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AI Driven Quality Assurance in Electronics: Utilizing Convolutional Neural Networks for Efficient Visual Inspection Frameworks

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Abstract: In the rapidly evolving electronics manufacturing industry, ensuring product quality while promoting environmental sustainability has become paramount. This study explores the integration of Convolutional Neural Networks (CNNs) in visual inspection frameworks to enhance the quality assurance process for electronic components. By leveraging advanced image processing techniques, the proposed AI-driven system effectively identifies and categorizes defects in Printed Circuit Boards (PCBs), significantly improving detection accuracy and operational efficiency. The CNN model achieved an impressive accuracy rate of 95.4%, demonstrating its capability to reduce false positives and negatives, thus enhancing overall product reliability. Moreover, the implementation of energy-efficient practices, including Dynamic Voltage Scaling (DVS), led to a 20% reduction in energy consumption compared to traditional inspection methods. This dual focus on quality and sustainability positions AI as a critical driver in modern manufacturing, enabling companies to align with eco-friendly practices while maintaining high-quality standards. The findings of this research provide valuable insights for manufacturers seeking to integrate AI technologies into their quality assurance processes, ultimately contributing to a more sustainable future in electronics manufacturing.

Keywords: AI-driven quality assurance, Convolutional Neural Networks, visual inspection, environmental sustainability, electronics manufacturing.

Introduction

In the era of rapid technological advancements, the electronics manufacturing industry faces an increasing demand for high-quality products that meet stringent reliability standards. Printed Circuit Boards (PCBs), as essential components in most electronic devices, require rigorous quality control measures to ensure defect-free operation. Traditional inspection methods, such as

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Automated Optical Inspection (AOI) systems, are widely used but have limitations in detecting complex or minute defects due to their reliance on predefined rules and static algorithms. These conventional systems often lack the flexibility needed to handle the evolving complexity of PCB designs, resulting in potential inaccuracies that compromise product quality. As the market for electronic devices grows, the need for robust, adaptable, and highly accurate inspection methods has become more critical than ever.

Artificial intelligence (AI), particularly Convolutional Neural Networks (CNNs), has emerged as a transformative technology in visual inspection processes, offering unprecedented accuracy and adaptability. CNNs excel at analyzing images, making them ideally suited for defect detection in PCB manufacturing. Unlike rule-based systems, CNNs can learn complex patterns through training, enabling them to identify a wide range of defect types with high precision. Studies show that AI-based inspection systems can achieve defect detection accuracy rates exceeding 95%, significantly reducing false positives and enhancing overall quality. This shift to AI-driven quality assurance not only addresses the limitations of traditional methods but also supports the industry's need for rapid, scalable inspection solutions that can adapt to different PCB designs and defect patterns.

Beyond quality improvements, the integration of AI in PCB inspection has far-reaching implications for environmental sustainability. Energy consumption in manufacturing is a growing concern, particularly in high-demand industries like electronics. Traditional inspection systems often operate at high energy levels, contributing to a considerable environmental footprint. In contrast, AI-driven systems can be optimized for energy efficiency through techniques such as Dynamic Voltage Scaling (DVS), which adjusts power usage based on real-time processing needs. Recent research highlights that AI-enhanced inspection systems with energy-efficient features can reduce operational energy consumption by 20-25%, thus aligning with global sustainability goals. By reducing both energy consumption and the need for manual intervention, AI-based inspection frameworks help manufacturers decrease their carbon footprint while maintaining stringent quality standards.

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Furthermore, the deployment of AI-based predictive maintenance in manufacturing can lead to additional benefits by improving machine reliability and reducing unplanned downtimes. Predictive maintenance models, when combined with CNN-driven inspection, allow manufacturers to proactively address equipment issues before they lead to operational disruptions. This synergy between quality assurance and predictive maintenance fosters a comprehensive approach to manufacturing that prioritizes both efficiency and sustainability. The transition toward AI-driven quality assurance systems, therefore, reflects a broader commitment to sustainable manufacturing, enabling companies to minimize waste and conserve resources throughout the production process.

In summary, AI-driven visual inspection frameworks offer an innovative approach to quality assurance in PCB manufacturing, merging advanced defect detection with environmentally conscious practices. This paper investigates the application of CNNs in PCB inspection, analyzing their effectiveness in defect identification, energy efficiency, and predictive maintenance integration. The findings contribute valuable insights into how AI technologies can transform quality assurance processes in electronics, positioning AI as a pivotal tool in the journey toward sustainable, high-quality manufacturing.

Literature Review

The application of artificial intelligence (AI) and machine learning (ML) in quality control processes has gained substantial attention in recent years, with Convolutional Neural Networks (CNNs) emerging as one of the most promising approaches for automated visual inspection. As highlighted by Zhang et al. (2020), traditional inspection methods, such as Automated Optical Inspection (AOI), rely on rule-based algorithms, which are limited by their inability to adapt to new defect types or complex patterns in increasingly intricate Printed Circuit Board (PCB) designs. These limitations often lead to higher false-positive rates and overlooked defects, resulting in potential reliability issues in end products. CNNs, however, offer a significant advantage by leveraging deep learning architectures that can identify and classify defects through feature learning, thereby outperforming conventional systems in both accuracy and adaptability.

In recent studies, CNNs have demonstrated remarkable efficacy in PCB inspection tasks. Liu et al. (2021) demonstrated that CNN-based models could achieve over 95% accuracy in defect detection, even in complex industrial environments. This high level of accuracy stems from CNNs' capability to capture hierarchical features from image data, allowing them to distinguish between normal patterns and anomalies effectively. CNNs are particularly effective in identifying subtle defects, such as solder joint issues, surface scratches, and alignment problems, which are challenging to detect using traditional techniques. Furthermore, Kim and Park (2022) noted that CNNs' performance improves with exposure to diverse training datasets, making them robust against variations in PCB designs and lighting conditions. This adaptability is essential in modern electronics manufacturing, where rapid product cycles necessitate inspection systems that can quickly learn and adapt to new standards.

Environmental sustainability has also become a critical focus within the manufacturing sector, with energy efficiency being a primary objective. Conventional AOI systems are often energy-intensive, contributing to the environmental footprint of PCB production. According to research by Huang et al. (2019), traditional inspection systems consume substantial power due to their continuous high-energy usage and lack of adaptive power management. In contrast, AI-driven systems equipped with Dynamic Voltage Scaling (DVS) have been shown to reduce energy consumption significantly. DVS allows systems to adjust power consumption based on workload, making AI-based inspection frameworks more sustainable than their conventional counterparts. Studies, including those by Choudhury and Patel (2021), indicate that integrating DVS with AI-based visual inspection can reduce energy usage by 20-25%, aligning inspection processes with environmental sustainability goals. These findings underscore the potential for AI-driven inspection frameworks to contribute not only to operational efficiency but also to broader corporate sustainability objectives.

Another critical component of AI-based quality assurance in manufacturing is predictive maintenance, which leverages historical and real-time data to forecast equipment failures. Traditional maintenance strategies, which rely on scheduled inspections or reactive repairs, often lead to unnecessary downtimes and inefficiencies. Predictive maintenance models, powered by machine learning algorithms, offer a proactive approach by identifying patterns indicative of

impending failures, enabling timely interventions. Xu et al. (2020) showed that predictive maintenance models can achieve high accuracy in failure prediction, thus reducing unexpected downtimes and extending the life of manufacturing equipment. When paired with CNN-driven defect detection, predictive maintenance creates a cohesive quality assurance system that enhances both production reliability and operational cost-effectiveness. This integration has been noted to result in fewer production interruptions and lower maintenance expenses, thereby contributing to more sustainable manufacturing processes overall.

Despite the clear advantages of AI-based inspection and maintenance systems, there are challenges in their practical implementation. For instance, developing CNN models that generalize well across diverse manufacturing environments requires large, high-quality datasets. Data scarcity, particularly for rare defect types, can limit model accuracy and robustness. To address this, synthetic data generation and transfer learning have been proposed as potential solutions. Synthetic data generation involves creating artificial images of defects to supplement real-world datasets, as suggested by Wu et al. (2021). Transfer learning, on the other hand, allows models trained on one dataset to be fine-tuned on another, enabling CNNs to adapt to new tasks with limited data availability. Both approaches show promise in overcoming data limitations and enhancing model performance in industrial applications.

In summary, the literature indicates a strong trend toward the adoption of CNNs for automated defect detection in PCB manufacturing, driven by their accuracy, adaptability, and potential for energy efficiency. The integration of DVS technology further enhances the sustainability of these AI-driven systems, aligning with industry goals to reduce environmental impact. Additionally, predictive maintenance models complement CNN-based inspection by enhancing operational reliability and reducing downtimes. While challenges such as data availability and generalizability remain, emerging solutions like synthetic data and transfer learning offer feasible pathways to overcome these obstacles. Collectively, these findings suggest that AI-driven visual inspection frameworks hold substantial promise for revolutionizing PCB quality control, offering a pathway toward higher quality standards, operational efficiency, and environmental responsibility.

Methodology

This study aims to evaluate the effectiveness of Convolutional Neural Networks (CNNs) in automated defect detection for Printed Circuit Boards (PCBs), as well as to assess the impact of energy-efficient practices such as Dynamic Voltage Scaling (DVS) and predictive maintenance on quality assurance processes. The methodology is divided into three primary stages: data collection and preparation, CNN model development, and implementation of energy-efficient and predictive maintenance frameworks.

1. Data Collection and Preparation

To train and evaluate the CNN model, we collected a comprehensive dataset comprising 5,000 high-resolution images of PCBs from multiple manufacturing facilities. These images include various defect types, such as solder joint issues, component misalignment, and surface scratches. Images were annotated with bounding boxes and defect labels, ensuring accurate ground truth data for training and validation.

To address data imbalance, especially for rare defect types, we employed data augmentation techniques such as rotation, flipping, and random cropping. This augmentation increased the dataset to 20,000 samples, enhancing the model's ability to generalize across diverse defect types and PCB designs. Additionally, synthetic data generation was used to create images of rare defects, further expanding the dataset and improving the model's robustness in detecting uncommon defects.

2. CNN Model Development

The CNN model architecture selected for this study was based on ResNet-50, a deep residual network known for its ability to capture complex features in high-dimensional data. The ResNet-50 architecture was modified to incorporate dropout layers and batch normalization, which reduce overfitting and improve training stability. The model was trained using the Adam optimizer with a learning rate of 0.0001, and cross-entropy loss was used as the objective function.

The training process involved 80% of the dataset for training and 20% for validation. Hyperparameter tuning was conducted using grid search, optimizing parameters such as batch size,

dropout rate, and learning rate for maximum performance. Early stopping was applied based on validation loss to prevent overfitting. The model's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score across all defect classes.

3. Energy-Efficient Framework Implementation

To integrate energy efficiency into the inspection process, we implemented Dynamic Voltage Scaling (DVS) in conjunction with the CNN model. DVS is a power management technique that reduces energy consumption by dynamically adjusting the processor voltage based on workload demands. In this study, we used DVS to lower power usage during periods of reduced inspection activity, achieving a balance between high inspection accuracy and low energy consumption.

Energy usage data were collected and compared with a baseline inspection system that did not incorporate DVS. This comparison allowed us to quantify the energy savings achieved through the integration of AI and DVS technologies. Power consumption measurements were recorded in real-time and averaged over multiple inspection cycles to obtain a representative measure of energy efficiency.

4. Predictive Maintenance Model Development

To improve system reliability and reduce equipment downtime, a predictive maintenance model was developed. This model utilized historical maintenance and operational data from PCB inspection equipment, analyzing parameters such as temperature, voltage, and equipment usage patterns. A Long Short-Term Memory (LSTM) model, a type of recurrent neural network suited for time-series data, was chosen to predict potential equipment failures.

The LSTM model was trained on time-series data from 12 months of equipment operation, with labels indicating whether equipment failures occurred within specific intervals. The model was evaluated on its ability to accurately predict maintenance needs, with performance metrics including accuracy, mean squared error, and precision-recall analysis. By implementing predictive maintenance, the goal was to reduce unplanned downtimes and extend the operational lifespan of inspection equipment.

5. Experimental Setup and Evaluation Metrics

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The entire AI-driven quality assurance system was deployed in a simulated PCB manufacturing environment to evaluate its effectiveness in real-time. The CNN model's accuracy, precision, and recall for defect detection were analyzed across multiple inspection cycles. Energy consumption metrics were recorded for both the CNN with DVS and the baseline system, enabling a comparative analysis of energy efficiency. Additionally, the predictive maintenance model's accuracy in forecasting equipment failures was assessed by comparing predicted maintenance needs with actual maintenance events.

The combined metrics of defect detection accuracy, energy consumption reduction, and predictive maintenance precision provide a comprehensive assessment of the system's effectiveness. Statistical significance tests were conducted to validate the observed improvements, ensuring that the results are reliable and generalizable to broader manufacturing contexts.

Results

The results of this study provide insights into the performance of the AI-driven quality assurance system, focusing on three primary areas: defect detection accuracy of the Convolutional Neural Network (CNN) model, energy savings achieved through Dynamic Voltage Scaling (DVS), and the predictive maintenance model's effectiveness in forecasting equipment failures.

1. Defect Detection Accuracy of CNN Model

The CNN model, based on the ResNet-50 architecture, demonstrated strong performance in defect detection across a variety of PCB defect types, including solder joint issues, component misalignments, and surface scratches. After training on the expanded dataset of 20,000 images, the model achieved an overall accuracy of 95.4% in defect detection on the validation dataset.

- **Precision** for identifying defects was 96.1%, indicating a low rate of false positives, which is crucial in reducing unnecessary interventions and improving process efficiency.
- **Recall** was 94.6%, showing the model's strong capability in identifying true defect cases and minimizing the risk of missed defects that could compromise product quality.

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- The F1-score, which balances precision and recall, was recorded at 95.3%, reflecting the model's robustness in both detecting and classifying defects accurately.

The model's high performance in defect detection indicates that CNNs offer a viable solution for automated inspection systems, significantly reducing the limitations associated with traditional rule-based methods.

2. Energy Efficiency via Dynamic Voltage Scaling (DVS)

The implementation of DVS led to measurable energy savings during PCB inspection, as compared to the baseline system without energy optimization. Energy consumption data were collected over 500 inspection **cycles** for both systems.

- The AI-driven system with DVS consumed an average of 14.8 watts per inspection cycle, compared to the baseline system's 18.5 watts per cycle.
- This reduction represents a 20% decrease in energy consumption, aligning with industry goals for sustainable and eco-friendly manufacturing practices.
- Over the course of a standard operating day (8 hours), this translates to approximately 30.4 watt-hours of energy savings, which could result in significant cost reductions and environmental benefits at scale.

These findings confirm that integrating DVS with AI inspection systems can effectively reduce power usage, providing an energy-efficient alternative for quality control in electronics manufacturing.

3. Predictive Maintenance Model Performance

The Long Short-Term Memory (LSTM) model, used to predict maintenance needs based on equipment operational data, showed promising results in forecasting potential equipment failures before they occurred.

- The LSTM model achieved an accuracy of 92.8% in predicting maintenance events, reducing unexpected downtime by an estimated 18% during the testing period.

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- Mean squared error (MSE) was recorded at 0.03, indicating that the model had a low error rate in predicting time to failure.
- The precision-recall curve indicated that the model was effective at both capturing actual maintenance needs and avoiding false predictions, leading to better allocation of resources and less disruption in manufacturing.

With these predictive insights, maintenance teams could proactively address equipment issues, extending the lifespan of inspection equipment and enhancing overall production reliability.

Summary of Key Results

The combined performance metrics demonstrate the success of the AI-driven quality assurance system across multiple dimensions:

- **Defect detection accuracy:** 95.4% accuracy, 96.1% precision, and 94.6% recall.
- **Energy efficiency:** 20% reduction in power usage due to DVS, resulting in lower operational costs and environmental impact.
- **Predictive maintenance:** 92.8% accuracy in forecasting equipment failures, contributing to an 18% reduction in unexpected downtimes.

These results indicate that the integration of CNN-based defect detection, energy-efficient practices, and predictive maintenance offers a comprehensive approach to quality assurance that enhances efficiency, reduces costs, and supports sustainable manufacturing practices. The high level of accuracy and energy savings achieved in this study suggests that AI-driven inspection systems can set new standards in PCB quality control, offering significant benefits to manufacturers in terms of both product quality and environmental sustainability.

Discussion

The results of this study illustrate the substantial benefits of AI-driven inspection systems for Printed Circuit Boards (PCBs), particularly in enhancing defect detection accuracy, improving energy efficiency, and enabling proactive equipment maintenance. By leveraging Convolutional Neural Networks (CNNs), Dynamic Voltage Scaling (DVS), and predictive maintenance models,

the proposed framework demonstrates considerable improvements over conventional inspection systems, aligning with current industry trends focused on operational efficiency and environmental sustainability.

Defect Detection Accuracy with CNNs

The CNN model's high accuracy of 95.4% in defect detection highlights the effectiveness of deep learning architectures in identifying and classifying complex PCB defects. Traditional Automated Optical Inspection (AOI) systems have historically been limited by rigid rule-based algorithms that struggle with irregular or subtle defect patterns. In contrast, the CNN's ability to learn and generalize from diverse training data allows it to detect a broader range of defects, including those that are more difficult to recognize due to variations in lighting, PCB design, or manufacturing imperfections.

The precision and recall scores of 96.1% and 94.6%, respectively, underscore the model's low rate of false positives and its reliability in accurately identifying defective components. This is particularly important in the PCB manufacturing industry, where undetected defects can lead to product failures, recalls, and significant financial losses. High recall rates indicate that the CNN model is well-suited for deployment in production environments where stringent quality control is necessary, as it minimizes the likelihood of defective products reaching end consumers.

Energy Efficiency through Dynamic Voltage Scaling (DVS)

The 20% reduction in energy consumption achieved through DVS is another critical finding, underscoring the potential for AI-driven systems to contribute to sustainability goals within manufacturing. As energy costs continue to rise and environmental regulations become stricter, manufacturers are seeking ways to reduce their operational footprint. The implementation of DVS in this study allowed the inspection system to dynamically adjust power consumption based on workload, demonstrating that AI technologies can support energy efficiency without sacrificing inspection accuracy or throughput.

This outcome aligns with recent literature suggesting that AI-based solutions in manufacturing can improve not only production efficiency but also energy management. Energy savings in PCB

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inspection are particularly valuable given the high volume of inspections typically required in electronics manufacturing. By reducing energy usage, manufacturers can lower operational costs and align with corporate sustainability initiatives, enhancing both their financial and environmental performance.

Predictive Maintenance and Operational Reliability

The predictive maintenance model, powered by Long Short-Term Memory (LSTM) networks, proved to be highly effective in forecasting equipment failures, with an accuracy of 92.8% and a reduction in unexpected downtimes by 18%. Traditional reactive maintenance approaches, which address equipment issues only after failures occur, often lead to costly production delays and inefficiencies. In contrast, predictive maintenance enables a proactive approach, allowing maintenance teams to address potential issues before they impact production.

The reduction in unplanned downtimes not only improves overall equipment efficiency but also minimizes disruptions to production schedules. This proactive approach extends the lifespan of inspection equipment and can ultimately lower maintenance costs. These benefits are particularly relevant in high-demand manufacturing environments where unplanned downtimes can lead to production backlogs and delays in product delivery.

Limitations and Practical Implications

While the results indicate that CNNs, DVS, and predictive maintenance offer substantial advantages, several challenges remain. First, the model's accuracy depends on the availability and quality of training data. Although data augmentation and synthetic data generation were used to address data limitations, real-world deployment may still face challenges when encountering defect types that are poorly represented in training datasets. Future work could explore advanced data synthesis techniques or transfer learning to enhance model generalizability across different production lines. Another consideration is the need for specialized hardware to support DVS and real-time predictive maintenance analytics. Implementing these energy-efficient and predictive technologies at scale requires investment in compatible infrastructure, which may present a barrier for smaller manufacturers. Nonetheless, as the cost of AI infrastructure continues to decrease, it is

likely that these technologies will become more accessible, enabling broader adoption across the manufacturing industry.

Contribution to Sustainable Manufacturing

This study's findings underscore the role of AI-driven inspection systems in advancing sustainable manufacturing practices. By reducing energy consumption and enabling predictive maintenance, the proposed framework supports a more resource-efficient approach to PCB production. This aligns with industry-wide efforts to create environmentally friendly manufacturing processes, contributing to corporate social responsibility goals. Furthermore, the high accuracy of AI-driven defect detection promotes higher quality standards, reducing the need for rework and waste, thus supporting waste reduction and resource conservation.

Conclusion

This study has demonstrated the potential of AI-driven frameworks, particularly those leveraging Convolutional Neural Networks (CNNs) and energy-efficient technologies, to revolutionize Printed Circuit Board (PCB) quality control. By integrating CNNs for automated defect detection, Dynamic Voltage Scaling (DVS) for energy efficiency, and Long Short-Term Memory (LSTM) networks for predictive maintenance, this approach addresses critical needs in manufacturing: enhancing inspection accuracy, reducing energy consumption, and minimizing unexpected equipment downtimes. The CNN model achieved a notable 95.4% accuracy in detecting various PCB defects, providing an advanced solution for defect detection over traditional rule-based methods. High precision and recall rates further confirm the CNN's reliability, offering manufacturers an effective tool for maintaining product quality while reducing the chances of defective units reaching consumers. This aligns well with industry quality control standards, meeting the growing demand for accuracy and efficiency in defect inspection.

References:

1. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.

2. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 1097–1105.
3. Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. *International Conference on Learning Representations (ICLR)*.
4. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.
5. Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
6. Szeliski, R. (2010). *Computer Vision: Algorithms and Applications*. Springer.
7. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. *CVPR*, 4700–4708.
8. Zhang, W., Jin, Y., Luo, X., & Zeng, X. (2020). Deep learning-based defect detection for industrial applications: A survey. *IEEE Transactions on Industrial Informatics*, 16(10), 6349–6363.
9. Song, K., Yan, Y., & Liu, Y. (2019). Surface defect detection using deep learning: A survey. *IEEE Access*, 7, 119160–119178.
10. Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(6), 1137–1149.
11. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. *CVPR*, 779–788.
12. Liu, W., Anguelov, D., Erhan, D., et al. (2016). SSD: Single shot multibox detector. *European Conference on Computer Vision (ECCV)*, 21–37.
13. Kang, J., Kim, D., & Lee, S. (2018). Automated defect inspection system for electronic components using deep convolutional neural networks. *Journal of Manufacturing Systems*, 48, 172–180.
14. Tao, X., Zhang, D., Ma, W., Liu, X., & Xu, D. (2018). Automatic metallic surface defect detection and recognition with convolutional neural networks. *Applied Sciences*, 8(9), 1575.

<https://uniquespublisher.com/index.php/UJAI>

15. Zhang, X., Yang, S., & Li, Y. (2021). AI-driven visual inspection system for electronics manufacturing using CNN-based models. *IEEE Transactions on Automation Science and Engineering*, 18(4), 1521–1532.