09822-9

Wang, Q. Q., & Li, C. B. (2022). Incident detection and classification in renewable energy news using pre-trained language models on deep neural networks. *Journal of Computational Methods in Sciences and Engineering, 22*(1), 57–76. https://doi.org/10.3233/jcm-215594

Wang, S. H., Wang, Q. Y., & Zhao, J. H. (2020). Deep neural networks for choice analysis: Extracting complete economic information for interpretation. *Transportation Research Part C-Emerging Technologies, 118*, 22. https://doi.org/10.1016/j.trc.2020.102701

Wang, W. H., & Li, W. P. (2020). Research on trend analysis method of multi-series economic data based on correlation enhancement of deep learning. *Neural Computing & Applications*, 17. https://doi.org/10.1007/s00521-020-05263-1

Wang, Y. L., & Zeng, D. S. (2020). Development of sports industry under the influence of covid-19 epidemic situation based on big data. *Journal of Intelligent & Fuzzy Systems, 39*(6), 8867–8875. https://doi.org/10.3233/jifs-189284

Wei, T. X., You, Y. N., & Chen, T. L. (2021). *Ar-stock: Deep augmented relational stock prediction*. Paper presented at the The AAAI-21 Workshop on Knowledge Discovery from Unstructured Data in Financial Services.

Wu, H., Xiao, B., Codella, N., et al. (2021). Cvt: Introducing convolutions to vision transformers. *arXiv*. https://doi.org/10.48550/arXiv.2103.15808

Wu, Q., Guo, Y., Chen, H., et al. (2019). Establishment of a deep learning network based on feature extraction and its application in gearbox fault diagnosis. *Artificial Intelligence Review, 52*(1), 125–149.

Wu, Y., Yuan, M., Dong, S., Lin, L., & Liu, Y. (2018). Remaining useful life estimation of engineered systems using vanilla LSTM neural networks. *Neurocomputing, 275*, 167–179. https://doi.org/10.1016/j.neucom.2017.05.063

Xu, J., Xiang, L., Liu, Q. S., et al. (2016). Stacked sparse autoencoder (ssae) for nuclei detection on breast cancer histopathology images. *Ieee Transactions on Medical Imaging, 35*(1), 119–130. https://doi.org/10.1109/tmi.2015.2458702

Xu, X. Y. (2020). Risk factor analysis combined with deep learning in the risk assessment of overseas investment of enterprises. *Plos One, 15*(10), e0239635. https://doi.org/10.1371/journal.pone.0239635

Xu, Y. Y., Liu, Z., Li, Y. J., et al. (2020). Feature data processing: Making medical data fit deep neural networks. *Future Generation Computer Systems-the International Journal of Escience, 109*, 149–157. https://doi.org/10.1016/j.future.2020.02.034

Yao, Y., Zhang, J. B., Hong, Y., et al. (2018). Mapping fine-scale urban housing prices by fusing remotely sensed imagery and social media data. *Transactions in Gis, 22*(2), 561–581. https://doi.org/10.1111/tgis.12330

Yasir, M., Durrani, M. Y., Afzal, S., et al. (2019). An intelligent event-sentiment-based daily foreign exchange rate forecasting system. *Applied Sciences-Basel, 9*(15), 2980. https://doi.org/10.3390/app9152980

Yeh, C., Perez, A., Driscoll, A., et al. (2020). Using publicly available satellite imagery and deep learning to understand economic well-being in africa. *Nature Communications, 11*(1), 2583. https://doi.org/10.1038/s41467-020-16185-w

Yu, B., Dong, Y., Chen, F., et al. (2020a). Economy estimation of mainland china at county-level based on landsat images and multi-task deep learning framework. *Photogrammetric Engineering and Remote Sensing, 86*(2), 99–105. https://doi.org/10.14358/pers.86.2.99

Yu, J., Li, J., Yu, Z., et al. (2020b). Multimodal transformer with multi-view visual representation for image captioning. *Ieee Transactions on Circuits and Systems for Video Technology, 30*(12), 4467–4480. https://doi.org/10.1109/tcsvt.2019.2947482

Yuan, F. C., & Lee, C. H. (2020). Intelligent sales volume forecasting using google search engine data. *Soft Computing, 24*(2), 2033–2047.

Yue, Z. R., Witzig, C. R., Jorde, D., et al. (2020). *Bert4nilm: A bidirectional transformer model for non-intrusive load monitoring*. Paper presented at the NILM'20: Proceedings of the 5th International Workshop on Non-Intrusive Load Monitoring. Conference Paper retrieved from <Go to ISI>://INSPEC:20207172

Zadeh, L. A. (1975). Concept of a linguistic variable and its application to approximate reasoning .2. *Information Sciences, 8*(4), 301–357. https://doi.org/10.1016/0020-0255(75)90046-8

Zhang, C., Li, R., Shi, H., et al. (2020). Deep learning for day-ahead electricity price forecasting. *Iet Smart Grid, 3*(4), 462–469. https://doi.org/10.1049/iet-stg.2019.0258

Zhang, J. H., Xu, Z. Y., Xu, W. S., et al. (2019). Bi-objective dispatch of multi-energy virtual power plant: Deep-learning-based prediction and particle swarm optimization. *Applied Sciences-Basel, 9*(2), 292. https://doi.org/10.3390/app9020292

Zhang, M. G., & Yang, Z. Y. (2019). Gacoforrec: Session-based graph convolutional neural networks recommendation model. *Ieee Access, 7*, 114077–114085. https://doi.org/10.1109/access.2019.2936461

Zhang, W. X., Witharana, C., Liljedahl, A. K., et al. (2018). Deep convolutional neural networks for automated characterization of arctic ice-wedge polygons in very high spatial resolution aerial imagery. *Remote Sensing, 10*(9), 1487. https://doi.org/10.3390/rs10091487

Zhang, Y., & Yang, Q. (2018). An overview of multi-task learning. *National Science Review, 5*(1), 30–43. https://doi.org/10.1093/nsr/nwx105

Zhang, Y. F., Shi, L., Wu, Y., et al. (2020). Gesture recognition based on deep deformable 3d convolutional neural networks. *Pattern Recognition, 107*, 107416. https://doi.org/10.1016/j.patcog.2020.107416

Zheng, Y. H., Xu, Z. S., & Wang, X. X. (2021). The fusion of deep learning and fuzzy systems: A state-of-the-art survey. *IEEE Transactions on Fuzzy Systems*. https://doi.org/10.1109/TFUZZ.2021.3062899

Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial Innovation, 5*(1), 435–454.

Zhou, S. Y., Zhou, L., Mao, M. X., et al. (2019). An optimized heterogeneous structure lstm network for electricity price forecasting. *Ieee Access, 7*, 108161–108173. https://doi.org/10.1109/access.2019.2932999

Zhou, W., Liu, M., Xu, Z. S., et al. (2020a). Investment decision making based on the probabilistic hesitant financial data: Model and empirical study. *Economic Research-Ekonomska Istrazivanja*. https://doi.org/10.1080/1331677x.2020.1842225

Zhou, Y. H., Zhang, B., Xu, C. L., et al. (2020b). A data-driven method for fast ac optimal power flow solutions via deep reinforcement learning. *Journal of Modern Power Systems and Clean Energy, 8*(6), 12. https://doi.org/10.35833/mpce.2020.000522

Zhu, X. L., Rehman, K. U., Wang, B., et al. (2020). Modern soft-sensing modeling methods for fermentation processes. *Sensors, 20*(6), 1771. https://doi.org/10.3390/s20061771

Zhuang, F. Z., Qi, Z. Y., Duan, K. Y., et al. (2021). A comprehensive survey on transfer learning. *Proceedings of the Ieee, 109*(1), 43–76. https://doi.org/10.1109/jproc.2020.3004555