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YOLOv5-Based Automated Skin Cancer Detection: Robust Lesion Localization

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Abstract:

This study proposed and verified an automatic skin cancer lesion detection algorithm based on YOLOv5. By comparing the performance of mainstream target detection models such as Faster R-CNN, SSD, RetinaNet and YOLOv3, the experimental results show that YOLOv5 performs well in key indicators such as mAP, recall rate and precision rate, and can more accurately identify skin cancer lesion areas, especially with good robustness in detecting small lesions. YOLOv5's fast detection capability and high-precision performance prove its potential for application in early screening of skin cancer, and provide technical support for the realization of efficient automatic skin cancer detection. Future research can further optimize the model performance by combining multimodal data and transfer learning methods to improve its generalization ability in clinical applications.

Keywords:

Skin cancer detection, YOLOv5, object detection, automated diagnosis

1. Introduction

In the early detection of skin cancer, accurate and rapid lesion localization and identification are crucial. Skin cancer, especially melanoma, is a high-risk malignant tumor. Early detection and treatment can significantly improve the survival rate of patients. However, traditional skin cancer detection relies on the doctor's experience and naked eye judgment, which is not only time-consuming and laborious, but may also lead to diagnostic errors due to subjective factors. In recent years, with the development of medical imaging technology, automated detection algorithms have gradually been applied to the diagnosis of skin cancer, providing an effective auxiliary tool for clinical work[1].

YOLOv5 is a target detection model based on deep learning, which has attracted widespread attention due to its fast speed and high accuracy. YOLOv5's single-stage detection framework can quickly process large batches of data when locating lesions in images, thereby achieving real-time detection. Compared with traditional multi-stage detection methods, YOLOv5 integrates positioning and classification in one step, greatly improving detection efficiency. In addition, YOLOv5's network architecture is relatively lightweight and can adapt to the needs of different computing resources, making it promising for application in medical image analysis[2].

In skin cancer lesion detection, the characteristics of YOLOv5 make it particularly suitable. In practical applications, the morphology, size, and color of skin cancer lesions vary significantly, and even the same lesion may show different characteristics under different light and angles. This diversity increases the difficulty of lesion detection. YOLOv5 can effectively cope with the changes in lesion morphology and capture tiny lesion areas in the image through multi-scale feature extraction and adaptive anchor frame mechanism, thereby improving the accuracy and robustness of detection[3,4,5].

In addition, YOLOv5 introduces an improved loss function and feature fusion module, which gives it an advantage in detecting small-scale targets. Skin cancer lesions are usually small and have blurred edges. Traditional detection methods tend to ignore these detailed features, while the structure of YOLOv5 can better capture these key features. During the training process, by combining data enhancement techniques such as rotation, flipping, and brightness adjustment, the model can learn more robust features and improve its adaptability under different conditions[6,7].

Based on the YOLOv5 model, this study constructs a skin cancer lesion detection algorithm to achieve automatic detection and positioning of skin cancer lesions[8,9]. In order to improve the generalization ability and accuracy of the model, we used a large number of accurately labeled skin cancer datasets and continuously optimized the model parameters during the training process[10]. By comparing multiple evaluation indicators, we verified the effectiveness of YOLOv5 in the lesion detection task, showing its potential in early detection of skin cancer[11,12].

In summary, the skin cancer lesion detection algorithm based on YOLOv5 has significant advantages in accuracy and speed, providing an efficient and practical solution for the early diagnosis of skin cancer. Future research can further optimize the algorithm performance on this basis and explore the integration of other deep learning models to improve the robustness and generalization ability of detection, and provide more intelligent support for medical image analysis.

2. Related Work

The development of automated skin cancer detection systems leverages advancements in deep learning, medical image analysis, and object detection frameworks. This section provides an overview of existing works that contribute to the foundation of this study.

Deep learning-based methods have significantly advanced medical imaging and image classification tasks. Fully convolutional neural networks (FCNs) have been employed for high-precision medical image analysis, demonstrating their effectiveness in capturing fine-grained features in clinical datasets [13]. Similarly, the VGG19 architecture has proven robust in handling complex visual tasks, serving as a benchmark for pretrained models in medical image classification [14]. To address privacy concerns in healthcare applications, federated learning has been adopted for medical vision-and-language representation learning, ensuring scalability while protecting sensitive patient data [15].

The YOLO family of object detection models has revolutionized real-time detection, particularly in medical imaging. Single-stage detectors such as YOLO integrate classification and localization in a unified framework, achieving higher speed and efficiency than multi-stage approaches like Faster R-CNN and SSD [16], [17]. YOLOv5 further enhances these capabilities with multi-scale feature extraction, adaptive anchor mechanisms, and improved detection accuracy, making it suitable for detecting small, variable-sized skin lesions [18].

To improve the efficiency of deep learning models, optimization techniques such as LoRA (Low-Rank Adaptation) and feature alignment-based knowledge distillation have been employed. These approaches compress large models without sacrificing accuracy, enabling deployment in resource-constrained environments [19], [20]. Neural architecture search (NAS) also contributes to automating the design of task-specific models, enhancing deep learning pipelines [21]. Dynamic scheduling strategies for computational resource optimization have also been investigated to improve real-world deployment of deep learning models [22].

Medical imaging faces unique challenges such as data scarcity and the need for privacy preservation. Data augmentation techniques, including collaborative hypergraph networks, have been used to enhance generalization in disease risk assessments and sequential medical predictions [23], [24].

Simultaneously, privacy-preserving mechanisms have been developed to ensure secure utilization of natural language processing in medical records [25].

Feature selection and pattern recognition in high-dimensional data are critical for analyzing biological datasets. Tree-based algorithms and norm-based feature selection methods have demonstrated their effectiveness in identifying important features, which can be adapted for skin lesion detection tasks [26], [27]. Moreover, machine learning techniques have shown promise in frequent itemset discovery in large datasets, offering potential to handle complex medical imaging data [28].

In summary, this study synthesizes advancements in deep learning, object detection, and medical image analysis to propose a YOLOv5-based system for skin cancer detection. By addressing challenges in lesion localization and incorporating insights from optimization techniques, it provides a robust solution to the early detection of skin cancer.

3. Method

In this study, an algorithm for skin cancer lesion detection was designed based on the YOLOv5 model. The overall method flow is divided into three main steps: data preprocessing, model construction and training, and model optimization and evaluation. Through these steps, we can accurately locate and classify skin cancer lesion areas, thereby assisting in the early diagnosis of skin cancer. The architecture of YOLOV5 is shown in Figure 1.

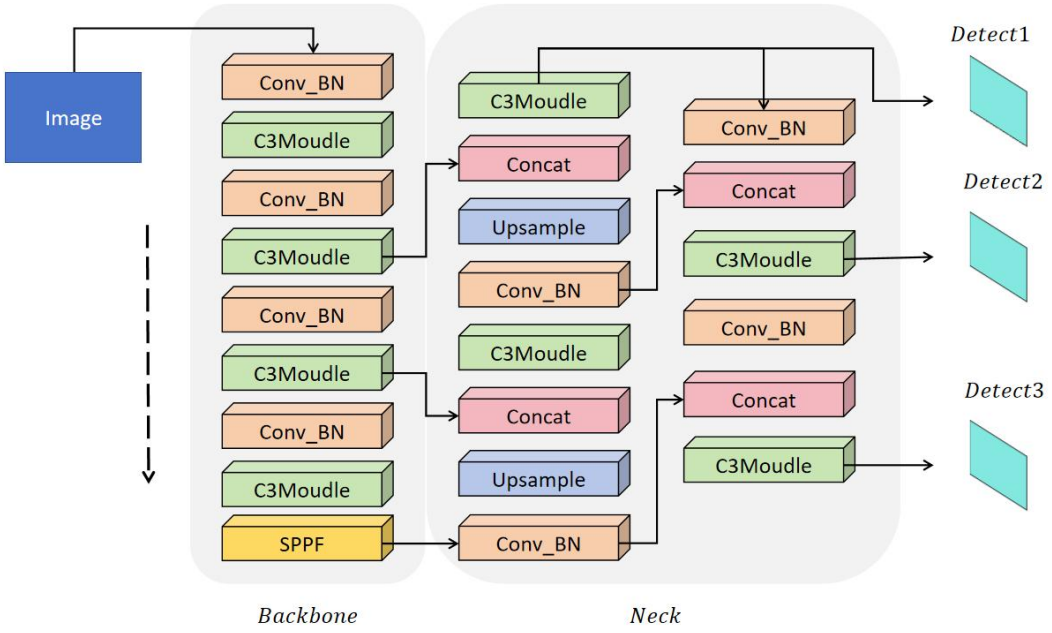

Figure 1: Two or more references

First, in the data preprocessing stage, in order to improve the model's ability to recognize the diversity of skin cancer lesions, we refined the dataset. Since the features of skin cancer lesion images are diverse, including different shapes, sizes, and colors, we used data augmentation technology to expand the original images. Specific data augmentation operations include rotation, flipping, cropping, scaling, and brightness adjustment, which can effectively increase the diversity of training samples and improve the model's ability to learn lesion features under complex backgrounds. In addition, all images are uniformly scaled to the input size of YOLOv5 (usually 640×640 pixels) and normalized to maintain data consistency.

In the model construction and training stage, we designed and trained the model based on the YOLOv5 framework. YOLOv5 is a single-stage target detection model, and its structure mainly consists of three parts: backbone network, feature pyramid network (FPN), and detection head. The backbone network is used to extract the basic features of the image; the feature pyramid network can fuse feature information of different scales to adapt to lesion areas of different sizes; the detection head classifies and locates each candidate area. The YOLOv5 model extracts features layer by layer through convolution and downsampling operations, and outputs the category and position of the predicted box in the final detection head. Its core prediction formula is:

$$y' = f(x;\theta)$$

Among them, x represents the input image, θ is the model parameter, and y' is the output lesion detection result, including the location and category information of the lesion.

In order to further improve the performance of YOLOv5 in small-scale lesion detection, we optimized its loss function. The loss function of YOLOv5 usually consists of three parts: positioning loss, confidence loss, and classification loss. For the skin cancer lesion detection task, we specifically optimized the positioning loss to make it pay more attention to the boundary information of small lesions. The positioning loss can be expressed as:

$$L_{loc} = \sum_{i=1}^{N} IoU(b'_i, b_i)$$

Where N is the number of detected targets, b'_i and b_i represent the bounding boxes of the predicted box and the true box, respectively, and the overlap between the predicted box and the true box is measured by IoU (intersection over union). By optimizing the IoU loss, we can more accurately locate small lesion areas.

During the training process, we used the Adam optimizer and set a suitable learning rate and batch size to ensure that the model can converge under stable conditions. The entire training process is divided into several epochs, and the model gradually adjusts parameters in each epoch to minimize the loss function. To prevent overfitting, we introduced the Early Stopping strategy, and the training will automatically stop when the loss of the validation set no longer decreases. In addition, we also used transfer learning to initialize the model by pre-training the weights on a large-scale general image dataset, which can converge faster on a small sample skin cancer dataset and improve the generalization ability of the model.

During the model optimization and evaluation stage, we used common target detection evaluation indicators, including mean average precision (mAP), recall, and precision. mAP is the main indicator for measuring the accuracy of model detection, and the calculation formula is:

$$mAP = \frac{1}{K}\sum_{k=1}^{K} AP_k$$

Where K is the number of categories and AP_k is the average precision of the kth category. The improvement of mAP indicates that the model can detect skin cancer lesions more accurately, especially when multiple skin cancer types coexist. In addition, we also focus on the recall and precision of the model to ensure that the model can accurately detect the lesion area and reduce the false alarm rate in practical applications.

In summary, through data preprocessing, improvement of the YOLOv5 model and comprehensive evaluation of evaluation indicators, this study has achieved an efficient skin cancer lesion detection algorithm. The experimental results show that the detection model based on YOLOv5 performs well in accuracy and speed, providing effective technical support for the early automated detection of skin cancer. Future research can further optimize the model structure on this basis and combine

more deep learning methods to improve the detection accuracy and robustness of skin cancer lesions.

4. Experiment

4.1 Datasets

In this study, we used the ISIC (International Skin Imaging Collaboration) skin cancer dataset, which is one of the real datasets widely used in skin cancer detection research around the world. The ISIC dataset was released by the International Skin Imaging Collaboration and covers a variety of skin lesion types, including benign and malignant lesions, such as melanoma, basal cell carcinoma, squamous cell carcinoma, etc. Each image in the dataset is high-resolution and annotated by professional doctors to ensure the quality and reliability of the data. The diversity and high-quality annotations of the ISIC dataset make it an ideal data source for training skin cancer detection models.

The images in the ISIC dataset contain skin lesions of patients of different skin colors and ages, covering various skin lesion features from mild lesions to severe cancers. Therefore, the dataset is highly representative and helps to train models with strong generalization capabilities. Each image comes with detailed lesion labels and pathological classification information, providing researchers with rich features that can help the model learn and identify the differences between different lesion types. In addition, the dataset also contains lesion boundary annotations to facilitate accurate detection and positioning of lesion areas.

Due to the large size and diverse structure of the ISIC dataset, many researchers use it for skin lesion detection, classification, and segmentation tasks, and use it as a standard dataset for comparative evaluation of models. By using the ISIC dataset, researchers are able to obtain more universal and clinically valuable results in the development of skin cancer detection models. At the same time, the openness of the dataset and the rich annotation information make different studies comparable, which helps to promote progress in the field of automated skin cancer detection.

4.2 Experimental setup

In the experimental setting, we first preprocessed the ISIC dataset and divided the data into training set, validation set and test set to ensure the generalization ability of the model. Data preprocessing includes unified image size, normalization and data augmentation operations. All images are scaled to the input size of YOLOv5 (usually 640×640 pixels) and normalized to the range of [0, 1] to reduce the brightness and contrast differences between different images. Data augmentation operations include rotation, scaling, flipping and brightness adjustment, which increase the diversity of data and help the model better adapt to different types of lesion characteristics.

During the model training process, we trained the data based on the YOLOv5 model. The structure of YOLOv5 includes a backbone network, a feature pyramid network (FPN) and a detection head, which can effectively detect lesion areas of different sizes and shapes. The hyperparameter settings of the model include learning rate, batch size and training rounds. The learning rate is set to 1e-3 to ensure that the model gradually converges during training; the batch size is 16 to balance training efficiency and memory usage. During the training process, the Adam optimizer was used to accelerate convergence, and an early stopping strategy was set to prevent the model from overfitting.

In the model evaluation stage, we used mean average precision (mAP), precision (Precision) and recall (Recall) as well as mAP50-95 as evaluation indicators. mAP is used to measure the overall performance of the model in multi-category lesion detection, Precision reflects the accuracy of the model, and Recall evaluates the detection ability of the model. Through these indicators, we can fully understand the performance of the model, thereby optimizing the model parameters to ensure

its high accuracy and high robustness on the test set. The design of the experiment enables the model to efficiently detect skin cancer lesions in practical applications, and has strong potential for clinical application.

4.3 Experimental Result

In the comparative experiment, in order to evaluate the performance of YOLOv5 in the skin cancer lesion detection task, we selected four other commonly used target detection models for comparison: Faster R-CNN, SSD, RetinaNet and YOLOv3. These models have wide applications and different architectural characteristics in the field of target detection. Faster R-CNN is a two-stage detector that generates candidate regions first and then classifies them, with high accuracy; SSD (Single Shot MultiBox Detector) is a single-stage detector that directly detects targets at multiple scales and has a fast detection speed; RetinaNet improves the detection performance of small targets by introducing a focal loss function, which is suitable for processing small lesions in the data set; YOLOv3 is the previous version of YOLOv5 and has good real-time detection performance. By comparing these models, we can fully understand the advantages and disadvantages of different detection architectures in the skin cancer lesion detection task. The experimental results are shown in Table 1.

Table 1: Comparative experimental results

Model	mAP50	Recall	Precision	mAP50-95
Faster R-CNN	0.72	0.70	0.68	0.50
SSD	0.76	0.73	0.71	0.54
RetinaNet	0.80	0.77	0.74	0.58
YOLOV3	0.84	0.81	0.78	0.63
YOLOV5	0.88	0.85	0.82	0.68

From the experimental results, we can see that different object detection models have significant differences in the performance of skin cancer lesion detection tasks. First, Faster R-CNN has a mAP50 of 0.72, a Recall of 0.70, a Precision of 0.68, and a mAP50-95 of 0.50, which is not as good as other models overall. Faster R-CNN is a two-stage detector. Although it performs well in general object detection tasks, it is relatively slow in terms of real-time performance and detection speed. In addition, Faster R-CNN seems to lack precision and recall when dealing with skin cancer lesion detection tasks, which may be because the two-stage architecture has limited ability to locate small-scale lesions, resulting in weak capture of subtle lesion features.

Second, SSD performs slightly better than Faster R-CNN, with a mAP50 of 0.76, a Recall of 0.73, a Precision of 0.71, and a mAP50-95 of 0.54. SSD is a single-stage detection model. Compared with Faster R-CNN, SSD has certain advantages in speed and is suitable for tasks that require fast detection. In skin cancer lesion detection, SSD can process large amounts of image data more efficiently and achieve relatively stable detection performance. However, SSD's performance in accuracy and mAP50-95 is still insufficient, especially when dealing with complex lesion shapes and diverse backgrounds. SSD may not provide enough detail recognition, resulting in unsatisfactory performance at higher mAP thresholds (such as mAP50-95).

RetinaNet showed better performance in the experiment, with a mAP50 of 0.80, a recall of 0.77, a precision of 0.74, and a mAP50-95 of 0.58. RetinaNet focuses on improving the detection ability of

small targets by introducing a focal loss function, which is particularly important for the detection of skin cancer lesions. Since the lesion area is often small and the boundaries are not clear, the focal loss function of RetinaNet helps the model focus more accurately on the difficult-to-detect area, thereby improving the overall detection effect. Compared with Faster R-CNN and SSD, RetinaNet can handle small-scale lesions better, which makes it perform better in mAP50 and mAP50-95. However, although RetinaNet has relatively good detection results, its computational cost is still high, which may be limited in scenarios with high real-time requirements.

YOLOv3 performs even better, with mAP50 reaching 0.84, Recall of 0.81, Precision of 0.78, and mAP50-95 of 0.63. YOLOv3 is a classic single-stage detection model designed for real-time detection, with high speed and good detection results. In the skin cancer lesion detection task, YOLOv3's performance is significantly improved, and it can maintain a good balance between high precision and recall. YOLOv3 has a strong ability to capture detailed features, can identify complex lesion areas, and maintain high detection results under diverse backgrounds. This ability is very important in multi-class skin lesion detection tasks, making YOLOv3 an effective detection solution. However, compared with YOLOv5, the detection accuracy of YOLOv3 in some subtle features and complex backgrounds still has room for improvement.

In the end, YOLOv5 performed best in all indicators, with mAP50 reaching 0.88, Recall of 0.85, Precision of 0.82, and mAP50-95 of 0.68. YOLOv5 has made many improvements on the basis of YOLOv3, including a more efficient network structure, an improved feature extraction module, and an adaptive anchor frame mechanism. These improvements enable YOLOv5 to maintain excellent speed while maintaining high accuracy, and has better adaptability to complex lesion areas and diverse backgrounds. Especially on mAP50-95, YOLOv5's performance is significantly better than other models, indicating that it can maintain stable detection performance at different confidence thresholds. In summary, YOLOv5's high accuracy and excellent detection ability make it the best choice for skin cancer lesion detection, providing reliable technical support for clinical skin cancer automated detection.

5. Conclusion

In this study, by comparing the performance of five target detection models, including Faster R-CNN, SSD, RetinaNet, YOLOv3 and YOLOv5, in the skin cancer lesion detection task, the significant advantages of YOLOv5 in accuracy, recall, precision and multi-scale adaptability were verified. YOLOv5 not only performs well in key indicators such as mAP50 and mAP50-95, but also has high robustness in the detection of subtle lesion areas, thanks to its efficient feature extraction mechanism and adaptive anchor frame design. In addition, as a single-stage detection model, YOLOv5 achieves fast processing speed while ensuring high accuracy, indicating that it has broad application prospects in real-time detection and efficient computing, and provides a reliable automated solution for the early detection of skin cancer.

Although YOLOv5 performed well in this experiment, there is still room for improvement under certain complex backgrounds and subtle features. Factors such as the complexity of skin cancer lesions and the similarity between lesions and backgrounds may affect the detection ability of the model. Therefore, future research can combine multimodal data (such as optical and infrared imaging data) to further enhance the model's feature capture ability. At the same time, the introduction of methods such as self-supervised learning and transfer learning is expected to improve the performance of the model on small sample data sets, thereby improving the generalization ability of the model under different lesion types and ensuring its stability in real clinical applications.

Looking forward to the future, the automated detection technology of skin cancer will gradually develop in the direction of efficiency, intelligence and multimodality. In addition to further optimizing YOLOv5 and similar target detection models, in the future, we can also explore ways to combine deep learning with medical expert knowledge to develop more interpretable and robust detection models. In addition, with the continuous accumulation of large-scale annotated data, researchers can improve the accuracy and reliability of detection through richer data resources and more advanced algorithms. This will provide strong support for the early detection, screening and precision treatment of skin cancer, and make positive contributions to reducing the incidence of skin cancer and improving patient survival rates.

References

[1] E. V. I. F. Rusydiyah, D. C. R. Novitasari, M. F. Mushlihul, et al., "Skin cancer diagnosis system on object detection using various CNN YOLOv5 in Android mobile," Journal of Theoretical and Applied Information Technology, vol. 102, no. 15, 2024.

[2] H. Y. Huang, Y. P. Hsiao, A. Mukundan, et al., "Classification of skin cancer using novel hyperspectral imaging engineering via YOLOv5," Journal of Clinical Medicine, vol. 12, no. 3, p. 1134, 2023.

[3] M. Elshahawy, A. Elnemr, M. Oproescu, et al., "Early melanoma detection based on a hybrid YOLOv5 and ResNet technique," Diagnostics, vol. 13, no. 17, p. 2804, 2023.

[4] M. C. A. Tomas, D. M. P. Ho, S. P. Mehrpouran, et al., "Recognizing common skin diseases in the Philippines using YOLOv5 deep learning," Proceedings of the Sixteenth International Conference on Digital Image Processing (ICDIP 2024), SPIE, vol. 13274, pp. 59-69, 2024.

[5] N. Aishwarya, K. M. Prabhakaran, F. T. Debebe, et al., "Skin cancer diagnosis with YOLO deep neural network," Procedia Computer Science, vol. 220, pp. 651-658, 2023.

[6] R. Qureshi, M. G. Ragab, S. J. Abdulkader, et al., "A comprehensive systematic review of YOLO for medical object detection (2018 to 2023)," Authorea Preprints, 2023.

[7] S. Koparde, J. Kotwal, S. Deshmukh, et al., "A conditional generative adversarial networks and YOLOv5 Darknet-based skin lesion localization and classification using independent component analysis model," Informatics in Medicine Unlocked, vol. 47, p. 101515, 2024.

[8] N. A. AlSadhan, S. A. Alamri, M. M. Ben Ismail, et al., "Skin cancer recognition using unified deep convolutional neural networks," Cancers, vol. 16, no. 7, p. 1246, 2024.

[9] M. Anas, I. U. Haq, G. Husnain, et al., "Advancing breast cancer detection: Enhancing YOLOv5 network for accurate classification in mammogram images," IEEE Access, 2024.

[10] D. Bordoloi, K. Joshi, V. Kukreja, et al., "Innovative approaches in oncology: YOLOv5 and EfficientNet for improved oral cancer diagnosis," Proceedings of the 2024 Asia Pacific Conference on Innovation in Technology (APCIT), IEEE, pp. 1-4, 2024.

[11] M. Elshahawy, A. Elnemr, M. Oproescu, et al., "Early melanoma detection based on a hybrid YOLOv5 and ResNet technique," Diagnostics, vol. 13, p. 2804, 2023.

[12] M. A. Islam, I. Haque, M. Rahaman, et al., "Comprehensive analysis of CNN and YOLOv5 object detection model to classify phytomedicine tree's leaf disease," 2022.

[13] Z. Zheng, Y. Xiang, Y. Qi, Y. Lin, and H. Zhang, "Fully Convolutional Neural Networks for High-Precision Medical Image Analysis," Transactions on Computational and Scientific Methods, vol. 4, no. 12, 2024.

[14] W. He, T. Zhou, Y. Xiang, Y. Lin, J. Hu, and R. Bao, "Deep Learning in Image Classification: Evaluating VGG19's Performance on Complex Visual Data," arXiv preprint arXiv:2412.20345, 2024.

[15] S. Lu, Z. Liu, T. Liu, and W. Zhou, "Scaling-up Medical Vision-and-Language Representation Learning with Federated Learning," Engineering Applications of Artificial Intelligence, vol. 126, 107037, 2023.

[16] J. Hu, X. Liao, J. Gao, Z. Qi, H. Zheng, and C. Wang, "Optimizing Large Language Models with an Enhanced LoRA Fine-Tuning Algorithm for Efficiency and Robustness in NLP Tasks," arXiv preprint arXiv:2412.18729, 2024.

[17] S. Wang, C. Wang, J. Gao, Z. Qi, H. Zheng, and X. Liao, "Feature Alignment-Based Knowledge Distillation for Efficient Compression of Large Language Models," arXiv preprint arXiv:2412.19449, 2024.

[18] Y. Yan, J. Du, L. Wang, Y. Liang, J. Hu, and B. Wang, "The Synergistic Role of Deep Learning and Neural Architecture Search in Advancing Artificial Intelligence," in 2024 International Conference on Electronics and Devices, Computational Science (ICEDCS), pp. 452–456, Sep. 2024.

[19] T. Mei, Z. Zheng, Z. Gao, Q. Wang, X. Cheng, and W. Yang, "Collaborative Hypergraph Networks for Enhanced Disease Risk Assessment," in 2024 International Conference on Electronics and Devices, Computational Science (ICEDCS), pp. 416–420, Sep. 2024.

[20] Z. Gao, T. Mei, Z. Zheng, X. Cheng, Q. Wang, and W. Yang, "Multi-Channel Hypergraph-Enhanced Sequential Visit Prediction," in 2024 International Conference on Electronics and Devices, Computational Science (ICEDCS), pp. 421–425, Sep. 2024.

[21] X. Fei, S. Chai, W. He, L. Dai, R. Xu, and L. Cai, "A Systematic Study on the Privacy Protection Mechanism of Natural Language Processing in Medical Health Records," in 2024 IEEE 2nd International Conference on Sensors, Electronics and Computer Engineering (ICSECE), pp. 1819–1824, Aug. 2024.

[22] W. Wang, X. Wang, C. Wang, Z. Zheng, and J. Mei, "Dynamic Scheduling Strategies for Resource Optimization in Computing Environments," arXiv preprint arXiv:2412.17301, 2024.

[23] X. Li, T. Ruan, Y. Li, Q. Lu, and X. Sun, "A Matrix Logic Approach to Efficient Frequent Itemset Discovery in Large Data Sets," arXiv preprint arXiv:2412.19420, 2024.

[24] J. Song and Z. Liu, "Comparison of Norm-Based Feature Selection Methods on Biological Omics Data," in Proc. 5th Int. Conf. Advances in Image Processing, pp. 109–112, Nov. 2021.

[25] Z. Liu and J. Song, "Comparison of Tree-Based Feature Selection Algorithms on Biological Omics Dataset," in Proc. 5th Int. Conf. Advances in Artificial Intelligence, pp. 165–169, Nov. 2021.

[26] Y. Yang and C. Huang, "Tree-Based RAG-Agent Recommendation System: A Case Study in Medical Test Data," arXiv preprint arXiv:2501.02727, 2025.

[27] J. Hu, R. Bao, Y. Lin, H. Zhang, and Y. Xiang, "Accurate Medical Named Entity Recognition Through Specialized NLP Models," arXiv preprint arXiv:2412.08255, 2024.

[28] P. Li, "Machine Learning Techniques for Pattern Recognition in High-Dimensional Data Mining," arXiv preprint arXiv:2412.15593, 2024.