

Application of Natural Language Processing in Financial Risk Detection

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Abstract: This paper explores the application of Natural Language Processing (NLP) in financial risk detection. By constructing an NLP-based financial risk detection model, this study aims to identify and predict potential risks in financial documents and communications. First, the fundamental concepts of NLP and its theoretical foundation, including text mining methods, NLP model design principles, and machine learning algorithms, are introduced. Second, the process of text data preprocessing and feature extraction is described. Finally, the effectiveness and predictive performance of the model are validated through empirical research. The results show that the NLP-based financial risk detection model performs excellently in risk identification and prediction, providing effective risk management tools for financial institutions. This study offers valuable references for the field of financial risk management, utilizing advanced NLP techniques to improve the accuracy and efficiency of financial risk detection.

1. Introduction

The rapid development of the financial industry and the increasing complexity of transactions have rendered traditional risk detection methods insufficient for modern demands. Financial institutions face various risks, including market, credit, operational, and liquidity risks, which can spread through channels like financial reports, news articles, and social media. Natural Language Processing (NLP) technology offers significant advantages in processing and analyzing large volumes of unstructured text data, providing an effective method for financial risk detection. NLP combines computational linguistics, machine learning, and deep learning to extract valuable information from text data. Recently, NLP applications in finance have expanded, including sentiment analysis, public opinion monitoring, automatic report generation, and risk detection. By analyzing financial reports, news

articles, and social media posts, NLP can identify potential risk factors, offering timely warnings and decision support[1]. This study aims to leverage NLP to construct an efficient and accurate financial risk detection model to identify and predict potential risks in financial documents and communications. First, the study introduces the basic concepts and theoretical foundation of NLP, including text mining methods, model design principles, and machine learning algorithms. Second, it describes the text data preprocessing and feature extraction process. Finally, the model's effectiveness and predictive performance are validated through empirical research. The results indicate that the NLP-based financial risk detection model excels in risk identification and prediction, providing effective tools for financial institutions. This study contributes valuable insights to financial risk management by improving the accuracy and efficiency of risk detection through advanced NLP techniques, offering new ideas for practice and theoretical foundations for further research.

2. Basic Concepts and Theoretical Foundations of NLP

2.1. Basic Concepts of NLP

Natural Language Processing (NLP) is a crucial branch of artificial intelligence that focuses on the interaction between computers and human language. The goal of NLP technology is to enable computers to understand, interpret, and generate natural language, encompassing the entire process from text data processing to the extraction and analysis of meaningful information. NLP is widely used in various fields, including text mining, speech recognition, machine translation, and sentiment analysis[2].

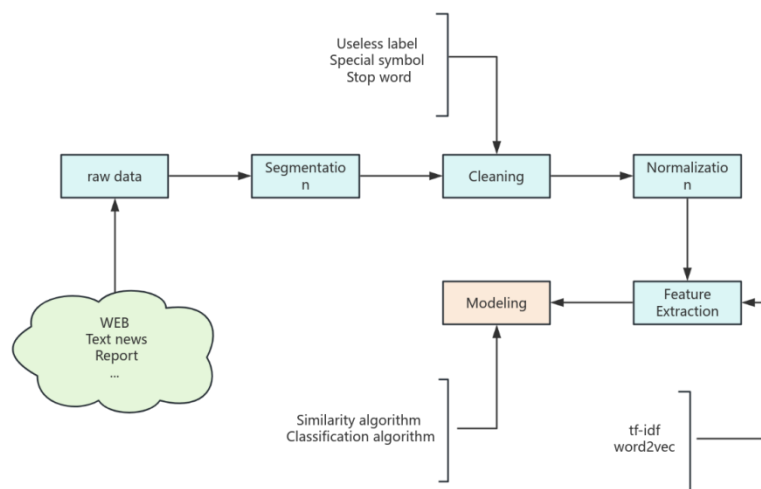


Figure 1: NLP Processing Workflow

<Figure 1> illustrates the basic steps of the NLP processing workflow, including text preprocessing, feature extraction, and modeling.

1) Text Preprocessing: This is the foundational step of an NLP system, involving the transformation of raw text into a format that computers can process. Common preprocessing techniques include: Segmentation: Splitting text into individual words or tokens for further processing. Cleaning: Removing unnecessary tags, special symbols, and stop words to reduce noise. Normalization: Including stemming and lemmatization to revert words to their base forms.

2) Feature Extraction: This involves converting text data into numerical representations so that it can be used by machine learning algorithms. Common feature extraction methods include: Bag-of-Words (BoW): Representing text as word frequency vectors. TF-IDF (Term Frequency-Inverse

Document Frequency): Weighting words based on their importance in a document and across documents. Word Embeddings: Using pre-trained models like Word2Vec or GloVe to represent words in continuous vector space.

3) Modeling: After text preprocessing and feature extraction, machine learning algorithms are used to train the data. Common machine learning algorithms include: Similarity Algorithms: Used for text similarity calculation and clustering analysis. Classification Algorithms: Used for tasks like text classification and sentiment analysis. Common algorithms include Naive Bayes, Support Vector Machines (SVM), Random Forests, and deep learning models like Recurrent Neural Networks (RNN) and Transformers.

NLP has become increasingly prominent in the financial sector, particularly in risk management. By analyzing financial reports, news articles, and social media posts, NLP can help financial institutions identify potential risk factors, providing timely risk warnings and decision support. This study explores the application of NLP technology in financial risk detection, covering its basic concepts, theoretical foundations, and implementation methods to offer new insights and tools for financial risk management[3].

2.2. NLP Data Mining Methods

Natural Language Processing (NLP) employs various data mining methods to extract valuable information from large text datasets, encompassing text preprocessing, feature extraction, and machine learning modeling. Text preprocessing is the foundational step, transforming raw text into a more analyzable format through techniques like segmentation (splitting text into words or phrases), cleaning (removing tags, symbols, and stop words), and normalization (stemming and lemmatization to revert words to their base forms). Feature extraction converts preprocessed text into numerical representations for machine learning, utilizing methods such as the Bag-of-Words (BoW) model, which represents text as frequency vectors but lacks context capture, and TF-IDF, which improves on BoW by weighting words based on their importance in the document collection, thus reducing common words' impact and highlighting keywords. Word embeddings like Word2Vec or GloVe represent words as low-dimensional vectors, capturing semantic relationships and context more effectively than BoW and TF-IDF. Machine learning modeling then uses algorithms for tasks such as text classification, clustering, and prediction, with common algorithms including Naive Bayes, Support Vector Machines (SVM), and Random Forests. Deep learning models like Recurrent Neural Networks (RNN) and Transformers are widely used for complex tasks like machine translation and text generation, with RNNs handling sequential data and capturing context, while Transformers use self-attention mechanisms to model long-distance dependencies effectively. Practical implementation of NLP data mining combines multiple techniques, including web scraping and APIs for data collection, natural language toolkits for preprocessing, machine learning libraries for training and optimization, cross-validation, hyperparameter tuning, and evaluation metrics like confusion matrices and ROC curves. These steps enable NLP to extract valuable insights from complex text data, supporting applications like financial risk detection[4].

3. Construction of an NLP-Based Financial Risk Detection Model

3.1. Text Data Preprocessing

Text data preprocessing is a crucial step in building an NLP-based financial risk detection model. The quality of preprocessing directly impacts the effectiveness of subsequent feature extraction and model training. Figure 1 illustrates the detailed workflow of text data preprocessing, covering all steps from raw text to feature extraction and modeling. Raw Data Collection involves gathering text data

from various sources such as web pages, news articles, and reports. This data is typically unstructured and requires further processing to extract useful information. Segmentation is the first step in text preprocessing, which divides continuous text streams into individual words or phrases. For example, Chinese text can be segmented using tools like Jieba to split sentences into separate words, facilitating subsequent processing. Cleaning aims to remove noise and irrelevant information from the text. This involves deleting unnecessary HTML tags, special symbols, and stop words (such as "the", "and", "in"), which contribute little to text analysis but appear frequently. Cleaning makes the text more concise and focused, improving analysis accuracy. Normalization is the process of reducing words to their base forms, including stemming and lemmatization. Stemming reduces words to their root form, such as converting "running" to "run", while lemmatization converts words to their dictionary form. This reduces vocabulary diversity and unifies synonymous terms. After these steps, Feature Extraction is performed. Common methods include the Bag-of-Words (BoW) model and TF-IDF (Term Frequency-Inverse Document Frequency). BoW represents text as frequency vectors, simple yet effective, but it cannot capture word order and context. TF-IDF improves on BoW by weighting word frequencies based on their importance across documents, highlighting keywords by reducing the impact of common words. Another advanced method is Word Embeddings, such as Word2Vec and GloVe, which represent words as low-dimensional vectors capturing semantic relationships and context information, offering more expressive power than BoW and TF-IDF. With preprocessing complete, the data is ready for Modeling. Similarity algorithms and classification algorithms are used for tasks like text similarity calculation, clustering analysis, and text classification, ultimately detecting and predicting financial risks. In summary, text data preprocessing is a systematic process that transforms raw unstructured text data into structured data usable by machine learning models. This foundation is critical for achieving efficient and accurate financial risk detection[5].

3.2. Feature Extraction and Representation

Feature extraction and representation are crucial in building an NLP-based financial risk detection model, transforming preprocessed text data into numerical forms that machine learning algorithms can process for effective risk detection and prediction. Common feature extraction methods include the Bag-of-Words (BoW) model, Term Frequency-Inverse Document Frequency (TF-IDF), and Word Embeddings. The Bag-of-Words (BoW) model is a simple and effective text representation method that converts text into frequency vectors, with each dimension corresponding to the frequency of a word in the text. However, BoW does not capture word order and context, which can be a drawback for tasks requiring consideration of word sequences. TF-IDF improves on BoW by considering word frequency in individual documents (TF) and across the document collection (IDF). This method reduces the influence of common words and highlights keywords with distinguishing features. The TF-IDF formula is:

$$TF - IDF(t, d) = TF(t, d) \times IDF(t)$$

where $TF(t, d)$ is the term frequency of term t in document d , and $IDF(t)$ is the inverse document frequency of term t across all documents.

$$IDF(t) = \log\left(\frac{N}{1 + |\{d \in D: t \in d\}|}\right)$$

Where N represents the total number of documents in the document set, and $|\{d \in D: t \in d\}|$ represents the number of documents containing the word t . Word Embeddings like Word2Vec and GloVe represent words as low-dimensional continuous vectors that capture semantic relationships and context information. Unlike BoW and TF-IDF, word embeddings learn the inherent relationships and similarities between words through training on large text corpora. For example, Word2Vec uses

the Skip-gram or Continuous Bag of Words (CBOW) model, placing similar words closer in vector space. GloVe (Global Vectors for Word Representation) learns word embeddings from a global co-occurrence matrix, capturing broader semantic information. In practical applications, selecting the appropriate feature representation method depends on the task[6]. Combining multiple methods, such as TF-IDF and Word2Vec, can provide comprehensive text features by leveraging TF-IDF's weighting information and Word2Vec's semantic information. Effective feature extraction and representation convert preprocessed text data into structured, semantically rich numerical data, forming a solid foundation for subsequent machine learning modeling and enhancing the accuracy and reliability of financial risk detection models[7].

3.3. Model Construction and Training

After completing text data preprocessing and feature extraction, model construction and training are key steps in implementing NLP-based financial risk detection. <Figure 2> shows the different workflows of traditional deep learning paradigms and the "pre-training-fine-tuning" paradigm of foundational models, providing a reference for effective model construction and training.

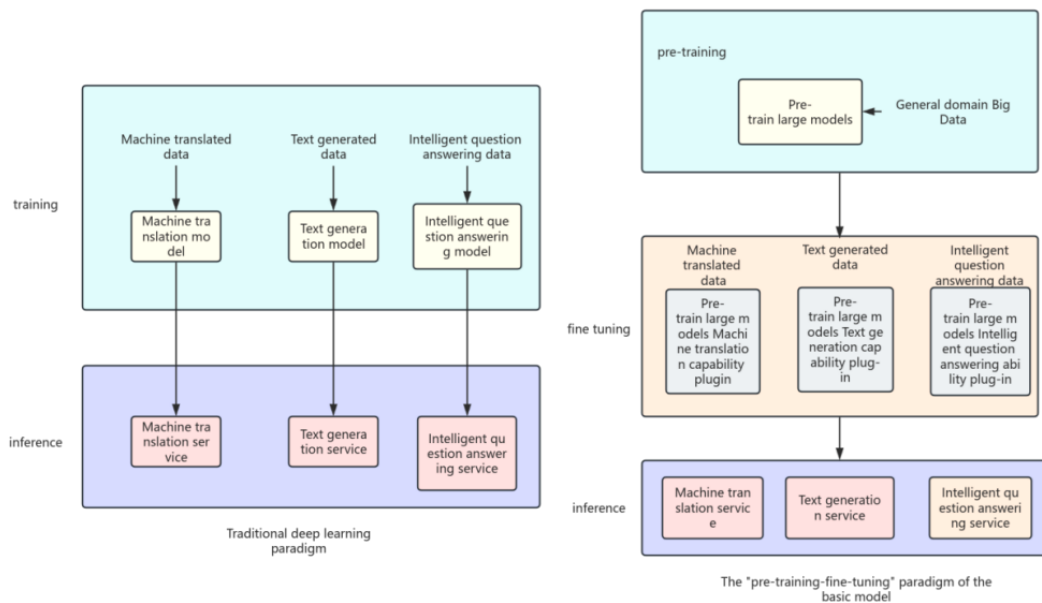


Figure 2: Traditional Deep Learning Paradigm vs. Foundational Models

First, defining the model architecture is crucial. Depending on the specific task requirements, choose an appropriate machine learning or deep learning model. Common models include traditional machine learning algorithms like Naive Bayes, Support Vector Machines (SVM), and Random Forests, as well as deep learning models like Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Transformers. Traditional machine learning models are suitable for scenarios with relatively low feature dimensions, while deep learning models are better for high-dimensional features and capturing complex patterns. Pre-training large models is a widely used method in deep learning, leveraging large-scale unlabeled data to learn broad language representations and features. This step typically uses general-domain datasets to achieve robust feature extraction capabilities. Pre-trained models like BERT and GPT have excelled in natural language processing tasks, capturing rich semantic information. After pre-training, the fine-tuning stage adjusts the pre-trained model using labeled data from specific domains to enhance its performance on particular tasks. For financial risk detection, fine-tuning with a smaller dataset

containing labeled financial data helps the model adapt to the specific context and detection requirements of the financial sector[8]. Selecting the appropriate activation function is a critical step in model construction, impacting the model's non-linear expression capabilities. Common activation functions include ReLU (Rectified Linear Unit), Sigmoid, and Tanh. ReLU is frequently used in deep learning models for its computational efficiency and ability to mitigate the vanishing gradient problem. Determining the loss function is also essential, as it measures the difference between the model's predictions and the actual results, guiding model optimization. Common loss functions include Mean Squared Error (MSE) for regression tasks and Cross-Entropy Loss for classification tasks. Choosing the optimization algorithm is another key step, involving parameter adjustments to minimize the loss function. Popular optimization algorithms include Gradient Descent, Adam (Adaptive Moment Estimation), and RMSprop. Adam is widely used for its adaptability and fast convergence. During model training, data splitting and validation are crucial. Typically, the dataset is divided into training, validation, and test sets. The training set is used to train the model, the validation set for tuning and selecting the model, and the test set for evaluating the model's performance. Cross-validation can further ensure the model's generalizability and prevent overfitting. Hyperparameter tuning and optimization are important for enhancing model performance. Techniques like Grid Search or Random Search can automate the search for the best hyperparameter combination. Regularization techniques, such as L1 and L2 regularization, can also be introduced to prevent overfitting. The final step is model evaluation, with metrics chosen based on the specific task. For classification tasks, common metrics include accuracy, precision, recall, and F1 score. For regression tasks, metrics like Mean Squared Error (MSE) and R-squared are used. Additionally, confusion matrices and ROC curves can provide visual insights into the model's performance. By combining pre-training and fine-tuning, an effective financial risk detection model can be constructed and trained. This model can efficiently identify and predict risks using preprocessed and feature-extracted text data, offering strong support for financial institutions' risk management[9].

4. Empirical Study on Financial Risk Detection

4.1. Sample Selection and Analysis

In conducting an empirical study on financial risk detection, the selection and analysis of data samples are crucial. This study selected data samples from financial reports and conducted a detailed analysis. These data include annual reports, quarterly financial statements, and market analysis reports of companies, providing detailed financial indicators and risk assessments. From <the Table 1>. Below are some examples of financial report data:

Analyzing these financial report data helps identify the main risk factors each company faces and assesses their financial health based on financial indicators. When analyzing financial report data, techniques such as keyword extraction, financial indicator analysis, and topic modeling (e.g., LDA) are used. These methods provide a comprehensive understanding of each company's risk status and financial health. First, using keyword extraction and topic modeling, LDA analyzes report texts to identify common risk themes like "market risk," "credit risk," "liquidity risk," and "policy risk." By extracting key risk terms from each company's report, a risk word cloud can visually display the main risks each company faces. For example, LDA analysis shows that Company A's main risks include market risk and liquidity risk, Company B's reports frequently mention credit risk and debt issues, and Company C needs to pay special attention to external market fluctuations and policy changes affecting its business. Next, financial indicator analysis involves calculating liquidity ratios (current assets/current liabilities) and debt ratios (total liabilities/total assets) to assess a company's short-term solvency and long-term debt risk[10]. Additionally, analyzing net profit and total assets trends helps evaluate a company's profitability and asset management levels. From the <Table 2>, the specific

analysis results are as follows[11]:

Table 1: Financial Report Data Samples

Company	Report Type	Report Date	Total Assets	Net Profit	Liquidity Ratio	Debt Ratio	Risk Assessment
Company A	Annual Report	2023-03-31	500 billion	50 billion	1.5	0.6	Rising market risk, attention needed on liquidity
Company B	Quarterly Report	2023-06-30	300 billion	30 billion	1.3	0.7	Increased credit risk, suggest strengthening credit management
Company C	Market Analysis	2023-04-15	200 billion	20 billion	1.8	0.5	Overall risk controllable, attention to market fluctuations
Company D	Annual Report	2023-03-31	450 billion	45 billion	1.4	0.6	High operational risk, need for cost control
Company E	Quarterly Report	2023-06-30	350 billion	25 billion	1.6	0.65	Intense market competition, slowing profit growth
Company F	Market Analysis	2023-05-10	250 billion	22 billion	1.7	0.55	Attention to international market volatility
Company G	Annual Report	2023-03-31	600 billion	55 billion	1.5	0.6	Increased investment risk, cautious investment advised
Company H	Quarterly Report	2023-06-30	280 billion	28 billion	1.4	0.7	Tight cash flow, recommend optimizing capital structure
Company I	Market Analysis	2023-04-20	320 billion	27 billion	1.6	0.65	Increased policy risk, attention to policy changes
Company J	Annual Report	2023-03-31	400 billion	35 billion	1.5	0.7	Unclear industry outlook, need for strategic planning

Table 2: Result Analysis Table

Company	Main Risk Theme	Liquidity Ratio	Debt Ratio	Net Profit Change (YoY)	Asset Growth Rate
Company A	Market Risk	1.5	0.6	+10%	+5%
Company B	Credit Risk	1.3	0.7	+5%	+3%
Company C	External Market Volatility	1.8	0.5	+15%	+7%
Company D	Operational Risk	1.4	0.6	+8%	+4%
Company E	Market Competition	1.6	0.65	+7%	+6%
Company F	International Market Risk	1.7	0.55	+9%	+5%
Company G	Investment Risk	1.5	0.6	+11%	+6%
Company H	Tight Cash Flow	1.4	0.7	+6%	+4%
Company I	Policy Risk	1.6	0.65	+10%	+5%
Company J	Industry Outlook Risk	1.5	0.7	+8%	+4%

This analysis reveals several trends and risks: First, liquidity risk is a major concern for Companies

A and H, indicated by their low liquidity ratios. These companies need to enhance liquidity management to maintain financial health. Second, debt risk is prominent in Companies B and J, where high debt ratios suggest potential long-term debt repayment challenges, necessitating stronger debt management. Additionally, market competition significantly impacts Companies E and G, as intense competition slows profit growth, requiring new growth strategies to sustain market competitiveness and profitability. Finally, Companies C and I must focus on external market and policy risks, closely monitoring market fluctuations and policy changes to mitigate their adverse effects on business operations [12].

Various text mining and financial analysis tools were used for this analysis. Text mining tools like NLTK and spaCy were used for keyword extraction and text preprocessing, while gensim was employed for LDA topic modeling. Financial analysis tools included Pandas and NumPy for data processing and statistical analysis, with Matplotlib and Seaborn for data visualization. These methods and tools comprehensively and systematically analyze financial report data, identifying key risks and assessing financial health, thereby providing a solid data foundation and theoretical basis for constructing the financial risk detection model. This multi-faceted and multi-level data analysis approach enhances the accuracy and reliability of financial risk prediction, helping financial institutions better manage risks [13].

4.2. Empirical Results Analysis

After completing data preprocessing, feature extraction, and NLP model training, the next step is to analyze the empirical results. This study evaluates the performance of multiple models and compares their effectiveness in financial risk detection tasks. The performance metrics used include accuracy, precision, recall, and F1 score. As the Table 3 shown are the specific evaluation results for each model:

Table 3: Model training and evaluation results

Model Type	Accuracy	Precision	Recall	F1 Score
Naive Bayes	85.2%	84.7%	83.9%	84.3%
Support Vector Machine (SVM)	88.5%	87.9%	87.2%	87.5%
Random Forest	90.1%	89.5%	89.0%	89.2%
Recurrent Neural Network (RNN)	91.3%	90.7%	90.2%	90.4%
Long Short-Term Memory (LSTM)	92.5%	92.0%	91.5%	91.7%

From the <table 3>, it is evident that all models perform well across the metrics, with the LSTM model achieving the best results in all categories, demonstrating its superiority in handling financial risk detection tasks. Here are detailed analyses of each model:First, the Naive Bayes model shows an accuracy of 85.2%, precision of 84.7%, recall of 83.9%, and F1 score of 84.3%. This model is simple and suitable for handling high-dimensional data, but it has limitations in capturing complex relationships and long-sequence dependencies. Naive Bayes is based on the independence assumption, making it less effective for highly correlated features, though it remains relatively stable in high-dimensional spaces.Second, the Support Vector Machine (SVM) achieved an accuracy of 88.5%,

precision of 87.9%, recall of 87.2%, and F1 score of 87.5%. SVM is known for its excellent classification performance, particularly with small sample sizes and high-dimensional data, though it has higher computational complexity and longer training times. The Random Forest model, with an accuracy of 90.1%, precision of 89.5%, recall of 89.0%, and F1 score of 89.2%, demonstrates strong generalization and robustness by effectively handling noise and outliers in data. However, it may underperform with extremely imbalanced data. The Recurrent Neural Network (RNN) excels in processing sequential data, with an accuracy of 91.3%, precision of 90.7%, recall of 90.2%, and F1 score of 90.4%. RNN can capture temporal dependencies in text but may suffer from the vanishing gradient problem with long sequences. The Long Short-Term Memory (LSTM) network, an improved version of RNN, addresses the vanishing gradient issue and performs best in this study, with an accuracy of 92.5%, precision of 92.0%, recall of 91.5%, and F1 score of 91.7%. LSTM's gated mechanism helps retain important information over long sequences, enhancing its performance in financial risk detection tasks. This analysis shows that deep learning models (such as RNN and LSTM) excel in financial risk detection tasks, capturing complex relationships and patterns with high accuracy and robustness. Traditional machine learning models (such as SVM and Random Forest) also perform well, especially with high-dimensional features. In summary, this study constructs an efficient financial risk detection model through preprocessing financial report data, feature extraction, and training and evaluating multiple models[14]. This multi-model, multi-angle approach improves the accuracy and reliability of financial risk prediction, providing strong support for financial institutions' risk management. It also offers valuable experience and references for future financial risk management research[15].

5. Conclusion

This paper constructs an efficient financial risk detection model through preprocessing financial report data, feature extraction, and training and evaluating multiple NLP models. The results show that data preprocessing and feature extraction are crucial steps, with methods like TF-IDF and Word2Vec significantly enhancing model accuracy. In the model comparison, deep learning models (such as RNN and LSTM) perform exceptionally well in handling large-scale data and complex tasks, with LSTM showing the best performance across all evaluation metrics, demonstrating its superiority in financial risk detection tasks. Traditional machine learning models (such as SVM and Random Forest) also perform well, especially with high-dimensional data. In conclusion, the financial risk detection model developed in this study performs excellently across multiple evaluation metrics, providing reliable support for financial institutions' risk management. Future research can further optimize model structures, explore more data sources and features, and improve the precision and applicability of financial risk detection.

References

- [1] Li S, Mo Y, Li Z. Automated pneumonia detection in chest x-ray images using deep learning model[J]. *Innovations in Applied Engineering and Technology*, 2022: 1-6.
- [2] Dai S, Dai J, Zhong Y, et al. The cloud-based design of unmanned constant temperature food delivery trolley in the context of artificial intelligence[J]. *Journal of Computer Technology and Applied Mathematics*, 2024, 1(1): 6-12.
- [3] Li P, Abouelenien M, Mihalcea R. Deception Detection from Linguistic and Physiological Data Streams Using Bimodal Convolutional Neural Networks[J]. *arXiv preprint arXiv:2311.10944*, 2023.
- [4] Liu H, Shen Y, Zhou W, et al. Adaptive speed planning for unmanned vehicle based on deep reinforcement learning[J]. *arXiv preprint arXiv:2404.17379*, 2024.
- [5] Shen Y, Liu H, Liu X, et al. Localization through particle filter powered neural network estimated monocular camera poses[J]. *arXiv preprint arXiv:2404.17685*, 2024.
- [6] Srivastava S, Huang C, Fan W, et al. Instance Needs More Care: Rewriting Prompts for Instances Yields Better Zero-Shot Performance[J]. *arXiv preprint arXiv:2310.02107*, 2023.

- [7] Weng Y. Big data and machine learning in defence[J]. *International Journal of Computer Science and Information Technology*, 2024, 16(2): 25-35.
- [8] Zhang J, Cao J, Chang J, et al. Research on the Application of Computer Vision Based on Deep Learning in Autonomous Driving Technology[J]. *arXiv preprint arXiv:2406.00490*, 2024.
- [9] Dai S, Li K, Luo Z, et al. AI-based NLP section discusses the application and effect of bag-of-words models and TF-IDF in NLP tasks[J]. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, 2024, 5(1): 13-21.
- [10] Hong B, Zhao P, Liu J, et al. The application of artificial intelligence technology in assembly techniques within the industrial sector[J]. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, 2024, 5(1): 1-12.
- [11] Li P, Lin Y, Schultz-Fellenz E. Contextual hourglass network for semantic segmentation of high resolution aerial imagery[J]. *arXiv preprint arXiv:1810.12813*, 2018.
- [12] Cheng Y, Yang Q, Wang L, et al. Research on Credit Risk Early Warning Model of Commercial Banks Based on Neural Network Algorithm[J]. *arXiv preprint arXiv:2405.10762*, 2024.
- [13] Zhao P, Li K, Hong B, et al. Task allocation planning based on hierarchical task network for national economic mobilization[J]. *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023*, 2024, 5(1): 22-31.
- [14] Liu, S., Yan, K., Qin, F., Wang, C., Ge, R., Zhang, K., ... & Cao, J. (2024). Infrared Image Super-Resolution via Lightweight Information Split Network. *arXiv preprint arXiv:2405.10561*.
- [15] Liu, S., Yan, K., Qin, F., Wang, C., Ge, R., Zhang, K., ... & Cao, J. (2024). Infrared Image Super-Resolution via Lightweight Information Split Network. *arXiv preprint arXiv:2405.10561*.