A Deep Learning Based Detection Method for Insulator Defects in High Voltage Transmission Lines

Wang Tingyu[1], Sun Xia[2*], Liu Jiaxing[3], Zhang Yue[4]
College of Intelligent Equipment, Shandong University of Science and Technology, Tai'an 27100, China[1, 2, 3]
College of Mechanical and Electrical Engineering, Zaozhuang University, Zaozhuang, 277160, China[4]

***Abstract*—The high-voltage transmission system is a key component of the power network, and the reliability of its insulators directly affects the safe operation of the system. Traditional insulator defect detection methods are reliant on manual inspection, which requires significant human resources and is prone to substantial subjectivity. To address this issue, this paper proposes an insulator defect recognition method based on the improved YOLOv5 algorithm. This method first collects images of insulator defects and then utilizes the YOLOv5 model for recognition training. To enhance multi-scale feature fusion capability, a bidirectional feature pyramid network (BiFPN) is introduced. During the training process, the SiUL function is used, and the SE attention mechanism has been integrated into the detection backbone network, which enhances the model's detection accuracy. Experimental results show that the model achieves a detection precision of 90.27%, a recall of 89.14%, and a mAP of 91.34% on the test set. To further enhance the model's practicality, a PyQt5-based user interface (GUI) for the inspection system is designed, enabling interactive functions such as image uploading, defect detection, and result display. In summary, the research presented in this paper provides efficient and accurate technical support for intelligent power inspection, offering a wide range of application prospects.**

Keywords*—*Insulators; insulator defect detection; improved YOLOv5; BiFPN network; PyQt5

I. Introduction

High-voltage transmission lines are a key component of the power system, assuming the important task of transmitting electric energy, and their operational status is directly related to the stability and safety of the power system. As a key component of high-voltage transmission lines, insulators not only support and secure wires but also protect them from environmental erosion and mechanical damage. Therefore, the performance of insulators directly affects the insulation effect and service life of transmission lines. The traditional method for detecting insulator defects mainly relies on manual visual inspection, which has many problems [1]. First of all, the detection efficiency is low, manual visual inspection requires a lot of time and manpower, making it difficult to meet the needs of large-scale and rapid detection. Secondly, the misdetection rate is high; due to human factors, it is easy to miss or incorrectly detect defects, which poses potential risks to the safe operation of the power system.

With the continuous development of science and technology, deep learning-based image recognition technology shows great potential in the field of insulator defect detection. Deep learning technology can automatically extract defect features by learning from insulator images, facilitating efficient and accurate defect detection. Jia Yujin et al. (2023) proposed two lightweight enhancements to YOLOv5, combining the classical YOLOv5 with the advantages of the lightweight convolutional neural networks MobileNetV3 and GhostNet, respectively. Experimental results showed that the enhanced model reduced computational load by 49.4% while maintaining detection accuracy [2]. Ru Hongfang et al. (2023) proposed an improved YOLO x method for detecting insulator self-explosion defects, incorporating the CBAM attention mechanism into the backbone network and optimizing the IoU calculation of the loss function to EIoU, achieving a detection accuracy of 97.26% [3]. Satyajit et al. proposed an automated inspection system utilizing a six-rotor UAV and the YOLOv8n model, achieving efficient real-time monitoring by training the model with a dataset of 6020 insulator images and using image enhancement techniques to avoid overfitting. The YOLOv8n model achieved a mAP@50 of 99.4%, significantly enhancing the efficiency and accuracy of insulator detection [4]. Souza developed a Hybrid-YOLO model based on the ResNet-18 classifier, trained using 1593 grid inspection images, with a mAP of 0.99262 and an F1 score of 0.96216 for the multiclassification task, significantly improving the efficiency and accuracy of insulator detection [5]. Additionally, Yi et al. proposed the GC-YOLO model, which integrates the Ghost convolution module and CA attention mechanism in the backbone network and adds a small target detection head in the detection layer. Experimental results show that GC-YOLO achieves a recall of 89.7% and a mAP@0.5 of 94.2%, which are 7% and 6.5% higher than YOLOv5s, respectively [6]. These studies demonstrate that deep learning-based insulator defect detection techniques have significant advantages in improving detection efficiency and accuracy, showing promising application prospects.

Collectively, these studies had underscored the remarkable advantages of deep learning-based insulator defect detection technologies in enhancing detection efficiency and accuracy. However, the pursuit of further improvements in detection precision and speed remained a focal point of ongoing research. Against this backdrop, this paper proposed an insulator defect detection method for high-voltage transmission lines based on an enhanced YOLOv5 model. By incorporating the SE attention mechanism, the BiFPN module, and employing the SiLU loss function, along with the development of an insulator interaction system interface, this method aimed to achieve efficient and precise detection of insulator defects, thereby improving detection accuracy and reducing the false detection rate.

*Corresponding Author.

II. Tests and Methods

A. Image Acquisition

In this study, the publicly available dataset of high-voltage transmission line insulators from Baidu AI Studio was used, along with insulator defect images obtained through web crawlers. Eventually, a total of 1033 insulator images were collected. Due to the limited number of insulator defect images in the original dataset, data augmentation techniques were applied to increase the dataset size and improve the model's generalization ability. After augmentation, the dataset contained 2066 images, some of which were shown in Fig. 1.

Fig. 1. Image of partial insulator defects.

B. YOLOv5 Model

The YOLOv5 model was the top-performing detection model in the YOLO family and consisted of four main modules: input, backbone network, neck, and head [7]. As shown in Fig. 2, the structure of the YOLOv5 model included techniques such as Mosaic data enhancement and adaptive anchor frame computation [8] in the input module. The backbone network employed Focus and CSPNet for feature extraction enhancement. The neck module combined different CSP modules and up-sampling techniques to obtain multi-scale contextual information. The head module was responsible for classification and regression tasks.

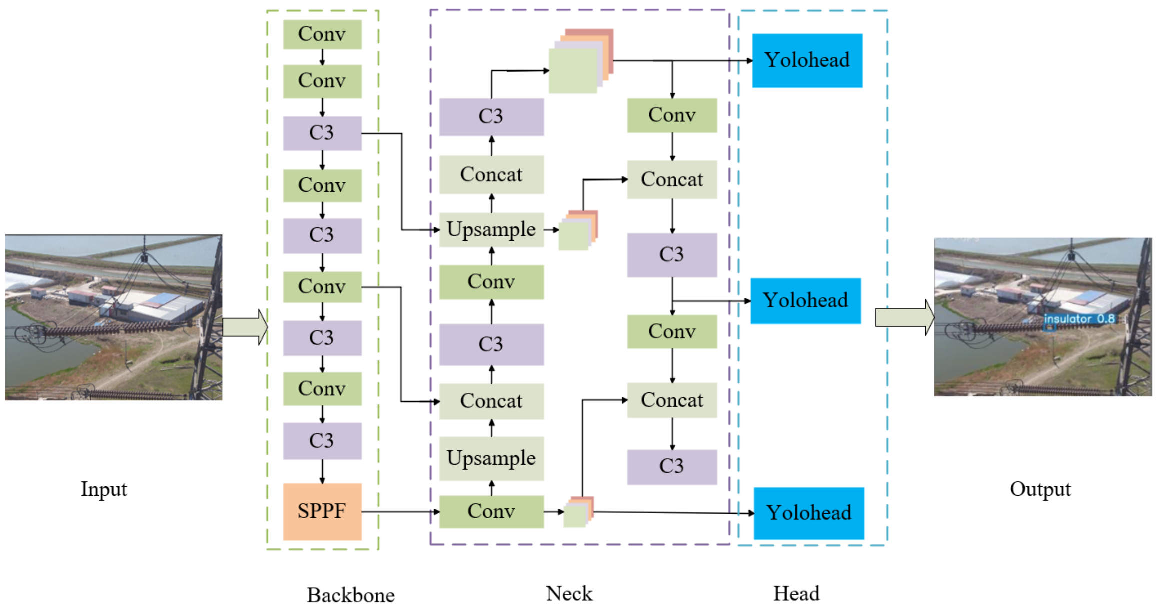

Fig. 2. YOLOv5 model structure.

C. YOLOv5 Improvements

1) SE attention mechanism: Squeeze-and-Excitation Networks (SE) [9] were implemented through two main steps: compression and excitation. As shown in Fig. 3, in the compression step, the SE module compressed the input feature map into a vector through a global average pooling operation, and then mapped it to a smaller vector through a fully connected layer. This process would be interpreted as summarizing and generalizing the overall information of the input features. In the excitation step, each element in this vector was scaled between 0 and 1 using a sigmoid function and multiplied with the original input feature map to obtain a weighted feature map [10]. This excitation operation would be understood as a recalibration of the local information of the input features. With the global averaged pooling and the excitation operations of the sigmoid function, the SE attention mechanism adapted to learn the importance of each channel, thus allowing the model to better understand the critical information in the input features and to focus on them more accurately in the output [11]. To improve the information interaction between each channel of the model and the utilization efficiency of feature information, this paper added the SE attention mechanism to the backbone network, and its specific position in the network was shown in Fig. 3.

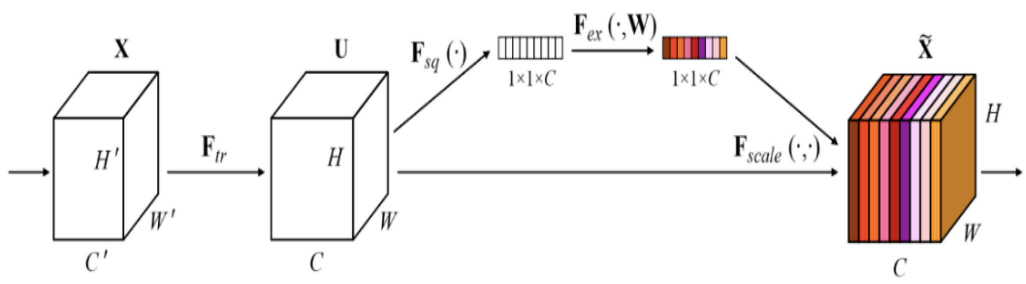

Fig. 3. Structure diagram of SE attention mechanism.

2) Bidirectional Feature Pyramid Network (BiFPN): BiFPN [12] achieved effective fusion of multi-scale features through both top-down and bottom-up pathways , with its structural diagram illustrated in Fig. 4. Its weighted feature fusion mechanism allowed the model to dynamically adjust the importance of different scale features based on task requirements, thereby enhancing feature representation accuracy. In the context of detecting insulator defects, which were typically small targets, a BiFPN module had been introduced into the model's neck section to replace the original feature pyramid network (FPN) [13]. This bi-directional feature fusion mechanism better integrated detailed information from low-level features with semantic information from high-level features, thereby improving the model's capability to detect defects across various scales.

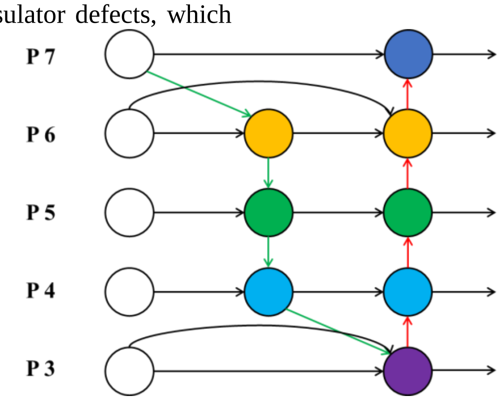

Fig. 4. Structure of bi-directional feature pyramid network.

3) SiLU activation function: In YOLOv5, the activation function introduced nonlinear factors, thereby enhancing the model's expressive power [14]. Activation functions playde a crucial role in neural networks by mapping neuron outputs to nonlinear intervals. This nonlinear mapping enabled neural networks to better adapt to complex patterns, thereby improving accuracy and performance. SiLU (Sigmoid-Weighted Linear Unit) acted as an implicit regularize with the following expression, suppressing the learning of numerous weights during training and enabling the model to focus more effectively on important features and patterns. This not only enhanced the model's generalization ability but also mitigates the risk of overfitting [15]. Additionally, due to SiLU's characteristics, the network's computational speed was improved. When the input x was large, SiLU's value was comparable to that of ReLU. Therefore, this paper adopted the SiLU activation function to enhance the overall performance of the model.

$$SiLU = x \times sigmoid(x) \tag{1}$$

$$sigmoid = \frac{1}{1+e^{-x}} \tag{2}$$

D. Interactive Interface Design for Detection Systems

In the development of an enhanced insulator defect detection system, designing an intuitive and user-friendly graphical user interface (GUI) was paramount. This section elaborated on the interactive interface design utilizing Python's PyQt5 library, as depicted in Fig. 5. The GUI aimed to streamline the interaction between users and the detection model, enhancing the system's usability and user experience.

The GUI integrated an image display area, an upload button, a detection button, and a feature for saving detection results in the backend. Users would effortlessly select an insulator image file for detection by clicking the upload button. Once loaded, the image was displayed in a designated area within the interface, facilitating user preview. Subsequently, upon clicking the detection button, the system automatically initiated the backend defect detection model, processing the image in real-time and instantly feeding back the detection results in graphical or textual form on the interface. This process not only visually showcased the detection effects but also significantly boosted detection efficiency.

To further augment the system's functionality and practicality, we had incorporated a logic for saving detection information in the backend after the detection process. Once users confirmed the accuracy of the detection results, the information saving process was automatically triggered. The system then collected relevant detection details, including image paths, detection timestamps, defect types, locations, and severities, and leverages Python's file manipulation capabilities to save this information in a local JSON file. This step ensured the traceability and analyzability of detection results, facilitating subsequent data management and report generation.

Moreover, to guarantee a seamless user experience, meticulous optimization and testing of the GUI were conducted. By arranging interface elements logically, refining interaction logic, and incorporating error handling and user feedback mechanisms, we ensured the GUI's ease of use, stability, and reliability. Ultimately, a fully-featured, straightforward, and user-friendly GUI for the enhanced insulator defect detection system was successfully implemented, providing robust technical support for insulator inspection tasks in the power industry.

Fig. 5. Detection system interaction interface.

III. Results and Discussion

A. Test Environment

For this model training experiment, the environment was configured as follows: Python 3.8.16 served as the primary programming language with PyTorch 2.0.0 as the chosen deep learning framework. Additional software environments included Torch 2.0.0 and CUDA 11.8.0. The system ran on Windows 11, utilizing an Intel Core i7-13900HX CPU paired with an NVIDIA GeForce RTX 3060 graphics card and 16 GB of RAM. This setup ensure stable and efficient model training, guaranteeing smooth experimentation and accurate results [16].

B. Evaluative Indicators

In this study, multiple evaluative indicators were used to comprehensively assess the performance of the trained model. These indicators included precision, recall, and average precision, [17] which provided comprehensive information for evaluating different aspects of the model.

C. Optimization of Model Training and Validation Parameters

In the development of the insulator defect detection system, the optimization of parameters during the model training and validation stages represents a pivotal aspect ensuring model performance and generalization capability.

Firstly, regarding the learning rate configuration, it served as a crucial hyperparameter modulating the step size of model weight updates, significantly impacting training efficiency and stability. This system employed an initial learning rate of 0.001, coupled with a learning rate decay strategy. Specifically, as training progresses, the learning rate was automatically adjusted to 10% of its previous value every 10 epochs. This strategy aimed to balance rapid convergence during initial training phases with fine-tuning in later stages, thereby preventing the model from becoming trapped in local optima or overfitting.

Secondly, the selection of batch size needed a comprehensive consideration of hardware resource constraints and data processing efficiency. After thorough evaluation, a batch size of 32 was established in this system, ensuring efficient utilization of computational resources while maintaining the stability of the training process and mitigating noise in gradient estimations.

An initial number of 100 epochs was prescribed for training iterations, with ongoing monitoring of validation set performance to facilitate dynamic adjustments. If stagnation or a downward trend in validation set performance metrics (such as loss or accuracy) was observed, it might indicate that the model is nearing optimality or beginning to overfit, necessitating timely termination of training.

In terms of optimizer selection, this system adopted the Adam optimizer, renowned for its adaptive learning rate adjustment capabilities, accelerating model convergence and minimizing computational resource consumption.

To further enhance model generalization, regularization techniques were integrated. Specifically, L2 regularization (weight decay) was employed, penalizing the squared sum of model weights to constrain model complexity. A weight decay coefficient of 0.0005 was set. Additionally, the Dropout strategy was implemented in select layers of the model, randomly discarding a proportion (0.3) of neuron outputs to bolster model robustness.

Through meticulous parameter optimization and effective training validation strategies, this system had successfully established a high-performance experimental environment for insulator defect detection models, laying a solid foundation for their stable performance and precise detection capabilities in practical applications.

D. Results and Analysis

1) Improved model validation analysis

a) Add SE attention mechanism analysis: To thoroughly evaluated the impact of incorporating SE attention mechanisms on the model's detection performance, this paper conducted a comparative analysis before and after their addition under identical hardware and software conditions. The specific results were presented in Table I, demonstrating that the inclusion of SE attention mechanisms notably enhances the model's accuracy in both feature extraction and classification. Specifically, precision increased by 1.3 percentage points, recall by 1.99 percentage points, and average precision by 1.79 percentage points.

TABLE I. COMPARISON OF TESTS BEFORE AND AFTER ADDING SE MODULE

Norm	Original model	After adding the SE module
Accuracy/%	88.72	90.02
Recall rate/%	86.36	88.35
Average precision/%	88.45	90.24

b) Adding Bidirectional Feature Pyramid Network (BiFPN) Analysis: To comprehensively assessed the impact of introducing a bidirectional feature pyramid network (BiFPN) on the model's detection performance, comparative experiments are conducted under identical hardware and software environments. The results, presented in Table II, demonstrate that the inclusion of BiFPN significantly enhances both the model's multi-scale feature fusion capability and its detection performance. Specifically, following the introduction of BiFPN, the precision rate increases by 1.06 percentage points, the recall rate by 2.7 percentage points, and the average precision by 1.92 percentage points.

TABLE II. COMPARISON OF TESTS BEFORE AND AFTER ADDING BIFPN

Norm	Original model	After adding BiFPN
Accuracy/%	88.72	89.78
Recall rate/%	86.36	89.06
Average precision/%	88.45	90.37

c) Analysis using the SiLU activation function: To evaluate the performance of the SiLU function, the activation function was tested before and after the enhancement of the YOLOv5 model on various datasets and models in this study. The results, presented in Table III, demonstrate that the SiLU activation function excels across all performance indicators. Specifically, the precision rate achieved 90.27%, the recall rate was 89.14%, and the average precision reached 90.34%.

TABLE III. COMPARISON OF TESTS BEFORE AND AFTER ADDING SE MODULE

Norm	Original model	SilU activation function
Accuracy/%	88.72	90.27
Recall rate/%	86.36	89.14
Average precision/%	88.45	90.34

Following the adoption of the SiLU function, the model's precision, recall, and average precision were further enhanced, underscoring SiLU's ability to optimize model parameters and improve generalization. The inclusion of the SE attention mechanism alongside the SiLU optimization function notably boost model performance. This synergy suggested that these dual enhancements effectively complement each other, resulting in improved overall model performance.

2) Comparative testing of different models: In this paper, several different models were tested against the improved YOLOv5 model. Specifically, YOLOv4, YOLOv5, and YOLOv8 were compared with the improved YOLOv5 model, and the results were shown in Table IV.

TABLE IV. TEST RESULTS OF DIFFERENT MODELS

Model	P/%	R/%	mAP/%
YOLOv4	86.35	85.26	86.88
YOLOv5	88.72	86.36	88.45
YOLOv8	90.12	88.95	90.22
This paper model	90.27	89.14	91.34

Based on the experimental results, the improved model in this study demonstrated superior performance compared to the YOLOv5, YOLOv4, and YOLOv8 models in terms of precision, recall, and average precision metrics. These findings underscored the effectiveness of the enhancement strategy proposed in this paper. Consequently, the improved model exceled across all performance metrics, affirming the efficacy of the enhancement strategy and providing robust support for future research and applications.

This paper compared and analyzed the image detection results of the YOLOv5 model on the test set before and after the enhancement, as shown in Fig. 6. Fig. 6(a) illustrates the target detection results of the original YOLOv5 model, while Fig. 6(b) showd the target detection results of the improved YOLOv5 model proposed in this study. It was evident from the figures that the enhanced model achieved more accurate identification of insulator defects and significantly improves detection accuracy, particularly for smaller and more challenging defects. This demonstrated the effectiveness of the enhancement strategy in improving the performance of the YOLOv5 model, making it suitable for practical applications.

(a) (b)

Fig. 6. Comparison of models before and after improvement.

IV. Conclusion

This paper proposed an improved method for detecting insulator defects in high-voltage transmission lines, with a focus on intelligent identification. By incorporating a bidirectional feature pyramid network (BiFPN), the YOLOv5 model had been significantly enhanced in terms of multi-scale feature fusion. Additionally, the detection performance had been further optimized through the integration of an SE attention mechanism and the adoption of the SiLU activation function. Experimental validation had demonstrated that the improved model exhibited significant improvements in performance metrics such as precision, recall rate, and average precision, particularly in the areas of small target recognition and positional accuracy. Furthermore, the developed graphical user interface (GUI) inspection system enhances the model's usability, allowing users to easily upload images and perform defect detection operations.

However, it should be noted that this study also had potential limitations and constraints. For instance, the performance of the model might be affected by variations in lighting conditions and image quality. Future work could involve exploring more robust methods to address these challenges and further improving the model's detection capabilities.

References

[1] Huo Chao, Gu Xiaogang, Huang Lingqin, et al. Improved YOLO v4 model for insulator defect detection using aerial imagery[J]. Electronic Measurement Technology, 2023, 46 (09): 175-181. DOI:10.19651/j.cnki.emt.2211518.

[2] Jia Yujin, Zhang Zhencheng, Li Ximing, et al. Transmission line insulator defect detection based on lightweight YOLOv5 network [J]. Journal of Electric Power, 2024, 39 (01): 36-44. DOI:10.13357/j.dlxb.2024.005.

[3] Ru Hongfang, Zuo Chao, Han Long. Self-explosion defect detection method of insulators based on improved YOLOx[J]. Heilongjiang Electric Power,2023,45(02):124-128.

[4] Panigrahy S, Karmakar S. Real-time Condition Monitoring of Transmission Line Insulators Using the YOLO Object Detection Model with a UAV[J]. IEEE Transactions on Instrumentation and Measurement, 2024.

[5] Souza B J, Stefenon S F, Singh G, et al. Hybrid-YOLO for classification of insulators defects in transmission lines based on UAV[J]. International Journal of Electrical Power & Energy Systems, 2023, 148: 108982.

[6] Yi W, Ma S, Li R. Insulator and defect detection model based on improved YOLO-S[J]. IEEE Access, 2023.

[7] Gao Ang, Lu Chuanbing, Ren Longlong et al. Detection of apple blossom growth status based on improved YOLOX-s and validation analysis[J]. Chinese Journal of Agricultural Chemistry,2023,44(08):162-167.

[8] SiYu Chen, Zhangjie Fu. Fusion of efficient attention for multi-scale transmission line component detection [J]. Computer Engineering and Applications, 2024, 60 (01): 327-336.

[9] Hao Weiguang. Research on gas meter flow anomaly detection based on improved generative adversarial network [D]. Wuhan University of Science and Technology, 2023.

[10] Kunpeng Zhang. Research on the method of infected region segmentation of CT images of new coronary pneumonia based on deep learning [D]. Shanghai University, 2021.

[11] Wang Q,Wu B,Zhu P,et al.ECA-Net:Efficient channel attention for deep convolutional neural networks[C]//Procee-dings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition,2020:11534-11542.

[12] Zhu L, Deng Z, Hu X, et al. Bidirectional feature pyramid network with recurrent attention residual modules for shadow detection[C]//Proceedings of the European Conference on Computer Vision (ECCV). 2018: 121-136.

[13] Deng C, Wang M, Liu L, et al. Extended feature pyramid network for small object detection[J]. IEEE Transactions on Multimedia, 2021, 24: 1968-1979.

[14] Zhang Xubo, Zhang Jiayu, Ben Zongyou et al. Research on the identification method of internal cracks in brown rice based on YOLO v5-RF[J/OL]. Journal of Nanjing Agricultural University,1-13.

[15] Dai Yunzhou, Lu Hong, Ji Chenyang. Grid worker defense detection based on improved YOLO v5[J]. Journal of Nanjing Engineering College (Natural Science Edition),2023,21(01):33-38

[16] Zou Huijun, Jiao Liangbao, Zhang Zhijian et al. Improved YOLO network for transmission line small target foreign object detection[J]. Journal of Nanjing Engineering College (Natural Science Edition),2022,20(03):7-14.

[17] Jubayer F, Soeb J A, Mojumder A N, et al. Detection of mold on the food surface using YOLOv5[J]. Current Research in Food Science, 2021, 4: 724-728.