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RESEARCH ARTICLE

Classification of Electronics Components using Deep Learning Methods

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ABSTRACT

In this study, we present an electronic component classification system with a classification accuracy exceeding 98%, achieved by utilizing state-of-the-art deep learning architectures. We employed EfficientNetV2B3, EfficientNetV2S, EfficientNetB0, InceptionV3, MobileNet, and Vision Transformer (ViT) models for the classification task. Our dataset comprises various electronic components, and it has been meticulously organized and labeled to provide high-quality training data. We conducted extensive experiments, utilizing data augmentation techniques and transfer learning, to fine-tune and optimize the models for the given task. The high classification accuracy achieved by our system indicates its readiness for real-world applications. It can be applied to advance automation and efficiency in the electronics industry.

Keywords: Electronic component classification, Deep learning, Transfer learning

1. Introduction

Fundamental to electronic circuitry and systems, electronic components represent indispensable units, meticulously engineered to fulfill precise functionalities. They are classified into two primary categories: active components, exemplified by transistors and diodes, and passive components, encompassing resistors and capacitors. These elements play pivotal roles in the processing, storage, and transmission of electrical signals [1]. Resistors, for instance, regulate the flow of electric current, often used to control voltage and current within a circuit. Capacitors, on the other hand, store and release electrical energy, proving valuable for tasks like energy storage and timing. Transistors are versatile, functioning as amplifiers or switches for electronic signals and serving as the backbone of modern electronics, including amplifiers and processors. LEDs (Light Emitting Diodes) are ubiquitous for their light emission when current flows through them, commonly applied in displays, indicators, and lighting. Potentiometers, or variable resistors, are useful for tasks like volume control and tuning in electronic devices. Buttons, which also go by the name of switches, control the electrical current's flow, often used for user input and control. In addition, ultrasonic sensors make use of sound waves to measure distance or detect objects. They have applications in robotics, automotive systems, and distance measurement. These components are deployed across various industries, from consumer electronics and automotive systems to industrial automation, telecommunications, medical devices, aerospace and defense, and renewable energy solutions. In essence, electronic components are the foundational elements that power the world of modern technology, enabling the development of advanced electronic devices and systems that have revolutionized everyday life and various industrial sectors [2]–[10].

Image classification is the process of assigning a specific class to an image, and within this domain, various techniques are employed [11]. Deep learning, particularly leveraging architectures such as Convolutional Neural Networks (CNNs), stands out as a robust approach [12]. Additionally, machine learning algorithms like Support Vector Machines (SVM) [13], decision trees [14], and random forests [15], as well as straightforward methods like K-Nearest Neighbors [16], are commonly utilized. Image features and descriptors, including color histograms, edge detectors, and Histogram of Oriented Gradients (HOG), contribute to the diverse array of methods. These techniques are often combined or customized based on factors such as dataset size, complexity, and specific requirements. The selection of a particular method is contingent upon the distinct usage scenarios and objectives.

Deep learning, a subfield of machine learning, involves training artificial neural networks with multiple layers to perform complex tasks. Its importance lies in its remarkable ability to automatically learn and extract intricate patterns and representations from large datasets, enabling the development of highly accurate predictive models. Deep learning has found diverse applications, one of which is in classification. It is used to categorize and identify objects or data, such as images, audio, or text, in various domains. For instance, in computer vision, deep learning is employed for image recognition, object detection, and facial recognition. In natural language processing, it aids in sentiment analysis, language translation, and chatbot development. Deep learning also has applications in healthcare for disease diagnosis, in autonomous vehicles for object detection and navigation, in finance for fraud detection, and in manufacturing for quality control. Its capacity to handle large and complex datasets makes deep learning a transformative technology with wide-ranging implications for automation, precision, and decision-making across industries [17]–[20]. Deep learning methods for electronic component classification involve the use of advanced neural networks, such as CNNs and transformers, to categorize electronic components based on their visual attributes and features. These methods are particularly valuable in automating the identification and sorting of electronic components, which can vary significantly in size and appearance. They are widely employed in quality control processes in electronics manufacturing, ensuring that the correct components are used in assembly. Additionally, this technology finds applications in inventory management, making it easier to track and manage the vast array of components used in various products. The importance of deep learning in this context lies in its ability to achieve high accuracy and speed in classification, reducing human error and increasing efficiency in the electronics industry. It also paves the way for the automation of tedious and time-consuming tasks, allowing human resources to be redirected to more complex and creative aspects of electronic design and production [21]–[28].

Our study focused on an extensive comparison of state-of-the-art deep learning models, including EfficientNet-V2B3 [29], EfficientNet-V2S [30], EfficientNet-B0 [31] , Inception-V3 [32], MobileNet [33], and Vision Transformer (ViT) [34], in the realm of electronic component classification. We evaluated their performance across various electronic component classes, such as capacitor, LED, potentiometer, button, resistor, transistor, and ultrasonic sensor. The significance of this research lies in its potential to bring about a significant transformation in the electronics industry by providing a robust and highly accurate automated solution for classifying electronic components. Such a system has the capacity to greatly enhance quality control, reduce errors, and expedite manufacturing processes. Furthermore, the unique value of our work is evident in its thorough examination of these advanced models in a practical, industrial context, highlighting their real-world applicability. By demonstrating the capabilities of these models in achieving exceptional accuracy in component classification, we contribute to the ongoing efforts aimed at advancing automation, efficiency, and precision in electronic component management, offering a compelling pathway to redefine modern electronics manufacturing. In the subsequent sections of this study, we will delve into the existing body of work within this domain, the dataset employed, the methodology employed, the experimental endeavors, and the outcomes obtained. We aim to provide a comprehensive overview of related research, illuminate the specifics of our dataset, elucidate the methods applied, chronicle our experimental investigations, and ultimately present the findings and results that have emerged from our efforts.

2. Relevant Work

The recognition of electronic components has been extensively studied, with methodologies that integrate image processing, machine learning, and deep learning techniques. Image processing methods involve the use of edge detection algorithms to outline the contours and edges of electronic components, with color and intensity analysis playing a crucial role, especially in identifying components on printed circuit boards. Machine learning approaches such as SVM leverage component features for classification, and decision trees and forests are employed for effective feature extraction. Deep learning methodologies, particularly CNN, demonstrate effectiveness, especially in the recognition of components on printed circuit boards. Transfer learning, utilizing pre-trained models from extensive datasets, enhances component recognition performance, even with smaller datasets. Object detection methods like R-CNN and its derivatives, as well as YOLO (You Only Look Once), offer effective strategies for recognizing components within images [28]. Tailored methods, specific to component characteristics, involve geometry analysis and Optical Character Recognition (OCR) for labels or text on components. This dynamic field continues to evolve, holding substantial potential, particularly in applications such as industrial automation, electronic manufacturing, and maintenance [21]–[28]. Table 1 represents various studies in the literature, each detailing their dataset, task, methodology, and the achieved results. For instance, reference [21] employed the ERFAM-YOLOv3 method for object detection on a dataset consisting of 1000 images with 29 instrument categories, achieving a notable 95.03% average accuracy. Similarly, other references provide insights into different approaches and outcomes in the field of electronic component recognition. According to the values provided in this table, the performance rates vary within the range of 90% to 100%.

3. Dataset

The images of various electronic components, including capacitors, LEDs, potentiometers, push buttons, resistors, transistors, and ultrasonic sensors, were collected from publicly available datasets for the purpose of classification in a research project. These datasets contain visual representations of these components, which are essential in electronic circuitry and various applications [35]–[37]. The dataset also includes images that we captured ourselves and images obtained from Google image search. Figure 1 illustrates randomly chosen samples within the dataset. Table 2 shows the number of training and testing samples for each component category in the study. The dataset has been partitioned with approximately 25% of the total data allocated for testing and 75% for training purposes. Since the dataset contains images of varying quality and from different perspectives, and it possesses enough data for classification, no augmentation process was performed. In Figure 2, a block diagram illustrating the data set preparation process is provided.

Table 1 Relevant work

Ref.	Dataset	Task	Method	Result
[23]	483 images, 5000 labeled IC instances	Object detection	VN-Siamesev2 network containing the backbone of VGG16 architecture	92.31% accuracy
[21]	1000 images, 29 instrument categories, 182900 electronic components	Object detection	ERFAM-YOLOv3	95.03%average accuracy
[22]	8000 images	Object detection	ECLAD-Net	90%-100%
[24]	60 images, 172 labeled components	Object detection	Image processing	91.28%
[25]	3094 images	Classification	Siamese network	99%
[26]	200340 images	Classification	Multilayer perceptron	92.3%
[27]	-	Classification	Back Propagation Neural Network	95.8%
[28]	1026 images, 4 categories	Object detection	YOLOv2 Network	0.27 error rate on test set 0.8743% on evaluation set

Figure 1 Sample images from the dataset.

4. Method

We used transfer learning based deep learning models in our study. Transfer learning in the context of deep learning refers to the practice of leveraging a pre-trained neural network model for a new, related task. It's a technique where a model developed for a particular task is adapted for a second related task. Transfer learning can significantly speed up the training process and often leads to better performance compared to training a model from scratch. Transfer learning typically involves starting with a pre-trained model that has been trained on a large dataset for a similar or related problem. These models are often trained on massive datasets and have learned useful features from them. After obtaining a pre-trained model, you fine-tune it for your specific task. Training deep neural networks from scratch can be computationally expensive and time-consuming, especially when dealing with large datasets and complex architectures. Transfer learning allows you to start with a pre-trained model, saving a significant amount of training time.

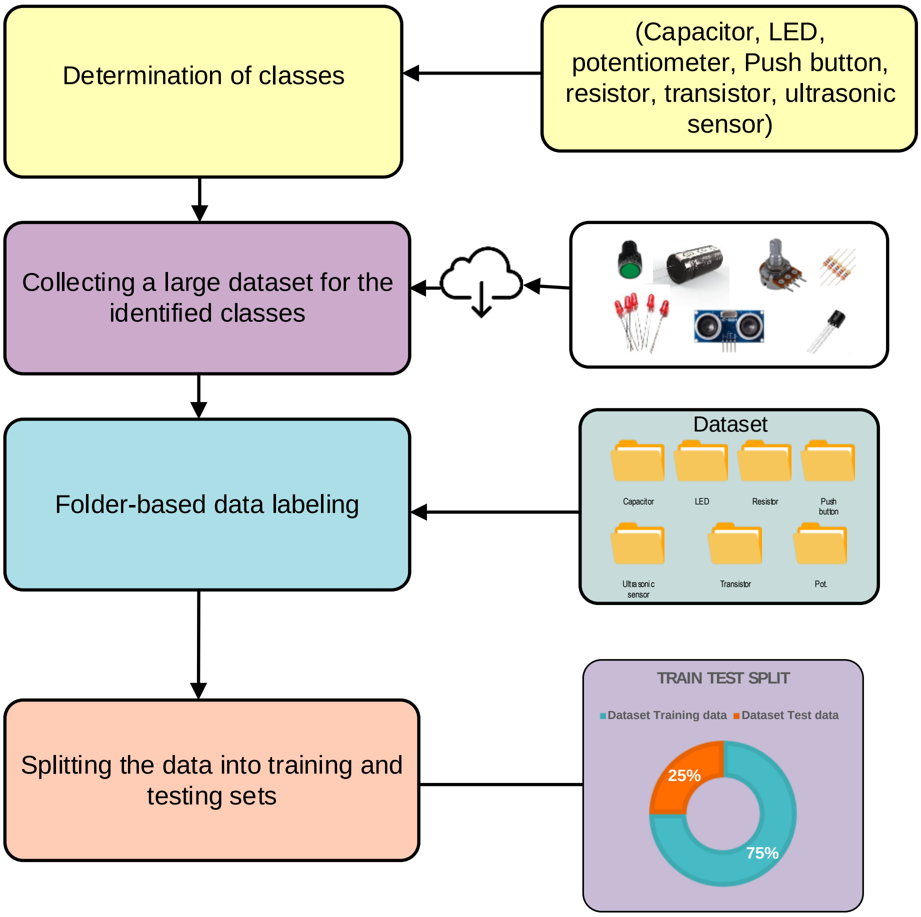

Figure 2 Dataset preparation diagram

Table 2 Component Classification Data: Training and Testing Split

Components	**Train**	**Test**
Capacitor	600	200
Led	375	100
Poentiometer	302	100
Push Button	301	100
Resistor	355	100
Transistor	281	100
Ultrasonic Sensor	300	100
Total	2514	800

We have leveraged a selection of pre-trained CNN architectures, including EfficientNet-V2B3, EfficientNet-V2S, EfficientNet-B0, Inception-V3, MobileNet, and Vision transformer based neural network (ViT), for the purpose of electronic component classification. These models can be readily accessed in Keras, an open-source neural network library written in Python [38].

Inception, also recognized as GoogleNet, represents a deep learning architecture tailored for CNNs, meticulously crafted to tackle the complexities of training exceptionally deep networks without compromising computational efficiency. Pioneered by researchers at Google, Inception introduces an ingenious 'inception module' that integrates multiple convolutional filter sizes and pooling operations within a single layer. This innovative approach empowers the network to capture features across various scales, thereby enhancing the robustness and precision of feature extraction. Inception has exerted a profound influence on the domain of computer vision, particularly in tasks such as image classification and object detection. Its aptitude for harmonizing model depth with computational efficiency has solidified its status as a widely adopted architectural solution in the realm of deep learning [39].

EfficientNet is a family of deep learning models specifically designed to achieve state-of-the-art performance with high efficiency in terms of computational resources. These models use a novel scaling method that uniformly scales the network's depth, width, and resolution. This approach ensures that the model adapts to different computational constraints while maintaining excellent performance on a wide range of computer vision tasks, such as image classification and object detection. EfficientNet's architecture efficiently balances model size and accuracy, making it a popular choice for various real-world applications where computational efficiency is a priority, such as edge devices and resource-constrained environments [40].

MobileNet is a CNN architecture designed for efficient and lightweight deep learning applications, particularly optimized for mobile and edge computing devices. Introduced by Google researchers in 2017, MobileNet addresses the challenge of deploying complex neural networks on resource-constrained platforms. It achieves computational efficiency through the use of depth wise separable convolutions, a key architectural element that significantly reduces the number of parameters and computations required. The network's core idea is to factorize a standard convolution into a depth wise convolution and a 1x1 pointwise convolution. The depth wise convolution applies a single filter per input channel, followed by a 1x1 pointwise convolution that combines the outputs from the depth wise convolution. This separation of spatial and channel-wise filtering allows MobileNet to maintain a good balance between accuracy and computational efficiency. With its lightweight design, MobileNet has become a popular choice for real-time image classification and object detection tasks on devices with limited computational resources.

The Vision Transformer (ViT) represents a groundbreaking architecture in the realm of computer vision and image processing. Introduced in a seminal paper by researchers from Google in 2020, ViT diverges from conventional CNN structures by exclusively relying on self-attention mechanisms. The architecture leverages the Transformer model, originally designed for natural language processing, to capture intricate hierarchical features within images. In ViT, the input image is divided into fixed-size non-overlapping patches, which are linearly embedded and flattened into sequences. These sequences serve as input tokens for the Transformer encoder, allowing the model to attend to relationships between different image patches. This mechanism enables ViT to grasp both local and global contextual information, crucial for understanding complex visual patterns. Additionally, ViT employs positional embeddings to preserve spatial information within the flattened sequences. Notably, ViT has demonstrated exceptional performance on various computer vision tasks, often surpassing traditional CNNs. Its remarkable ability to scale to large datasets and capture long-range dependencies positions ViT as a versatile architecture for vision-based applications, showcasing its potential impact on the evolution of deep learning models for image understanding.

The metrics employed for the comparative assessment of the performance of these architectures include Accuracy (Acc.), Precision, Recall, and F1 Score values. These metrics serve as quantitative indicators to evaluate the effectiveness and capabilities of the different models in a rigorous and systematic manner. Precision measures the model's ability to accurately identify positive instances among the instances it predicts as positive as given in Eq.1. Recall, also known as the true positive rate or sensitivity, assesses the model's ability to correctly identify all positive instances, as defined in Equation 2. The F1 score, a harmonic mean of precision and recall, strikes a balance between precision and recall, proving valuable for imbalanced datasets according to Equation 3. Accuracy, measured by the formula in Equation 4, evaluates the overall correctness of the model's predictions. A block diagram of the deep learning-based classification system is given in Figure 3.

$$\boldsymbol{P = \frac{TP}{TP+FP}} \tag{1}$$

$$\boldsymbol{R = \frac{TP}{TP+FN}} \tag{2}$$

$$\boldsymbol{F1\ Score = 2 \cdot \frac{P \cdot R}{P+R}} \tag{3}$$

$$\boldsymbol{Accuracy = \frac{TP+TN}{TP+TN+FP+FN}} \tag{4}$$

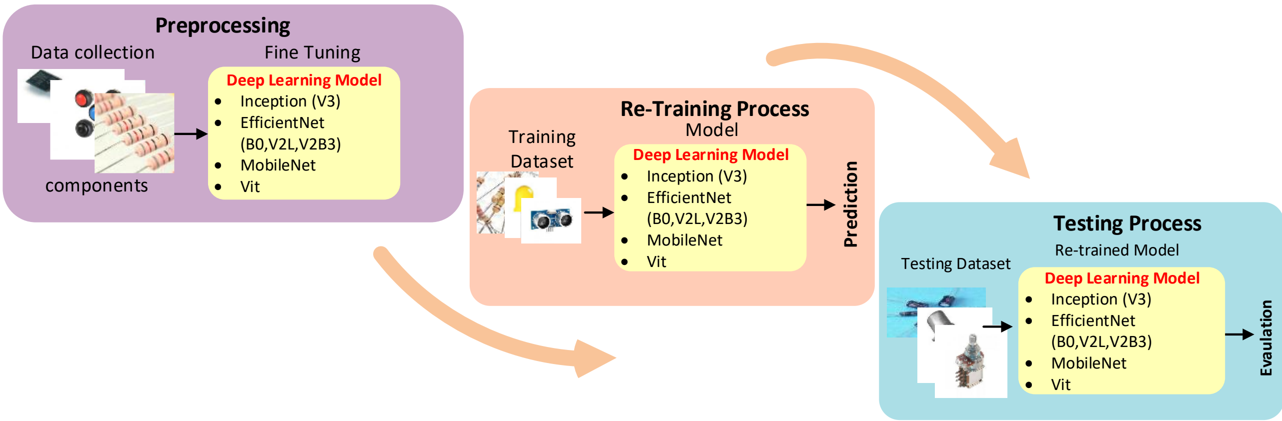

Figure 3 Block diagram of the deep learning-based classification system

5. Results

Table 3 presents the training performance metrics for various base models used in the first approach. The metrics include training accuracy, acc-loss (accuracy loss), validation accuracy, and val-loss (validation loss). The presented data illustrates the training accuracy, accuracy loss, validation accuracy, and validation loss for each base model after 100 epochs. Notably, the EfficientNet-0V2S model achieved the highest training accuracy of 99.50%, with a relatively low accuracy loss of 0.0234. However, each model's performance is comprehensively evaluated based on both training and validation metrics, providing a comprehensive overview of their effectiveness in the first approach. Table 4 presents the performance metrics of re-trained models for the first approach, considering various classification tasks. The metrics include accuracy (Acc.), precision, recall, F1 score, and overall accuracy. The provided table details the performance metrics for re-trained models in the first approach across various classes. For instance, the MobileNet model demonstrates high accuracy for LED classification (96.68%), while ViT achieves perfect accuracy (100%) across all classes, indicating excellent overall performance. Precision, recall, and F1 score metrics offer insights into the models' ability to correctly classify instances, providing a comprehensive evaluation of their effectiveness in differentiating electronic components. The overall accuracy metric presents a consolidated measure of each model's performance across all classes, facilitating a holistic assessment of their classification capabilities.

Table 3 Training performance table for the first approach

Base Model	Training Accuracy	Acc-loss	Validation accuracy	Val-loss
EfficientNet-V2B3	0.9876	0.0475	0.8044	0.1107
EfficientNet-V2S	0.9930	0.0210	0.8523	0.6433
EfficientNet-B0	0.9911	0.0299	0.8184	1.0668
Inception-V3	0.9892	0.0442	0.6617	2.5616
MobileNet	0.9958	0.0167	0.7143	2.4491
ViT	0.9850	0.2477	0.9621	0.41

Table 4 Performance metrics of re-trained models for the first approach

Method	Class	n truth	n classified	Acc.	Precision	Recall	F1 Score	Overall Acc.
MobileNet	Capacitor	184	200	89.26%	0.74	0.81	0.78	87.27%
	LED	99	100	99%	0.95	0.97	0.96	
	Potentiometer	87	100	98.13%	0.86	0.99	0.92	
	Button	136	100	94.01%	0.94	0.69	0.80	
	Resistor	89	100	98.63%	0.89	1.0	0.94	
	Transistor	113	100	97.13%	0.95	0.84	0.89	
	Ultrasonic Sensor	93	100	98.38%	0.90	0.97	0.93	
Inception-V3	Capacitor	153	200	89.39%	0.67	0.88	0.76	84.39%
	LED	112	100	97.88%	0.97	0.88	0.92	
	Potentiometer	102	100	97.5%	0.91	0.89	0.90	
	Button	87	100	96.38%	0.79	0.91	0.84	
	Resistor	101	100	96.63%	0.87	0.86	0.87	
	Transistor	109	100	96.63%	0.91	0.83	0.87	
	Ultrasonic Sensor	137	100	94.38%	0.96	0.70	0.81	
EfficientNet-B0	Capacitor	227	200	88.13%	0.83	0.73	0.78	85.13%
	LED	102	100	99%	0.97	0.95	0.96	
	Potentiometer	85	100	97.63%	0.83	0.98	0.90	
	Button	92	100	95.5%	0.78	0.85	0.81	
	Resistor	78	100	97%	0.77	0.99	0.87	
	Transistor	126	100	96%	0.97	0.77	0.86	
	Ultrasonic Sensor	90	100	97%	0.83	0.92	0.87	
EfficientNet-V2B3	Capacitor	153	200	88.88%	0.66	0.86	0.75	86.63%
	LED	96	100	99%	0.94	0.98	0.96	
	Potentiometer	112	100	97.75%	0.97	0.87	0.92	
	Button	110	100	97.5%	0.95	0.86	0.90	
	Resistor	105	100	98.63%	0.97	0.92	0.95	
	Transistor	144	100	94%	0.98	0.68	0.80	
	Ultrasonic Sensor	80	100	97.5%	0.80	1.0	0.89	
EfficientNet-V2S	Capacitor	80	200	85%	0.40	1.0	0..57	82.5%
	LED	106	100	97.25%	0.94	0.89	0.91	
	Potentiometer	117	100	97.13%	0.97	0.83	0.89	
	Button	144	100	94%	0.98	0.68	0.80	
	Resistor	115	100	97.88%	0.99	0.86	0.92	
	Transistor	138	100	95.25%	1.0	0.72	0.84	
	Ultrasonic Sensor	100	100	98%	0.92	0.92	0.92	
ViT	Capacitor	206	200	99%	0.99	0.97	0.98	**98.5%**
	LED	100	100	100%	1.0	1.0	1.0	
	Potentiometer	101	100	99.88%	1.0	0.99	1.0	
	Button	100	100	99.28%	0.97	0.97	0.97	
	Resistor	98	100	99.75%	0.98	1.0	0.99	
	Transistor	101	100	99.88%	1.0	0.99	1.0	
	Ultrasonic Sensor	94	100	99.25%	0.94	1.0	0.97	

6. Conclusions

In this study, we successfully implemented an accurate electronic component classification system using state-of-the-art deep learning architectures. The models, including EfficientNet-V2B3, EfficientNet-V2S, EfficientNet-B0, Inception-V3, MobileNet, and Vision Transformer (ViT), achieved a classification accuracy of over 98%. The comprehensive evaluation across various electronic component classes demonstrated the models' effectiveness in complex visual recognition tasks within the electronic components' domain. Training metrics further confirmed the models' efficiency, displaying high accuracy and minimal loss during both training and validation phases. Given the achieved high classification accuracy, we recommend considering the real-world deployment of the developed electronic component classification system. This system has the potential to significantly improve automation and efficiency in the electronics industry, particularly in tasks related to quality control, manufacturing, and inventory management. To enhance the system's generalization capability, expanding the dataset to include a wider variety of electronic components and variations in environmental conditions is advised. This expansion ensures the model's effectiveness in recognizing a broader range of components under various circumstances. As technology and industry standards evolve, continuous monitoring, feedback loops, and model updates become crucial. Regular assessments and updates are essential to ensure the system's adaptability to changing requirements and emerging technologies in the electronics sector. In conclusion, the successful implementation of this electronic component classification system opens doors for transformative applications in the electronics industry. The combination of advanced deep learning models and meticulous experimental methodologies positions this system as an asset for driving innovation, precision, and efficiency in electronic component management and manufacturing processes.

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Conflict of Interest Notice

Authors declare that there is no conflict of interest regarding the publication of this paper.

Ethical Approval

It is declared that during the preparation process of this study, scientific and ethical principles were followed, and all the studies benefited from are stated in the bibliography.

Availability of data and material

Not applicable.

Plagiarism Statement

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