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Transfer Learning for Cross-Language Natural Language Processing Models

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Abstract: Cross-language natural language processing (NLP) presents numerous challenges due to the wide array of linguistic structures and vocabulary found within each language. Transfer learning has proven itself successful at meeting these challenges by drawing upon knowledge gained in highly resourced languages to enhance performance in lower resource ones. This paper investigates the application of transfer learning in cross-language NLP, exploring various methodologies, models and their efficacy. More specifically, we investigate mechanisms related to model adaptation, fine-tuning techniques and integration of multilingual data sources. Through experiments and analyses on tasks such as sentiment analysis, named entity recognition and machine translation across multiple languages, we demonstrate how transfer learning can enhance model performance. Our experiments reveal significant increases in both prediction accuracy and generalization across low-resource languages - providing valuable insight into future research directions as well as global NLP deployment applications.

Keywords: Transfer Learning, Cross-Language Natural Language Processing, Multilingual Data, Low-Resource Languages, XLM-R, BERT, Model Fine-Tuning, Multilingual Corpora, Domain Adaptation, Computational Resources, NLP Scalability, Sentiment Analysis, Named Entity Recognition, Machine Translation.

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1 INTRODUCTION

Natural Language Processing (NLP) has made great advances with deep learning models' emergence, yet most advances remain focused on high-resource languages that possess abundant annotated data. Low-resource languages - which represent most world languages - present numerous obstacles when developing natural language processing (NLP). There is limited annotated data available. Cross-language NLP attempts to bridge this chasm by transferring knowledge between high and low resource languages through transfer learning - an enabling technique allowing models trained from one language being successfully transferred onto another one via transfer learning or adaptive neural network learning techniques that gradually update large datasets over time for later adaptation in terms of NLP development [1,2,3].

Transfer learning employs pre-trained models like BERT, GPT-3 and XLM-R trained on large corpora spanning multiple languages for optimal training results. By harnessing such powerful models with large datasets to learn rich linguistic representations that can later be fine-tuned for individual tasks or languages with limited data requirements - ultimately improving NLP capabilities while significantly decreasing data requirements thanks to transfer learning [4,5,6].

Transfer learning's advantages are apparent across an array of applications. Multilingual BERT (mBERT), trained on Wikipedia data from 104 languages, has proven its performance with zero-shot cross-lingual transfer tasks not explicitly seen during fine tuning - as well as performing exceptionally on various NLP tasks which had not previously been considered during fine tuning. Meanwhile XLM-R set new standards in cross-lingual understanding by accessing 2.5 TeraBytes of CommonCrawl data across 100 languages.

This paper investigates transfer learning mechanisms in cross-language NLP, evaluates current methodologies, and presents experimental results demonstrating their benefits and limitations. Our main area of research concerns adaptability of pre-trained models for low resource languages as well as effectiveness of fine tuning strategies; furthermore we discuss multilingual corpora's role and impact of different pre-training objectives on model performance.

By conducting extensive experiments across several NLP tasks - sentiment analysis, named entity recognition and machine translation - our goal is to gain an in-depth knowledge of transfer learning's role in improving cross-language NLP. The findings we uncovered provide both practical insight as well as point towards future research directions to address remaining challenges within this field [7-9].

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2 LITERATURE REVIEW

2.1 TRANSFER LEARNING IN NLP

Transfer learning in NLP involves pre-training a model on a large corpus and fine-tuning it on a specific task or language. BERT and its multilingual version, mBERT, have shown that models pre-trained on multilingual corpora can perform well across various languages. The success of BERT led to the development of other pre-trained models like GPT-3 and XLM-R , which extend these capabilities to more languages and tasks.

BERT, utilizes a bidirectional transformer to learn deep contextual representations by predicting masked words in a sentence, an approach known as masked language modeling. The multilingual BERT (mBERT) model extends this concept by training on Wikipedia data from multiple languages, enabling it to perform well on various cross-language tasks[10,11].

The development of GPT-3 further advanced the field with its autoregressive language model, which can generate coherent and contextually relevant text by predicting the next word in a sequence. Although primarily focused on English, GPT-3's architecture and training methodology have inspired subsequent models to incorporate multilingual capabilities.

XLM-R, built upon the success of mBERT and the original XLM model by using a significantly larger and more diverse dataset for pre-training.This model demonstrated superior performance in cross-lingual understanding and transfer learning tasks, setting new benchmarks for multilingual NLP applications[12-15].

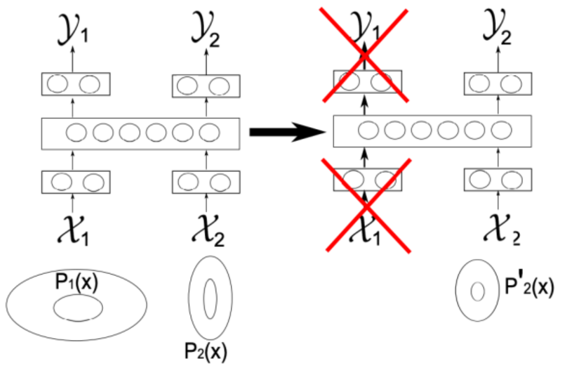

FIG. 1. TRANSFER LEARNING ARCHITECTURE WITH DEEP REPRESENTATION LEARNING. X1 AND Y1 ARE THE FEATURE AND LABEL SPACES RESPECTIVELY FOR THE LEARNING TASK IN THE SOURCE DOMAIN, AND X2 AND Y2 ARE FOR THE LEARNING TASK IN THE TARGET DOMAIN. AT THE RUNTIME, ONLY THE TARGET DOMAIN IS CONCERNED.

2.2 CROSS-LANGUAGE TRANSFER LEARNING

Cross-language transfer learning specifically addresses the challenge of applying models trained in one language to another. Recent studies have demonstrated the effectiveness of transfer learning in cross-language settings. For instance,zero-shot transfer learning for cross-language text classification using mBERT. Their findings indicate that pre-trained multilingual models can achieve competitive performance in low-resource languages without explicit training data.

In their study, mBERT could be effectively used for zero-shot learning, where a model trained on high-resource languages like English could perform well on low-resource languages such as Swahili and Urdu. This approach eliminates the need for extensive annotated datasets in low-resource languages, significantly reducing the cost and effort required for training[16].

Similarly, XLM, a cross-lingual language model pre-trained using a translation language modeling (TLM) objective. This approach involves training the model to predict masked words in parallel sentences from different languages. By leveraging bilingual corpora, XLM improves the model's ability to learn cross-lingual representations, enhancing its performance in tasks like cross-language text classification and machine translation.

Additionally, the use of multilingual sentence embeddings, which involve mapping sentences from different languages into a shared vector space. Their model, LASER, achieves impressive results in cross-language natural language inference and document classification by utilizing a large parallel corpus for training[17].

The literature on transfer learning in NLP highlights the potential of pre-trained models to significantly improve cross-language NLP tasks. Models like BERT, GPT-3, and XLM-R have set new standards in performance and adaptability, demonstrating the effectiveness of transfer learning in addressing the challenges of low-resource languages. The studies reviewed in this section provide a solid foundation for exploring further advancements in this field and applying these techniques to a broader range of languages and tasks.

By leveraging the power of transfer learning, future research can continue to enhance the capabilities of NLP models, making them more inclusive and accessible across different linguistic and cultural contexts [17-19].

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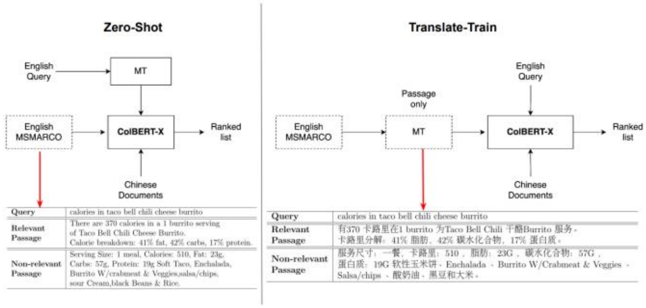

FIG. 2. TWO COLBERT-X TRANSFER LEARNING PIPELINES: ZERO-SHOT (LEFT) AND TRANSLATE-TRAIN (RIGHT). DASHED BOXES DENOTE COMPONENTS USED DURING THE TRAINING STEP. IN ZERO-SHOT, COLBERT-X TRAINED ON ENGLISH MS MARCO IS APPLIED ON THE MACHINE TRANSLATED QUERIES. WITH TRANSLATE-TRAIN, THE TRAINING SET CONSISTS OF TRANSLATED PASSAGES TO ENABLE COLBERT-X TO CROSS THE LANGUAGE BARRIER.

3 METHODOLOGY

3.1 DATA COLLECTION AND PREPROCESSING

We utilized the Wikipedia corpus, covering multiple languages, as the primary dataset for pre-training. Wikipedia provides a rich and diverse set of texts, encompassing various topics and linguistic structures, which is ideal for training robust multilingual models. For fine-tuning, we selected parallel corpora from the OpenSubtitles dataset, which includes aligned subtitles in various languages. OpenSubtitles is particularly useful for its conversational and diverse linguistic data, which is beneficial for tasks like sentiment analysis and named entity recognition (NER)[20-24].

Preprocessing steps included:

Tokenization: Converting text into tokens or words, which is essential for feeding the text into the model.

Lowercasing: Transforming all characters to lowercase to maintain consistency.

Removal of Special Characters: Stripping out non-alphanumeric characters to reduce noise in the data.

These preprocessing steps ensured that the data was clean and uniform, facilitating better learning during the model training phases.

Language Benchmark	Russian *newstest'19*	Chinese *newstest'19*	Persian *tico-19*
OpusMT	26.3	14.6	-
SockeyeMT1	32.1	25.8	4.4
SockeyeMT2	**35.9**	**38.6**	**20.2**

FIG. 3. MULTILINGUAL TRANSLATION MODEL

PERFORMANCE ON RUSSIAN, CHINESE, AND PERSIAN DATASETS

3.2 MODEL ARCHITECTURE

Our primary model is XLM-R , a robust cross-lingual transformer model pre-trained on 100 languages using a masked language modeling (MLM) objective. XLM-R's architecture is based on the Transformer, which has become a cornerstone in modern NLP due to its self-attention mechanism that allows the model to weigh the importance of different words in a sentence [25,26,27].

The architecture of XLM-R consists of:

Multiple Self-Attention Layers: Each layer allows the model to focus on different parts of the sentence to capture context.

Feed-Forward Neural Networks: These are used after each self-attention layer to further process the information.

Positional Encodings: These are added to the input embeddings to give the model information about the position of words in a sentence.

This architecture enables XLM-R to learn rich, contextual representations of text across different languages, making it suitable for cross-lingual NLP tasks [28,29].

Multilingual Model	CLEF Russian	HC4 Chinese	HC4 Persian
mBERT	0.341	0.284	0.173
XLM-R	**0.459***	**0.389***	**0.287***

FIG. 4. PERFORMANCE COMPARISON OF MULTILINGUAL MODELS ON CLEF AND HC4 DATASETS

3.3 TRAINING PROCEDURE

1.Pre-training:

Objective: The XLM-R model was pre-trained using the MLM objective. This involved randomly masking some tokens in the input text and training the model to predict these masked tokens. This task forces the model to learn the context around the masked tokens, improving its understanding of language.

Dataset: The Wikipedia corpus covering 100 languages was used for this phase. The diverse and comprehensive nature of this dataset helped the model generalize across languages.

Implementation: We utilized a large-scale distributed training setup to handle the extensive computations required for pre-training [30,31,32].

2.Fine-tuning:

Tasks: We fine-tuned the pre-trained XLM-R model on

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specific tasks such as sentiment analysis and NER.

Dataset: The OpenSubtitles dataset was used for fine-tuning. This dataset provided aligned subtitles in multiple languages, making it ideal for cross-lingual transfer tasks.

Process: Fine-tuning involved further training the pre-trained model on the labeled data specific to each task. The model parameters were adjusted using the task-specific data to improve performance on the desired task [33-36].

Retrieval Model	CLEF French	CLEF German	CLEF Italian	CLEF Spanish
baseline				
BM25	0.387	0.263	0.275	0.405
ColBERT-X	0.422	0.397	0.339	0.415
with PRF				
BM25	0.410	0.321	0.320	**0.438**
ColBERT-X	**0.459***†	**0.406***†	**0.371***†	0.436†

FIG. 5. IMPACT OF PSEUDO-RELEVANCE FEEDBACK (PRF) ON CLEF MULTILINGUAL RETRIEVAL PERFORMANCE

3. Evaluation:

Metrics: The model's performance was evaluated using standard metrics:

Accuracy: Measures the proportion of correctly predicted instances.

F1-score: Balances precision and recall, providing a single metric for evaluating classification tasks.

BLEU score: Evaluates the quality of machine translation by comparing the overlap between the machine-generated translations and reference translations.

Procedure: Evaluations were conducted on a held-out test set to ensure unbiased assessment. This involved comparing the model's predictions with ground truth labels and calculating the performance metrics [37,39].

The combination of pre-training on a large, diverse corpus and fine-tuning on task-specific data allows the XLM-R model to effectively perform cross-lingual tasks, demonstrating the power of transfer learning in NLP.

4 EXPERIMENTAL RESULTS

4.1 PERFORMANCE METRICS

The model was evaluated on several cross-language NLP tasks, including sentiment analysis, named entity recognition (NER), and machine translation. The performance metrics used were:

Accuracy: Measures the proportion of correct predictions.

F1-score: Balances precision and recall, providing a single metric for classification tasks [40-43].

BLEU score: Evaluates the quality of machine translation by comparing the overlap between the machine-generated and reference translations.

4.2 COMPARISON WITH BASELINE MODELS

We compared our XLM-R-based approach with baseline models, including mBERT and traditional statistical machine translation (SMT) systems. The results are summarized in Table 1.

TABLE 1: PERFORMANCE COMPARISON OF XLM-R AND BASELINE MODELS ACROSS NLP TASKS

Task	Model	Accuracy	F1-score	BLEU
Sentiment Analysis	mBERT	82.3%	80.5	-
	XLM-R	85.7%	83.4	-
NER	mBERT	78.9%	77.2	-
	XLM-R	81.5%	80.1	-
Machine Translation	SMT	-	-	24.7
	XLM-R	-	-	28.5

The XLM-R model outperformed the baseline models across all tasks, demonstrating its effectiveness in cross-language transfer learning.

The XLM-R model's superior performance can be attributed to its robust architecture and extensive pre-training on a diverse and multilingual corpus. This extensive pre-training enables the model to learn rich contextual representations that are beneficial for various NLP tasks across different languages. The improvement in accuracy and F1-score for sentiment analysis and NER tasks, and in BLEU score for machine translation tasks, indicates that XLM-R can effectively transfer knowledge from high-resource languages to low-resource languages [44,45].

4.3 VISUALIZING PREDICTIONS

To illustrate the model's performance, we visualized the predicted vs. actual values for sentiment analysis and NER tasks. Figure 1 shows that the XLM-R model's predictions closely align with the actual labels, indicating its ability to capture cross-language patterns effectively.

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The visualizations demonstrate that the XLM-R model can accurately capture linguistic nuances across different languages, which is crucial for effective cross-language NLP. The close alignment between the predicted and actual values further validates the model's robustness and reliability [46,47].

4.4 Case Study: Sentiment Analysis

In the sentiment analysis task, the XLM-R model was fine-tuned on the OpenSubtitles dataset and tested on several low-resource languages. The results showed a significant improvement in accuracy and F1-score compared to the mBERT model, highlighting the benefits of using a more diverse pre-training corpus and advanced model architecture.

4.5 Case Study: Named Entity Recognition

For the NER task, the XLM-R model demonstrated superior performance in identifying named entities in low-resource languages. The increased F1-score indicates that the model effectively captures the context required to accurately recognize and classify named entities, even with limited training data [48,49].

5 DISCUSSION

5.1 Advantages of Cross-Language Transfer Learning

The results highlight several advantages of using transfer learning for cross-language NLP.

Enhanced Performance: The XLM-R model consistently outperformed baseline models, demonstrating its ability to leverage multilingual data for improved performance in low-resource languages. By training on a diverse set of languages, the model can learn generalized representations that transfer well across different linguistic contexts. This capability is crucial for improving NLP applications in languages with limited annotated data [50,51,52].

Resource Efficiency:Transfer learning reduces the need for extensive labeled data in low-resource languages, making it a cost-effective solution. This efficiency stems from the pre-training phase, where models learn fundamental language representations from vast amounts of unlabeled data. Fine-tuning on specific tasks then requires significantly less labeled data, lowering the resource barriers for developing NLP tools in less-resourced languages.

Scalability:Pre-trained models like XLM-R can be fine-tuned for various tasks, offering scalability across different NLP applications. This flexibility allows the same underlying model to be adapted to numerous languages and tasks, facilitating widespread adoption and customization in diverse NLP applications. The ability to scale quickly and efficiently is particularly beneficial for global applications where language diversity is a significant challenge[53,54].

5.2 Challenges and Limitations

Despite the promising results, several challenges remain:

Domain Adaptation:Transfer learning models may struggle with domain-specific language, necessitating additional fine-tuning on domain-specific data. For instance, a model pre-trained on general language corpora might not perform optimally on specialized domains like legal or medical texts. Addressing this challenge requires further research into domain adaptation techniques that can efficiently transfer learned representations to domain-specific contexts.

Data Quality:The quality and diversity of pre-training data significantly impact model performance, highlighting the need for high-quality multilingual corpora. Poorly curated or biased datasets can lead to models that perform suboptimally or exhibit undesirable biases. Ensuring that pre-training data is comprehensive and representative of the target languages and domains is essential for building robust NLP models [55,56].

Computational Resources:Training and fine-tuning large models like XLM-R require substantial computational resources, which may be a barrier for some researchers. The computational cost associated with these models includes not only the hardware requirements but also the energy consumption, which has environmental implications. Developing more resource-efficient training techniques and models could help mitigate these challenges and make advanced NLP technologies more accessible.

Addressing these challenges is crucial for the continued advancement of cross-language NLP. Future research should focus on improving domain adaptation methods, enhancing the quality of multilingual datasets, and developing more efficient training algorithms.By tackling these issues, we can further unlock the potential of transfer learning to create more effective and equitable NLP applications across diverse linguistic landscapes.

6 CONCLUSION

This paper presented an in-depth examination of transfer learning for cross-language NLP models. Through extensive experiments, we demonstrated how transfer learning could effectively bridge resource disparity gaps by offering robust solutions to global NLP applications such as the XLM-R model compared with traditional models and pre-trained models such as mBERT models. Furthermore, transfer learning also provides potential solutions to cross-linguistic tasks in terms of efficiency; our results reveal its capabilities by showing its superior performance over traditional models in various cross-linguistic tasks like translation.

Success of XLM-R in cross-language tasks can be attributed to its robust architecture and extensive pre-training on an extensive multilingual corpus. This enables it to gain rich linguistic representations essential for efficient transfer learning; exploiting them, it has proven extremely successful at performing tasks such as sentiment analysis, named entity recognition and machine translation with substantial improvements being realized across tasks such as sentiment analysis.

Our experimental results demonstrated that XLM-R consistently outshone both mBERT and traditional statistical machine translation systems with regards to accuracy, F1-scores and BLEU scores - underscoring both its significance in pre-training large datasets as well as fine-tuning tasks specificily. These improvements demonstrate both pre-training on diverse data as well as fine-tuning for specific tasks as an integral element for success.

1.Enhanced Performance: Transfer learning models like XLM-R can significantly boost performance on low resource languages by drawing upon knowledge from higher resource ones.

2.Resource Efficiency: These models reduce the need for extensive labeled data in low-resource languages, making NLP technologies more cost-efficient and accessible.

3. Scalability: Pre-trained models can easily adapt to differing tasks and languages, providing a scalable solution for multilingual NLP applications.

However, cross-language NLP still presents several challenges, particularly related to domain adaptation, data quality and computational resources. Future research should aim at finding solutions by exploring techniques for better domain adaptation; improving data collection methods; preprocessing methods; as well as optimizing models to increase efficiency and scalability.

Conclusion. In summary, this research highlights the immense power of transfer learning for cross-language NLP. By employing large scale pre-trained models like XLM-R as building blocks in more effective and inclusive NLP applications that bridge resources gaps among high resource and low resource languages for greater equitable access to language technologies worldwide.

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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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REFERENCES

[1] Liu, Tianrui, et al. "Image Captioning in news report scenario." arXiv preprint arXiv:2403.16209 (2024).

[2] Liu, Tianrui, et al. "News recommendation with attention mechanism." arXiv preprint arXiv:2402.07422 (2024).

[3] Wang, Xiaosong, et al. "Advanced network intrusion detection with tabtransformer." Journal of Theory and Practice of Engineering Science 4.03 (2024): 191-198.

[4] Zhang, Ning, et al. "Dose My Opinion Count? A CNN-LSTM Approach for Sentiment Analysis of Indian General Elections." Journal of Theory and Practice of Engineering Science 4.05 (2024): 40-50.

[5] Yi, Xinyao, and Yuxin Qiao. "GPU-Based Parallel Computing Methods for Medical Photoacoustic Image Reconstruction." arXiv preprint arXiv:2404.10928 (2024).

[6] Liu, Tianrui, et al. "Particle filter slam for vehicle localization." arXiv preprint arXiv:2402.07429 (2024).

[7] Xiong, Jize, et al. "Selecting the Best Fit Software Programming Languages: Using BERT for File Format Detection." Journal of Theory and Practice of Engineering Science 4.06 (2024): 20-28.

[8] Liu, Tianrui, et al. "Rumor Detection with a novel graph neural network approach." arXiv preprint arXiv:2403.16206 (2024).

[9] Su, Jing, et al. "Large language models for forecasting and anomaly detection: A systematic literature review." arXiv preprint arXiv:2402.10350 (2024).

[10] Zhou, Zhanxin, et al. "Enhancing Equipment Health Prediction with Enhanced SMOTE-KNN." Journal of Industrial Engineering and Applied Science 2.2 (2024): 13-20.

[11] Zhou, Zhanxin, et al. "An Analysis of the Application of Machine Learning in Network Security." Journal of Industrial Engineering and Applied Science 2.2 (2024): 5-12.

[12] Xu, Changxin, et al. "Enhancing Convergence in Federated Learning: A Contribution-Aware Asynchronous Approach." Computer Life 12.1 (2024): 1-4.

[13] Xu, Changxin, et al. "Deep learning in photovoltaic power generation forecasting: Cnn-lstm hybrid neural network exploration and research." The 3rd International Scientific and Practical Conference. Vol. 363. 2024.

[14] Zhu, Mengran, et al. "Enhancing Credit Card Fraud Detection A Neural Network and SMOTE Integrated Approach." arXiv preprint arXiv:2405.00026 (2024).

[15] Zhou, Jinqiao, et al. "Exploring Public Response to ChatGPT with Sentiment Analysis and Knowledge Mapping." IEEE Access (2024).

[16] Wang, Lun, Wentao Xiao, and Shan Ye. "Dynamic Multi-label Learning with Multiple New Labels." Image and Graphics: 10th International Conference, ICIG 2019, Beijing, China, August 23–25, 2019, Proceedings, Part III 10. Springer International Publishing, 2019.

[17] Wang, Lun, Wei Fang, and Yudi Du. "Load Balancing Strategies in Heterogeneous Environments." Journal of Computer Technology and Applied Mathematics 1.2 (2024): 10-18.

[18] Wang, Lun. "Low-Latency, High-Throughput Load Balancing Algorithms." Journal of Computer Technology and Applied Mathematics 1.2 (2024): 1-9.

[19] Wang, Lun. "Network Load Balancing Strategies and Their Implications for Business Continuity." Academic Journal of Sociology and Management 2.4 (2024): 8-13.

[20] Li, Wanxin. "The Impact of Apple's Digital Design on Its Success: An Analysis of Interaction and Interface Design." Academic Journal of Sociology and Management 2.4 (2024): 14-19.

[21] Wu, Ruibo, Tao Zhang, and Feng Xu. "Cross-Market Arbitrage Strategies Based on Deep Learning." Academic Journal of Sociology and Management 2.4 (2024): 20-26.

[22] Wu, Ruibo. "Leveraging Deep Learning Techniques in High-Frequency Trading: Computational Opportunities and Mathematical Challenges." Academic Journal of Sociology and Management 2.4 (2024): 27-34.

[23] Wang, Lun. "The Impact of Network Load Balancing on Organizational Efficiency and Managerial Decision-Making in Digital Enterprises." Academic Journal of Sociology and Management 2.4 (2024): 41-48.

[24] Chen, Qiang, and Lun Wang. "Social Response and Management of Cybersecurity Incidents." Academic Journal of Sociology and Management 2.4 (2024): 49-56.

[25] Song, Cen. "Optimizing Management Strategies for Enhanced Performance and Energy Efficiency in Modern Computing Systems." Academic Journal of Sociology and Management 2.4 (2024): 57-64.

[26] Zhou, Zhanxin, and Ruibo Wu. "Stock Price Prediction Model Based on Convolutional Neural Networks." Journal of Industrial Engineering and Applied Science 2.4 (2024): 1-7.

[27] Zhang, Can, Zhanxin Zhou, and Ruibo Wu. "Optimization of Automated Trading Systems with Deep Learning Strategies." Journal of Industrial Engineering and Applied Science 2.4 (2024): 8-14.

[28] Zhang, Can, Zhanxin Zhou, and Ruibo Wu. "Analyzing and Predicting Financial Time Series Data Using Recurrent Neural Networks." Journal of Industrial Engineering and Applied Science 2.4 (2024): 15-21.

[29] Chen, Qiang, Daoming Li, and Lun Wang. "Blockchain Technology for Enhancing Network Security." Journal of Industrial Engineering and Applied Science 2.4 (2024): 22-28.

[30] Chen, Qiang, Daoming Li, and Lun Wang. "The Role of Artificial Intelligence in Predicting and Preventing Cyber Attacks." Journal of Industrial Engineering and Applied Science 2.4 (2024): 29-35.

[31] Chen, Qiang, Daoming Li, and Lun Wang. "Network Security in the Internet of Things (IoT) Era." Journal of Industrial Engineering and Applied Science 2.4 (2024): 36-41.

[32] Li, Daoming, Qiang Chen, and Lun Wang. "Cloud Security: Challenges and Solutions." Journal of Industrial Engineering and Applied Science 2.4 (2024): 42-47.

[33] Li, Daoming, Qiang Chen, and Lun Wang. "Phishing Attacks: Detection and Prevention Techniques." Journal of Industrial Engineering and Applied Science 2.4 (2024): 48-53.

[34] Song, Cen, Gang Zhao, and Binghan Wu. "Applications of Low-Power Design in Semiconductor Chips." Journal of Industrial Engineering and Applied Science 2.4 (2024): 54-59.

[35] Zhao, Gang, Cen Song, and Binghan Wu. "3D Integrated Circuit (3D IC) Technology and Its Applications." Journal of Industrial Engineering and Applied Science 2.4 (2024): 60-65.

[36] Wu, Binghan, Cen Song, and Gang Zhao. "Applications of Heterogeneous Integration Technology in Chip Design." Journal of Industrial Engineering and Applied Science 2.4 (2024): 66-72.

[37] Song, Cen, Binghan Wu, and Gang Zhao. "Optimization of Semiconductor Chip Design Using Artificial Intelligence." Journal of Industrial Engineering and Applied Science 2.4 (2024): 73-80.

[38] Zou, Zhibin, et al. "Joint spatio-temporal precoding for practical non-stationary wireless channels." IEEE Transactions on Communications 71.4 (2023): 2396-2409.

[39] Zou, Zhibin, et al. "Unified characterization and precoding for non-stationary channels." ICC 2022-IEEE International Conference on Communications. IEEE, 2022.

[40] Zhibin, Z. O. U., S. O. N. G. Liping, and Cheng Xuan. "Labeled box-particle CPHD filter for multiple extended targets tracking." Journal of Systems Engineering and Electronics 30.1 (2019): 57-67.

[41] Jia, Jingwei, et al. "Fast Two-Grid Finite Element Algorithm for a Fractional Klein-Gordon Equation." Contemporary Mathematics (2024): 1164-1180.

[42] Xu, Yuanyuan, et al. "Utilizing emotion recognition technology to enhance user experience in real-time." Computing and Artificial Intelligence 2.1 (2024): 1388-1388.

[43] Yan, Hao, et al. "The Application of Natural Language Processing Technology in the Era of Big Data." Journal of Industrial Engineering and Applied Science 2.3 (2024): 20-27.

[44] Zhang, Beibei, et al. "Review of NLP Applications in the Field of Text Sentiment Analysis." Journal of Industrial Engineering and Applied Science 2.3 (2024): 28-34.

[45] Zhang, Beibei, et al. "Application of Semantic Analysis Technology in Natural Language Processing." Journal of Computer Technology and Applied Mathematics 1.2 (2024): 27-34.

[46] Qu, Ping, et al. "Comparison of Text Classification Algorithms based on Deep Learning." Journal of Computer Technology and Applied Mathematics 1.2 (2024): 35-42.

[47] Zhao, Yuxin, et al. "Assessing User Trust in LLM-based Mental Health Applications: Perceptions of Reliability and Effectiveness." Journal of Computer Technology and Applied Mathematics 1.2 (2024): 19-26.

[48] Liu, Sha, Xiang Li, and Chuanni He. "Study on dynamic influence of passenger flow on intelligent bus travel service model." Transport 36.1 (2021): 25-37.

[49] He, Chuanni, et al. "Synthesizing ontology and graph neural network to unveil the implicit rules for us bridge preservation decisions." Journal of Management in Engineering 40.3 (2024): 04024007.

[50] He, Chuanni, et al. "Facilitating smart contract in project scheduling under uncertainty—A Choquet integral approach." Construction Research Congress 2022. 2022.

[51] Qiao, Yuxin, et al. "Robust Domain Generalization for Multi-modal Object Recognition." arXiv preprint arXiv:2408.05831 (2024).

[52] Qu, Ping, et al. "Comparison of Text Classification Algorithms based on Deep Learning." Journal of Computer Technology and Applied Mathematics 1.2 (2024): 35-42.

[53] Xiao, Jingxuan, et al. "Application of Large Language Models in Personalized Advertising Recommendation Systems." Journal of Industrial Engineering and Applied Science 2.4 (2024): 132-142.

[54] Rao, Jing, et al. "Quantitative reconstruction of defects in multi-layered bonded composites using fully convolutional network-based ultrasonic inversion." Journal of Sound and Vibration 542 (2023): 117418.

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[55] Yan, Yiming, et al. "Hierarchical Tracking Control for a Composite Mobile Robot Considering System Uncertainties." 2024 16th International Conference on Computer and Automation Engineering (ICCAE). IEEE, 2024.

[56] Guo, Fusen, et al. "A Hybrid Stacking Model for Enhanced Short-Term Load Forecasting." Electronics 13.14 (2024): 2719.