**Journal of Computer Technology and Applied Mathematics**
**Vol. 1, No. 1, 2024**

SUAS Press

# Application of AI-based Data Analysis and Processing Technology in Process Industry

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**Abstract:** In recent years, the rapid advancement of artificial intelligence (AI) has spurred progress across various industries, including manufacturing, propelled further by the advent of big data. Notably, the processing industry, encompassing sectors like metal smelting, chemical production, cement manufacturing, and glass production, generates vast amounts of data due to the nature of its operations. This paper employs AI-driven data analysis techniques, specifically utilizing association rule data analysis and dynamic clustering-based discretization technology, to comprehensively study and summarize this data. Test data from cement clinker and cement grinding processes are employed to validate the efficacy of these methods, with the analysis results visualized and outputted for use by enterprise analysts. This approach offers significant advantages over traditional data analysis methods, notably in terms of time, efficiency, and cost savings, thereby bridging the gap in intelligent development within the manufacturing industry.

**Keywords:** Process Industry, Data Processing and Analysis, Correlation Analysis, Artificial Intelligence.

**DOI:** https://doi.org/10.5281/zenodo.11003949

## 1 Introduction

The process industry encompasses production processes involving physical and chemical changes, with prominent sectors including metal smelting, chemical manufacturing, cement production, papermaking, and glass manufacturing. In recent years, the process industry has exhibited characteristics characterized by "two highs and two lows," namely high production energy consumption, high production costs, low productivity, and low resource utilization [1-2]. This trend is particularly evident in industries such as cement manufacturing. Research on process industry data, both domestically and internationally, primarily focuses on data mining, data cleaning, and data integration.

Given that many process industries continuously record vast amounts of process parameter data at each production node—such as in cement production, iron and steel smelting, pulp washing, and glass manufacturing—this data can be analyzed and processed in real-time using relevant data mining algorithms to uncover hidden correlations. By establishing correlation models between product quality, energy consumption, and other process parameters, decision-makers can adjust market strategies, reduce costs, and make informed decisions [3-4]. Currently, data mining methods for processing process industry parameters primarily include cluster analysis, association rules, classification algorithms, and bias analysis [5].

This paper focuses on elucidating the variable factors influencing cement production in a specific cement company. It employs association rules data methodology in artificial intelligence for data processing and analysis, aiming to delineate the impact of different variables within the production environment. Additionally, the paper introduces a process industry data analysis system developed based on association rules data analysis and processing in artificial intelligence [6-7]. Compared with traditional data analysis methods, this approach offers more precise, accurate, and efficient assistance to enterprises.

## 2 Related Work

### 2.1 Process Industry

The manufacturing sector, comprising both discrete and process manufacturing, encapsulates diverse industries vital to global production. [8] Discrete manufacturing spans sectors such as automotive, home appliances, electronics, machinery, and equipment, where products are distinct entities assembled from various components. On the other hand, process manufacturing includes sectors like petrochemicals, steel, cement, glass, and food, where raw materials undergo chemical or physical transformations to produce goods.

In the intricate landscape of the process industry, the manufacturing process involves a multitude of chemical and physical alterations. These transformations must be carefully controlled and optimized to ensure efficient production [9]. Such optimization often demands extensive data support, as process parameters, environmental conditions, and material characteristics play crucial roles in determining the outcomes of manufacturing processes.

Recognizing the complexity and scale of data involved, an increasing number of process enterprises are turning to artificial intelligence (AI) for solutions. AI offers powerful tools and techniques for analyzing vast amounts of data, identifying patterns, and optimizing processes to enhance productivity and efficiency. In recent years, numerous AI-driven optimization software solutions have matured, catering to the diverse needs of enterprises across various industries [10].

The adoption of AI in the process industry represents a strategic move for enterprises seeking practical solutions to production challenges. AI-powered systems can leverage historical data to predict outcomes, optimize processes in real-time, and even autonomously adjust production parameters for optimal results. By harnessing AI technologies, process enterprises can unlock new levels of efficiency, quality, and cost-effectiveness, thereby gaining a competitive edge in the market.

In summary, the integration of artificial intelligence into the process industry heralds a new era of intelligent manufacturing. As AI continues to evolve and mature, its transformative impact on process optimization and production management will become increasingly pronounced, driving innovation and growth across the manufacturing landscape.

## 2.2 Industrial Data Analysis Technology

Industrial big data refers to the utilization of intelligent and interconnected information and communication technology within the operational framework of the industrial Internet of Things, encompassing the organic integration of products, machinery, resources, and human involvement. This integration results in a significant influx of data generated by industrial equipment at a rapid pace [11]. The analysis of industrial big data involves a diverse array of methodologies aimed at extracting meaningful insights and facilitating informed decision-making.

Predictive analysis stands out as a cornerstone of industrial big data analysis. This method entails the extraction of features from large datasets and the application of data modeling techniques to anticipate future trends. By incorporating new data and employing predictive analytics, stakeholders gain the ability to make intuitive and informed decisions based on predictive insights. [12] This predictive capability enhances the agility and responsiveness of industrial operations, enabling proactive measures to be taken in response to emerging trends and potential challenges.

Alongside predictive analytics, data visualization plays a crucial role in industrial big data analysis. Through intuitive visual representations, data visualization tools offer invaluable insights into complex datasets, enabling users to grasp intricate patterns and relationships more effectively. By presenting data in a visually compelling manner, these tools empower stakeholders to make data-driven decisions with confidence, fostering a deeper understanding of operational dynamics and facilitating strategic planning initiatives.

## 2.3 Association Rule

Association rule mining, also referred to as "association analysis," constitutes an unsupervised learning algorithm widely employed in various domains, including educational data mining, due to its fundamental significance. This technique serves to uncover correlations or relationships within extensive datasets, identifying rules and patterns wherein specific attributes co-occur across multiple instances. Consider a scenario where I represents an item set within a given transaction set T [13]. Let X and Y denote subsets of I. If there exist transactions within T containing both X and Y, an association between X and Y is established, denoted as X→Y. Within this association, X is termed the antecedent or first term, while Y is referred to as the consequent or last term of the rule. Typically, when the proportion of transactions containing both X and Y relative to the total number of transactions within the transaction set is high, the correlation between X and Y is deemed strong [14-15].

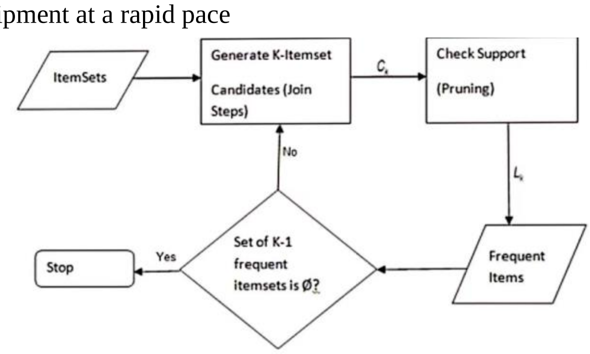


**Figure 1 Association rule algorithm example diagram**

The discovery of compelling association patterns or interrelationships among sets of items from vast datasets represents a core objective of association rule mining. Serving as an unsupervised learning approach, it stands as one of the primary techniques in the realm of data mining. In a recent study [16], this method was applied within the context of process industry data analysis. Leveraging the distinctive attributes of association rules, researchers analyzed the correlation among various data variables within the process industry domain, thereby facilitating the identification of optimal solutions. This application underscores the versatility and efficacy of association rule mining in uncovering valuable insights and informing decision-making processes within complex industrial settings.

# 3 AI Association Rules in Process Industry

In the era of big data, leveraging data has become a pivotal challenge, particularly for decision-makers in concrete production who can no longer rely solely on their intuition and experience [17]. This challenge is even more pronounced in process production enterprises, where a multitude of environmental and chemical data, coupled with high data volume, renders traditional analysis methods inadequate for modern enterprise needs. To enhance production efficiency, reduce energy consumption, and minimize environmental impact, artificial intelligence algorithms are increasingly employed to extract meaningful insights from vast datasets, leading to optimal solutions through thorough processing and analysis [18]. This paper focuses on a case study of a cement company within the process industry, aiming to discretize parameter data to establish a robust link between the discretized data and the original industrial dataset. This approach aims to preserve the essence of the original data while enhancing data accuracy post-discretization [19-20]. Leveraging association rule data analysis enables analysts to uncover valuable patterns associated with specific parameters, facilitating intelligent enterprise management.

## 3.1 Experimental model

The Association Rules Analysis Data Algorithm utilizes the Apriori algorithm, leveraging prior knowledge of frequent itemset attributes and employing an iterative layer-by-layer search method [21]. Initially, the algorithm identifies the set of frequent 1-item sets, denoted as L1. Subsequently, L1 is used to derive the set of frequent 2-item sets, denoted as L2, and this process continues until no frequent set of k items can be identified. The Apriori algorithm operates through two key steps: connection and trimming.

Firstly, in the connection step, candidate k-item sets are generated by concatenating LK-1 with itself, forming a set known as Ck. Secondly, in the pruning step, Ck is pruned to obtain Lk. Notably, Ck serves as a superset of Lk, meaning it may contain both frequent and non-frequent itemsets, but all frequent k-item sets are guaranteed to be included in Ck.

To determine the support count of each candidate in Ck, the algorithm scans the database, subsequently identifying the frequent itemsets and producing Lk. This systematic approach ensures the efficient mining of association rules from large datasets, facilitating valuable insights into underlying patterns and relationships.

## 3.2 Experimental Process

**(A) Extraction database and data preprocessing**

In the data preparation stage, the original data of factory A is simply cleaned and extracted locally to form a local data center, in which homologous and heterogeneous data of various industrial fields and various time periods will be integrated. The research in this field of data integration has been relatively in-depth. When raw data for process industry parameters is obtained locally, the maximum, minimum, average, and median values for each attribute in the data are calculated. This paper takes cement data as an example, and part of the calculation results are shown in Table 1. In order to see the distribution of each attribute more intuitively, the frequency distribution histogram of each attribute should be drawn. Figure 2 is the frequency distribution histogram of the "free calcium" attribute in Table 1, with two decimal values reserved.

**Table 1: Cement clinker data parameter original value and interval**

| Stats | Maximum value | Minimum value | Mean value | median |
|---|---|---|---|---|
| Feed rate (t/h) | 450.42 | 343.88 | 410.55 | 414.98 |
| Kiln speed (rpm) | 5.16 | 2.98 | 3.69 | 3.72 |
| Fineness of raw material (%) | 20.17 | 10.38 | 11.48 | 11.53 |
| C1 tube outlet temperature (° C) | 342.75 | 261.05 | 321.05 | 320.36 |
| C2 tube outlet temperature (° C) | 525.40 | 353.53 | 493.14 | 483.29 |
| C3 cylinder outlet temperature (° C) | 654.63 | 436.95 | 612.61 | 608.75 |
| C4 cylinder outlet temperature (degrees C) | 786.38 | 541.47 | 755.32 | 758.83 |
| C5 cylinder outlet temperature (degrees C) | 870.17 | 596.08 | 842.65 | 846.10 |
| Smoke chamber temperature (C) | 1285.42 | 933.84 | 1254.24 | 1263.58 |

| | | | | |
|---|---|---|---|---|
| Secondary air Temperature (C) | 1248.67 | 700.58 | 1143.51 | 1150.08 |
| Tertiary air temperature (C) | 994.33 | 491.88 | 905.56 | 913.13 |
| Free calcium (%) | 2.85 | 0.84 | 1.47 | 1.43 |
| Vertical weight (G/L) | 1284.67 | 843.00 | 1250.79 | 1259.00 |
| Unit coal consumption (kg/kg.Cl) | 0.18 | 0.13 | 0.15 | 0.14 |
| Clinker 28-day Strength (MPa) | 61.30 | 53.30 | 56.28 | 56.80 |

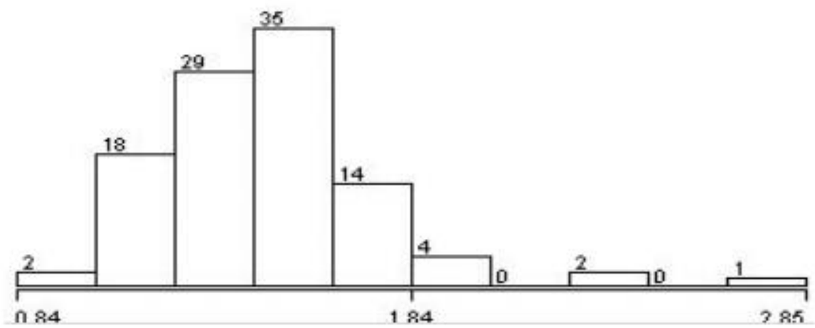


**Figure 2: Distribution of free calcium frequency**

After determining the reasonable range of industrial production parameters for each process, including the maximum and minimum values, and the optimal value within this range (typically the midpoint), data points outside this range are removed. Subsequently, the average and median of each attribute are checked to ensure they are within 10% of the optimal value. If not, extreme data points (maximum and minimum values) are iteratively removed until the criteria are met, ensuring high concentration of industrial data.

Following preprocessing of the parameter data, the processed data is discretized for input. However, traditional algorithms often yield unstable clustering results. To address this issue, this paper employs an artificial intelligence association rule algorithm for training, resulting in improved clustering effectiveness.

**(B) Establish the model**

Input process industry data set X = {x1,x2,... , xn}, the data object xi is the data, xj is the dimension of the data, the distance between xi and xj is defined as:

i = 1,2... ,n;  j = 1,2,... ,n (3-1)        (1)

The density of xi is defined as:

Density(xi) = Count{x |x∈X, |x - xi| <  r}        (2)

The sample density threshold is defined as:

c is a constant. The scope of the initial cluster center field is defined as:

δm = {x |x∈X, min(xi) +(m-1)×R≤ x < min(xi) + m× R}        (3)

R represents the width of the central field of each initial cluster, defined as:

R =(1/k)*(max(xi) -min (xi)), i = 1, 2,... , n;  m = 1, 2, … , k        (4)

k is the number of cluster centers. Define the data sets X' and Y' as:

X' = {x |x∈X, density(x) ≥ threshold}        (5)

Y' = {y |y∈X, density(y) <  threshold}        (6)

X' represents the set of all sample points whose density is not less than the threshold, and Y' represents the set of sample points whose density is less than the threshold.

**(C) Network training**

In the first step, input process industry parameter data set D and cluster number k. The sample distribution density and minimum sample density threshold of each sample point are calculated, and the sample points not less than the threshold are stored in the set X', and the others are stored in the set Y'.

The second step is to select the sample point with the largest sample distribution density in each domain in the dataset X' as the initial cluster center domain.

In the third step, the clustering center generated in the second step is taken as the initial clustering center, and the clustering is completed by the general K-Means method.

The fourth step is to calculate the distance between the outlier sample point and the cluster center after K-Means clustering, and divide it into the nearest cluster. Finally output cluster C = {C1,C2,... ,Ck}.

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**Table 2:Some cement clinker production data discrete results**

| Stats | Interval 1 | Interval 2 | Interval 3 | Interval 4 | Interval 5 | Interval 6 |
|---|---|---|---|---|---|---|
| Feed rate (t/h) | (390402, 7 | [402409] | (409,412] | (412,416] | (416,424] | (424,435] |
| Kiln speed (rpm) | (3.6, 3.65] | (3.65, 3.7] | (3.7,3.73] | (3.73,3.78] | (3.78,3.85] | (3.85,3.9] |
| Fineness of raw material (%) | (10.45, 11] | (11,11.23] | (11.23,11.35] | (11.35,11.42] | (11.42,11.5] | (11.5,11.85 |
| Free calcium (%) | (1.2, 1.32] | (1.32, 1.43] | (1.43,1.5] | (1.5,1.54] | (1.54,1.6] | (1.6,1.7] |
| Vertical weight (G/L) | (1200,1230] | (1230,1243] | (1243,1255] | (1255,1260] | (1260,1264] | (12641280] |

It can be seen that the division of data is a dynamic result, and the artificial intelligence association rule algorithm is used to make the data range of interval division more refined. Moreover, the experimental results of this method for cement clinker data mining have more valuable association rules and higher confidence than the experimental results of traditional classification methods [22]. For example, when excavating the strength of cement clinker, this method can excavate the influence of "free calcium" on the strength of cement clinker, which is not available in traditional methods.

## 3.3 Experimental algorithm

By preprocessing the data collected from enterprise A and conducting association analysis, association rules between parameters were mined by setting parameters such as support degree and confidence degree. According to the standard of the general process industry, a minimum support of 20% and a minimum confidence of 0.5 were set, resulting in 26,609 association rule results.

However, traditional data analysis and calculation methods prove insufficient for handling massive data calculations. Most parameters under the traditional algorithm are irrelevant to our requirements, and the number of rules related to the 28-day strength of cement clinker and unit coal consumption exceeds 1000, adding complexity to statistics.

Given the vast amount of cement clinker production data and the intricate relationship between parameters, this paper employs an artificial intelligence association rule algorithm for analysis, focusing on the 28-day strength of clinker as the target parameter. With a minimum confidence of 0.5, minimum support of 0.2, and minimum weight of 0.05, association rules regarding the relationship between cement clinker strength and each parameter variable were established.

Among these, 6 variables were identified as correlated with cement strength: C4 tube outlet temperature, smoke chamber temperature, raw material fineness, C2 tube outlet temperature, tertiary air temperature, and free calcium.

**Table 3:Association rules for cement strength data**

| Target attribute | Related attribute | Interval minimum | Interval maximum | Confidence degree |
|---|---|---|---|---|
| Cement clinker 28d strength | C4 simple exit temperature | 755.0 | 770.0 | 0.93 |
| | Smoke chamber temperature | 1265.0 | 1285.0 | 0.93 |
| | Fineness of raw material | 11.0 | 11.5 | 0.55 |
| | C2 tube outlet temperature | 490.0 | 500.0 | 0.55 |
| | Tertiary wind temperature | 900.0 | 940.0 | 0.55 |
| | Free calcium | 1.5 | 1.6 | 0.55 |

There are 11 associated variables related to cement unit energy consumption: smoke chamber temperature, C4 barrel exit temperature, C5 barrel exit temperature, vertical lifting weight, kiln speed, decomposition furnace exit temperature, secondary air temperature, C2 barrel exit temperature, C1 barrel exit temperature, raw material fineness, and C3 barrel exit temperature. Among these, C1 cylinder exit temperature, C2 cylinder exit temperature, C3 cylinder exit temperature, C4 cylinder exit temperature, C5 cylinder exit temperature, and kiln speed are directly controllable.

Utilizing these data, which exhibit strong correlation among variables, can guide major cement enterprises in controlling unit coal consumption during cement clinker production. By maintaining these parameters within a low range, energy savings can be achieved.

**Table 4:** Association rules for unit energy consumption data

| Target attribute | Related attribute | Interval minimum | Interval maximum | Confidence degree |
|---|---|---|---|---|
| Unit energy consumption (0.141-0.145) | C4 cylinder outlet temperature | 753 | 770 | 0.88 |
| | Smoke chamber temperature | 1260 | 1285 | 0.92 |
| | Fineness of raw material | 479 | 11.5 | 0.50 |
| | C2 simple exit temperature | 1165 | 491 | 0.58 |
| | Secondary air temperature | 833 | 1198 | 0.69 |
| | C5 simple exit temperature | 1260 | 851 | 0.85 |
| | Litre weight | 3.7 | 1280 | 0.79 |
| | Kiln speed | 876 | 3.85 | 0.69 |
| | Calciner outlet temperature | 315 | 894 | 0.69 |
| | C1 Simple outlet temperature | 597 | 321 | 0.54 |
| | C3 tube outlet temperature | Interval minimum | 611 | 0.50 |

### 3.4 Practical Conclusions

Through the specific application of association rules data analysis in A cement company, it becomes evident that the outlet temperature of the decomposing furnace is primarily influenced by factors such as feed amount and kiln speed, which can be indirectly controlled [23-25]. Conversely, vertical lifting, a variable challenging to regulate, is influenced by factors including fueling methods, choice of calcining process, kiln atmosphere, and operator proficiency. Lower vertical lifting reflects greater technical proficiency and is advantageous for coal conservation. Consequently, major cement enterprises can manage unit coal consumption in cement clinker production by adjusting association rule parameters obtained through artificial intelligence, thereby achieving energy efficiency and increased production.

Comparing the data rules extracted using artificial intelligence association rule data analysis with those from traditional methods reveals richer and more confident rules. [26]For instance, association rules regarding free calcium and clinker 28d strength unearthed through this approach are absent in traditional mining methods. This discovery enhances the optimization and control of clinker product quality in cement industry production, elevating energy utilization efficiency and mitigating environmental impact.

# 4 Conclusion

In conclusion, the application of artificial intelligence-driven data analysis, particularly through association rule mining and dynamic clustering-based discretization technology, holds immense promise for optimizing processes and improving efficiency in the processing industry. [27-29] By leveraging these advanced techniques, valuable insights can be gleaned from vast datasets, enabling enterprises to make informed decisions, reduce costs, and enhance productivity. The case study conducted on a cement company demonstrates the efficacy of these methods in identifying key parameters influencing production outcomes, thereby facilitating targeted interventions for energy savings and increased efficiency.

Looking ahead, the integration of artificial intelligence into process industry data analysis is poised to revolutionize manufacturing practices further. As AI technologies continue to advance, the scope and depth of insights derived from industrial data are expected to expand, enabling enterprises to achieve unprecedented levels of optimization and performance. Moreover, ongoing research and development in AI-driven data analysis methodologies will likely yield even more sophisticated tools and techniques, further enhancing the competitiveness and sustainability of the manufacturing sector in the years to come.

## Acknowledgments

I would like to express my sincere gratitude to Wu, Jiang, and their research team for their groundbreaking work on the practical application of advanced cloud services and generative AI systems in medical image analysis, as documented in literature [1]. Their insightful research has significantly expanded our understanding of the potential of big data analytics and AI applications in the field of medicine. Through their diligent efforts and pioneering spirit, they have made invaluable contributions to the advancement of medical image analysis. Additionally, I extend my appreciation to Ni, Chunhe, and their team for their innovative research on the enterprise digital intelligent remote control system based on the Industrial Internet of Things, as outlined in literature [2]. Their study sheds light on the potential of IoT technology in the realm of enterprise intelligence, offering fresh ideas and methodologies for achieving digital transformation. Their comprehensive exploration of the industrial Internet of Things and digital intelligent systems has played a vital role in advancing the field of enterprise intelligence. Through the insightful research and innovative thinking of these two teams, I have gained deeper insights into the application and potential of advanced cloud services, generative artificial intelligence systems, and industrial Internet of Things technologies across different domains. Their findings have served as valuable references for my own work, enabling me to delve deeper into related topics in the fields of big data analysis and artificial intelligence. I am truly grateful for their contributions and efforts, and I am committed to continuing my endeavors to make further progress and contribute more to these areas.

## Funding

Not applicable.

## Institutional Review Board Statement

Not applicable.

## Informed Consent Statement

Not applicable.

## Data Availability Statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

## Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Not applicable.

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## References

[1] Wu, Jiang, et al. "Case Study of Next-Generation Artificial Intelligence in Medical Image Diagnosis Based on Cloud Computing." Journal of Theory and Practice of Engineering Science 4.02 (2024): 66-73

[2] Ni, Chunhe, et al. "Enhancing Cloud-Based Large Language Model Processing with Elasticsearch and Transformer Models." arXiv preprint arXiv:2403.00807 (2024).

[3] Zhou, Y., Tan, K., Shen, X., & He, Z. (2024). A Protein Structure Prediction Approach Leveraging Transformer and CNN Integration. arXiv preprint arXiv:2402.19095.

[4] Zhu, Mingwei, et al. "Enhancing Collaborative Machine Learning for Security and Privacy in Federated Learning." Journal of Theory and Practice of Engineering Science 4.02 (2024): 74-82.

SUAS Press

[5] Li, X., Zong, Y., Yu, L., Li, L., & Wang, C. (2024, February). OPTIMIZING USER EXPERIENCE DESIGN AND PROJECT MANAGEMENT PRACTICES IN THE CONTEXT OF ARTIFICIAL INTELLIGENCE INNOVATION. In The 8th International scientific and practical conference "Priority areas of research in the scientific activity of teachers"(February 27–March 01, 2024) Zagreb, Croatia. International Science Group. 2024. 298 p. (p. 214).

[6] Wang, Y., Bao, Q., Wang, J., Su, G., & Xu, X. (2024). Cloud Computing for Large-Scale Resource Computation and Storage in Machine Learning. Journal of Theory and Practice of Engineering Science, 4(03).

[7] Xu, J., Jiang, Y., Yuan, B., Li, S., & Song, T. (2023, November). Automated Scoring of Clinical Patient Notes using Advanced NLP and Pseudo Labeling. In 2023 5th International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 384-388). IEEE.

[8] Xu, Z., Yuan, J., Yu, L., Wang, G., & Zhu, M. (2024). Machine Learning-Based Traffic Flow Prediction and Intelligent Traffic Management. International Journal of Computer Science and Information Technology, 2(1), 18-27.

[9] Zhu, Mengran, et al. "THE APPLICATION OF DEEP LEARNING IN FINANCIAL PAYMENT SECURITY AND THE CHALLENGE OF GENERATING ADVERSARIAL NETWORK MODELS." The 8th International scientific and practical conference "Priority areas of research in the scientific activity of teachers"(February 27–March 01, 2024) Zagreb, Croatia. International Science Group. 2024. 298 p.. 2024.

[10] Sun, Guolin, et al. "Revised reinforcement learning based on anchor graph hashing for autonomous cell activation in cloud-RANs." Future Generation Computer Systems 104 (2020): 60-73.

[11] Li, H., Wang, X., Feng, Y., Qi, Y., & Tian, J. (2024). Integration Methods and Advantages of Machine Learning with Cloud Data Warehouses. International Journal of Computer Science and Information Technology, 2(1), 348-358.

[12] Lei, H., Chen, Z., Yang, P., Shui, Z., & Wang, B. (2024). Real-time Anomaly Target Detection and Recognition in Intelligent Surveillance Systems based on SLAM.

[13] Xu, J., Wu, B., Huang, J., Gong, Y., Zhang, Y., & Liu, B. (2024). Practical Applications of Advanced Cloud Services and Generative AI Systems in Medical Image Analysis. arXiv preprint arXiv:2403.17549.

[14] Zhang, Y., Liu, B., Gong, Y., Huang, J., Xu, J., & Wan, W. (2024). Application of Machine Learning Optimization in Cloud Computing Resource Scheduling and Management. arXiv preprint arXiv:2402.17216.

[15] Gong, Y., Huang, J., Liu, B., Xu, J., Wu, B., & Zhang, Y. (2024). Dynamic Resource Allocation for Virtual Machine Migration Optimization using Machine Learning. arXiv preprint arXiv:2403.13619.

[16] Liu, B. (2023). Based on intelligent advertising recommendation and abnormal advertising monitoring system in the field of machine learning. International Journal of Computer Science and Information Technology, 1(1), 17-23.

[17] Che, C., Lin, Q., Zhao, X., Huang, J., & Yu, L. (2023, September). Enhancing Multimodal Understanding with CLIP-Based Image-to-Text Transformation. In Proceedings of the 2023 6th International Conference on Big Data Technologies (pp. 414-418).

[18] Huang, Zengyi, et al. "Research on Generative Artificial Intelligence for Virtual Financial Robo-Advisor." Academic Journal of Science and Technology 10.1 (2024): 74-80.

[19] Huang, Zengyi, et al. "Application of Machine Learning-Based K-Means Clustering for Financial Fraud Detection." Academic Journal of Science and Technology 10.1 (2024): 33-39.

[20] Wu, Binbin, et al. "Enterprise Digital Intelligent Remote Control System Based on Industrial Internet of Things." (2024).

[21] Pan, Y., Wu, B., Zheng, H., Zong, Y., & Wang, C. (2024, March). THE APPLICATION OF SOCIAL MEDIA SENTIMENT ANALYSIS BASED ON NATURAL LANGUAGE PROCESSING TO CHARITY. In The 11th International scientific and practical conference "Advanced technologies for the implementation of educational initiatives"(March 19–22, 2024) Boston, USA. International Science Group. 2024. 254 p. (p. 216).

[22] K. Xu, X. Wang, Z. Hu and Z. Zhang, "3D Face Recognition Based on Twin Neural Network Combining Deep Map and Texture," 2019 IEEE 19th International Conference on Communication Technology (ICCT), Xi'an, China, 2019, pp. 1665-1668, doi: 10.1109/ICCT46805.2019.8947113.

[23] Shi, Peng, Yulin Cui, Kangming Xu, Mingmei Zhang, and Lianhong Ding. 2019. "Data Consistency Theory and Case Study for Scientific Big Data" Information 10, no. 4: 137. https://doi.org/10.3390/info10040137.

[24] Zhenghua Hu, Xianmei Wang, Kangming Xu, and Pu Dong. 2020. Real-time Target Tracking Based on PCANet-CSK Algorithm. In Proceedings of the 2019 3rd International Conference on Computer Science and Artificial Intelligence (CSAI '19). Association for Computing Machinery, New York, NY, USA, 343–346. https://doi.org/10.1145/3374587.3374607.

[25] Medication Recommendation System Based on Natural Language Processing for Patient Emotion Analysis.

(2024). Academic Journal of Science and Technology, 10(1), 62-68. https://doi.org/10.54097/v160aa61

[26] Li, X., Zheng, H., Chen, J., Zong, Y., & Yu, L. (2024). User Interaction Interface Design and Innovation Based on Artificial Intelligence Technology. Journal of Theory and Practice of Engineering Science, 4(03), 1-8.

[27] Xu, K., Zhou, H., Zheng, H., Zhu, M., & Xin, Q. (2024). Intelligent Classification and Personalized Recommendation of E-commerce Products Based on Machine Learning. arXiv preprint arXiv:2403.19345.

[28] Zhou, H., Xu, K., Bao, Q., Lou, Y., & Qian, W. (2024). Application of Conversational Intelligent Reporting System Based on Artificial Intelligence and Large Language Models. Journal of Theory and Practice of Engineering Science, 4(03), 176-182.

[29] Li, L., Xu, K., Zhou, H., & Wang, Y. (2024). Independent Grouped Information Expert Model: A Personalized Recommendation Algorithm Based on Deep Learning.