
Implementation Convolutional Neural Network for Visually Based Detection of Waste Types

Bayu Yasa Wedha¹⁾, Ira Diana Sholihati³⁾, Sari Ningsih⁴⁾

¹⁾Prodi Informatika, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional Jakarta

^{2,3)}Prodi Sistem Informasi, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional Jakarta

¹⁾bayu.yasa.wedha@civitas.unas.ac.id, ²⁾ira.diana@civitas.unas.ac.id, ³⁾sari.ningsih@civitas.unas.ac.id

ABSTRACT

Waste detection plays an essential role in ensuring efficient waste management. Convolutional Neural Networks are used in visual waste detection to improve waste management. This study uses a data set that covers various categories of waste, such as plastic, paper, metal, glass, trash, and cardboard. Convolutional Neural Networks are created and trained with refined architecture to achieve precise classification results. During the model development stage, the focus is on utilizing transfer learning techniques to implement Convolutional Neural Networks. Utilizing pre-trained models will speed up and improve the learning process by enriching the representation of waste features. By using the information embedded in the trained model, the Convolutional Neural Network can differentiate the specific attributes of various waste categories more accurately. Utilizing transfer learning allows models to adapt to real-world scenarios, thereby improving their ability to generalize and accurately identify waste that may exhibit significant variation in appearance. Combining these methodologies enhances the ability to identify waste in diverse environmental conditions, facilitates efficient waste management, and can be adapted to contemporary needs in environmental remediation. The model evaluation shows satisfactory performance, with a recognition accuracy of about 73%. Additionally, experiments are conducted under authentic circumstances to assess the reliability of the system under realistic circumstances. This study provides a valuable contribution to the advancement of waste detection systems that can be integrated into waste management with optimal efficiency.

Keywords: Garbage Detection; Convolutional Neural Network; Waste Management; Object Segmentation; Transfer Learning

INTRODUCTION

Effective waste management is essential for ensuring environmental cleanliness and sustainability in the modern era. The development of visual waste detection technology has emerged as a crucial research focus to tackle the escalating issue of rapidly expanding waste volumes. Given the intricate task of categorizing and handling waste, particularly with the rise in diverse waste types and their growing volumes, there is a pressing necessity to discover practical solutions. The utilization of Convolutional Neural Network (CNN) (Hindarto & Amalia, 2023), (Hindarto et al., 2023) in this research is a critical factor in advancing visual waste detection and classification capabilities. Due to the swift expansion of urbanization and the continuously rising levels of consumption, the generation of waste is unavoidable. The wide range and assortment of waste types encountered pose a challenge in effectively managing waste. Implementing visual waste detection is an innovative measure that can overcome these challenges. This research aims to utilize advanced artificial neural networks, specifically Convolutional Neural Networks, to gain a comprehensive understanding of the visual attributes associated with different types of waste. By employing this method, it is anticipated that waste management can be optimized, thereby reducing negative environmental consequences, and establishing a foundation for future sustainable waste management practices.

This research aims to enhance waste management efficiency by leveraging Convolutional Neural Network technology to enhance visual waste detection and classification capabilities. The dataset utilized in this research encompasses diverse classifications of waste that are frequently encountered in our daily surroundings. From durable plastic to plentiful paper, diverse metals, fragile glass, common waste, and cardboard are prominent waste contributors. Every category of waste possesses distinct visual attributes, which adds complexity to the task of effectively and efficiently handling waste. Plastic, being a highly conspicuous form of waste that has garnered worldwide attention, exists in diverse manifestations, ranging from bottles to shopping bags, and exhibits a wide array of colours and

* Corresponding author



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textures. Paper, which is consistently produced in significant volumes by industries, businesses, and daily operations, constitutes a substantial portion of this waste classification. The wide range of metal types, including cans, wire, and other metal pieces, poses unique challenges in terms of visual detection. In addition, glass, a delicate material that can originate from diverse sources, is also classified as waste, and requires meticulous management. This research encompasses general waste, encompassing diverse types of waste that are challenging to categorize precisely, as well as cardboard, which frequently serves as the primary receptacle for packaging and shipping. Distinguishing the visual disparities among these waste classifications is a crucial phase in this study. A CNN (Hindarto, 2023b), (Hindarto, 2023a) is employed to acquire the discernible visual patterns of each category of waste, enabling the system to recognize and categorize waste more precisely. By comprehending the visual attributes linked to each category of waste, it is anticipated that visual waste detection utilizing this methodology will be more accurate, bolstering more effective and sustainable waste management endeavours.

The field of waste management encounters substantial difficulties in the identification and categorization of the diverse types of waste that exist. Each type of waste, ranging from prevalent plastic to abundant paper, various types of metal, fragile glass, unclassifiable general waste, and cardboard, which is frequently a significant waste source, possesses distinct visual attributes. The challenge lies in precisely identifying these categories of waste, as any mistakes made during the classification procedure can lead to significant disruptions in waste management. An erroneous classification of waste can lead to the commingling of waste that should be segregated, resulting in diminished efficacy in waste management and potentially causing substantial harm to the environment. Precise differentiation between plastic and paper, metal, and glass, as well as the identification of general waste and cardboard, becomes essential in this scenario. The nuanced visual distinctions among various types of waste contribute to the intricacy of waste management. Failure to accurately identify the various categories of waste leaves the waste management procedure susceptible to potentially expensive mistakes, which can have negative consequences for both the environment and the economy. Hence, conducting research that prioritizes the creation of solutions to distinguish between various classifications of waste effectively is crucial for enhancing efficiency and sustainability in waste management.

The research employs a Convolutional Neural Network as the primary foundation for visual waste detection. CNN, short for Convolutional Neural Network, is a specific type of artificial neural network design that has demonstrated remarkable efficacy in handling visual data. The model was constructed and trained using a dataset encompassing diverse waste categories, enabling the network to acquire knowledge and recognize visual patterns linked to each specific waste type. Moreover, employing transfer learning techniques allows the model to leverage the knowledge acquired from prior training models, thereby accelerating the learning process, and enhancing classification accuracy.

The primary aim of this study is to enhance the efficiency of waste management by employing Convolutional Neural Networks for precise visual waste detection. By harnessing this technology, it is anticipated that the system's capacity to detect and categorize different types of waste will be significantly enhanced. This is expected to bolster more effective waste management, mitigate environmental losses, and have a favourable impact on environmental remediation endeavours.

Utilizing Convolutional Neural Networks for visual waste detection holds the potential for substantial enhancements in waste management efficiency across diverse environmental circumstances. By leveraging CNN's capacity to handle intricate visual variations, transfer learning models can effectively and precisely recognize and categorize diverse forms of waste. How can implementing Convolutional Neural Networks for visual waste detection enhance the effectiveness of waste management across various environmental conditions? Research Question 1. Can models employing transfer learning techniques accurately identify and categorize various types of waste? Research Question 2.

LITERATURE REVIEW

Recent garbage collection methods using Convolutional Neural Networks (CNN) have been studied. The potential of CNN in waste identification was highlighted by (Wu et al., 2023) exploration of CNN's application in waste management. Learning models in waste classification are the subject of a comprehensive literature review by (Anjum et al., 2022), which delves deeply into the variety of methods employed in waste management. At the same time, (Wulansari et al., 2022) reviewed the literature on garbage classification using CNN, drawing attention to recent developments and trends in the field. In his discussion of intelligent waste classification using deep CNN, (Wu et al., 2023) traces the development of ever-more-complicated methods for trash management. Adding to the growing body

* Corresponding author



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of evidence regarding the efficacy of CNN in trash identification, (Meng & Chu, 2020) zeroed in on studies involving garbage classification using CNN. To demonstrate advancements in trash object recognition, (Rahman, 2020) highlighted a technique for trash detection in real-time video that achieved 74% accuracy. In addition, there are cases of illegal waste imports and rising waste imports that require attention, as discussed in (Shafira et al., 2022). (Alden & Sari, 2023) demonstrated the practical application of CNN in waste sorting by studying its implementation in this process. This work explores the feasibility of Federated Learning (FL) using Active Learning (AL) instead of manual annotation. It proposes an AL-based FL framework, showing it is equally valuable for federated and centralized learning and is dataset/application independent in natural disaster analysis and waste classification (Ahmed et al., 2020). These works illustrate the importance of CNN in trash management (from sorting to identification) and the challenges and opportunities for more efficient and environmentally friendly garbage collection and disposal. Research using data utilized to train CNN models may have restrictions on the quantity and type of trash examined. An incomplete or inaccurate depiction of various forms of waste in multiple settings may result from an absence of diverse data.

METHOD

The research methodology employed involves the utilization of a Convolutional Neural Network (Hindarto, 2023c) as the primary framework for visual waste detection. CNN, short for Convolutional Neural Network, is a well-established and highly efficient design for processing visual data. The utilization of CNN as the primary approach in this study entails a sequence of meticulously organized procedures to guarantee the precision and dependability of waste identification.

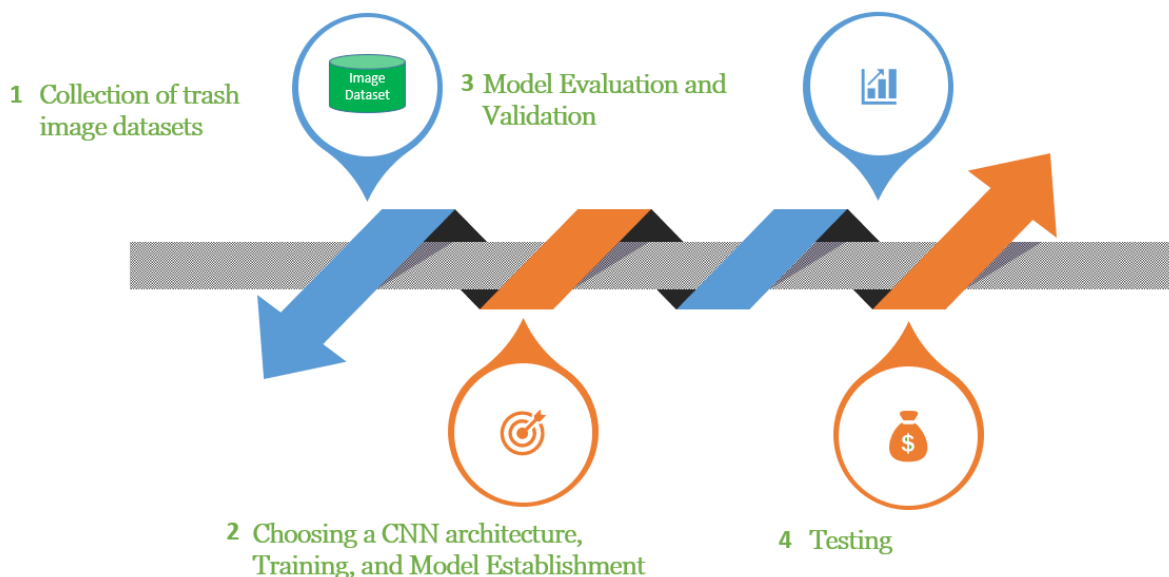


Figure 1. Research Method
Source: Researcher Property

1. Collection of trash image dataset: Waste or rubbish image data includes images of plastic, paper, metal, glass, general waste, and cardboard. Each image in this dataset shows different environmental conditions, views, and viewpoints. A CNN model for visual waste detection is trained on this data set. This dataset represents a wide range of waste categories by considering the diversity of everyday waste. The model learns the unique visual characteristics of each type of waste, improving its ability to identify and classify waste in different environmental conditions.
2. Choosing a CNN architecture (Li et al., 2023) is the first step in selecting a suitable model for visual waste detection. This entails choosing the suitable layer type, determining the number of layers, and configuring the network settings. An optimized CNN architecture serves as the foundation for constructing a model that can

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accurately identify visual patterns across different waste categories. Model Establishment and Training: After selecting the CNN architecture, the subsequent step involves establishing a model according to the specified architecture. A lot of different kinds of waste are used to train the model, enabling CNN to acquire knowledge about the visual attributes specific to each waste type. The model is trained using optimization techniques, which makes sure that the training process runs smoothly. Transfer learning techniques are a crucial component of this methodology. Pre-trained models from various datasets can be utilized to enhance the knowledge of waste detection models. Transfer learning is employed to improve the efficiency and precision of waste classification by leveraging knowledge acquired from pre-existing models.

3. Model Evaluation and Validation (Szegegy et al., 2016): After the model has been trained, the subsequent step involves assessing and validating its performance. The model underwent evaluation using previously unseen data to quantify its accuracy in classifying various categories of waste. Model validation guarantees that the model can effectively apply visual patterns to various environmental conditions with a strong level of dependability.
4. Testing image (Hendriyana & Yazid Hilman Maulana, 2020): Test images are used to evaluate the model's visual waste detection performance after training. The model is tested on its ability to identify different types of waste in new situations using representative images from this dataset. Each image in the test dataset has different environmental conditions, lighting, viewing angles, and waste appearance. This diverse test dataset verifies the CNN model's generalization abilities, ensuring that it can classify waste in various environmental contexts. Using this test dataset to evaluate the model's reliability before applying it in real-world scenarios ensures that it can handle significant waste appearance variations and still make accurate predictions.

The research methodology involves employing Convolutional Neural Networks (Gessert et al., 2020) as the primary framework, which is backed by a systematic approach to construct, train, and evaluate a visual waste detection model. The diagrams provided alongside each step in this process illustrate the actions taken to guarantee the achievement and soundness of this research.

RESULT

A laptop was used for the investigation that was equipped with 16 GB of RAM, used an Intel Core i7 processor, and was operating under the Windows 10 operating system. The experiment utilized the Python programming language. This laptop's specifications offer robust computing capabilities for conducting the training process of Convolutional Neural Networks models in visual waste detection. An optimal pairing of a robust processor and ample memory enables the efficient execution of intricate algorithms in machine learning for waste identification.

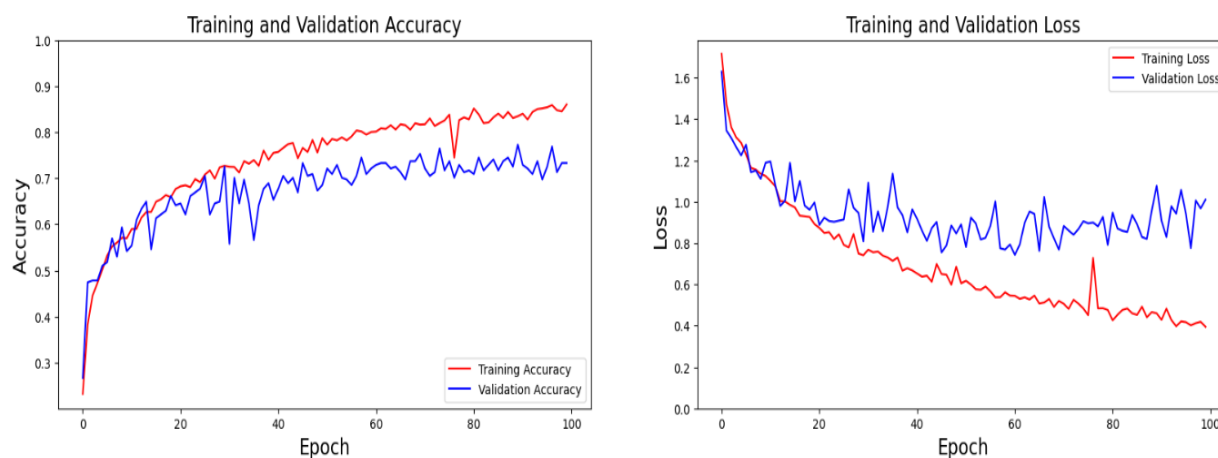


Figure 2. Result training with Convolutional Neural Network

Source: Researcher Property

Figure 2 illustrates the outcomes of training with a Convolutional Neural Network (CNN) in the field of visual waste detection. This graph offers a comprehensive representation of the model's performance throughout the training process. It illustrates the variations in evaluation metrics, such as accuracy, loss, and potentially the learning curve, over each iteration or epoch. The graph illustrates the progressive enhancement of the CNN model's capacity to

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identify and categorize different forms of waste within the waste detection framework as the training process advances. Generally, the accuracy of a model tends to improve as the epoch advances, while the loss or error rate tends to decrease. These graphs offer a comprehensive perspective on the progression of model performance during training, enabling a thorough assessment of the model's capability to detect visual waste and aiding in the determination of the point at which the model achieves optimal performance.

CNN is a highly efficient model for garbage detection due to its capacity to extract distinctive characteristics from images. The assessment of CNN models for garbage detection entails several crucial stages. Initially, it is necessary to partition the data into distinct sets for training, validation, and testing purposes. Following the training of the model using the training set, the evaluation process commences by utilizing the dataset used for model performance evaluation. Widely employed metrics encompass accuracy, precision, recall, and F1-score. Accuracy quantifies the degree of precision exhibited by the model in correctly classifying garbage. In contrast, precision and recall gauge the extent of positive accuracy and the model's capability to identify all instances of garbage in the dataset. The F1 score is a metric that integrates precision and recall offering a comprehensive assessment of model performance. Following the evaluation of the validation set, the model is then examined using a distinct test set to verify its ability to perform well on novel, previously unseen data. By meticulously evaluating and choosing suitable metrics, CNNs can be thoroughly assessed in garbage detection to guarantee optimal performance in accurately identifying and categorizing garbage in images.

Table 1. Convolutional Neural Network model evaluation

	precision	Recall	f1-score	support
cardboard	0,96	0,55	0,70	40
glass	0,71	0,82	0,76	50
metal	0,56	0,78	0,65	41
paper	0,90	0,95	0,93	59
plastic	0,59	0,46	0,52	48
trash	0,79	0,85	0,81	13
accuracy			0,73	251
macro avg	0,75	0,73	0,73	251
weighted avg	0,75	0,73	0,73	251

Table 1 displays the assessment outcomes of the Convolutional Neural Network model in identifying garbage using various widely used evaluation metrics. Assessments are conducted to categorize different forms of waste, including cardboard, glass, metal, paper, plastic, and other types of garbage. The precision results reflect the model's ability to classify each waste category accurately. As an illustration, when it comes to cardboard, the model demonstrates a precision of 0.96, denoting a notable degree of accuracy in categorizing cardboard. The recall metric, which measures the model's ability to identify all instances of a specific class correctly, is also provided. The recall for paper is the highest, with a value of 0.95, indicating that the model successfully identifies most of the paper waste in the dataset. The F1-score, which is a composite measure of precision and recall, offers a comprehensive assessment of the model's performance. An accuracy of 0.73 was used to judge how well the model worked, indicating the degree of success in classifying the entire dataset. A comprehensive evaluation of the model's waste classification performance includes average (macro average) and weighted average. This evaluation provides valuable insights into the CNN model's ability to identify different types of trash in the dataset by considering the varying values associated with each trash class.

* Corresponding author





Figure 3. Maximum Probability: 99,8%, Class Predicted: Plastic
Source: Researcher Property

A maximum probability of 99.8 percent is shown in Figure 3, which contains data pertaining to the model's prediction results. According to this forecast, picture objects belong in the Plastic category. This represents the maximum degree of certainty that the image object belongs to the plastic category according to the model. With a probability of 99.8 percent, the model is highly confident in its predictions, suggesting that the item in the picture is probably plastic trash. All signs point to the model's self-assurance when it comes to the plastic trash categorization in the captured photos. Such confident predictions may show that the CNN model has a good grasp on the key characteristics that set plastic trash apart from other types of trash. The model gives a solid and trustworthy indication in identifying and categorizing plastic trash in images with such a probability. An essential component of waste detection applications utilizing machine learning technology, this model demonstrates a high degree of accuracy in distinguishing plastic waste.

DISCUSSIONS

How can implementing Convolutional Neural Networks for visual waste detection enhance the effectiveness of waste management across various environmental conditions?

Utilizing Convolutional Neural Networks (CNNs) for visual waste detection has the potential to improve waste management effectiveness significantly in various environmental conditions. The application of CNNs in waste detection introduces a potent tool that improves the accuracy and effectiveness of waste classification and control, regardless of different ecological conditions. Convolutional Neural Networks (CNNs), which are specifically tailored for processing visual data, provide a reliable framework for accurately identifying and categorizing various types of waste. CNNs excel at identifying distinctive characteristics among multiple types of waste, such as plastics, metals, paper, glass, common waste, and cardboard, by utilizing their ability to perceive complex visual patterns. The ability to categorize waste comprehensively is crucial in waste management, as it simplifies the sorting process, reducing the likelihood of errors that could disrupt waste handling and disposal systems.

Furthermore, the versatility of CNNs in different environmental conditions is a crucial advantage. These neural networks can adjust to various lighting conditions, different textures, and even changing backgrounds, allowing for accurate waste detection in real-life situations. CNNs demonstrate a solid ability to identify waste in various environmental settings, including urban areas, industrial sites, and natural landscapes, making them highly versatile in different ecological contexts. By incorporating transfer learning, the efficacy of CNNs in waste detection is enhanced. CNNs utilize knowledge obtained from prior training models to improve their comprehension of waste characteristics, facilitating rapid adjustment and acquisition of knowledge when confronted with novel environmental circumstances. The network's ability to learn adaptively dramatically enhances its capacity to identify and classify waste in various environments precisely. CNNs play a crucial role in improving waste management strategies by enhancing the precision and effectiveness of waste categorization. They optimize the sorting procedure, minimizing

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inaccuracies, decreasing the likelihood of pollution, and ultimately resulting in enhanced waste disposal or recycling methods. This technological innovation in waste detection not only provides accuracy but also can reduce environmental risks and alleviate the ecological consequences of improper waste management. The utilization of Convolutional Neural Networks in visual waste detection provides a strong, flexible, and effective solution that surpasses changes in the environment, transforming waste management practices for a more sustainable future.

Can models employing transfer learning techniques accurately identify and categorize various types of waste? Transfer learning models have significant potential in accurately identifying and classifying different types of waste. By employing this technique, the model can leverage previously acquired knowledge from diverse datasets, enhancing the depiction of visual characteristics associated with each category of garbage. Consequently, the model can acquire knowledge from previous encounters and utilize it to improve the accuracy of waste identification. Transfer learning techniques enable models to leverage acquired knowledge from training on analogous tasks or datasets. Transfer learning allows a CNN model, which has been trained on a diverse dataset encompassing different waste categories, to adjust its learned feature representation to a particular waste recognition scenario. Hence, the model possesses the ability to identify visual patterns linked to specific categories of waste, even in instances where it has not been previously exposed to them during the primary training phase.

Transfer learning offers a significant benefit by accelerating the learning process and enhancing the precision of waste classification. Pretrained models trained on extensive and varied datasets can capture broad knowledge that is valuable for distinguishing various categories of waste. When the model is used with a more specific dataset, it can accurately and precisely identify and categorize waste. Nevertheless, it is crucial to acknowledge that the efficacy of transfer learning is contingent upon the resemblance between the source of learning and the specific task being executed. More remarkable similarity and relevance between the initial learning dataset and the waste identification dataset leads to a higher potential for transfer learning to enhance waste identification accuracy. Transfer learning techniques applied to CNN models have demonstrated substantial enhancements in the capacity to detect and categorize different forms of waste within the domain of visual waste detection. Through the utilization of pre-existing knowledge, the model is capable of accurately identifying and classifying waste, thereby significantly aiding in the enhancement of waste management efficiency across diverse environmental circumstances.

CONCLUSION

This study validates the significance of utilizing Convolutional Neural Networks for visual waste detection as a crucial measure to enhance waste management efficiency. This research demonstrates that by using CNN as the primary platform, models trained with diverse waste datasets can accurately identify and categorize waste. Transfer learning techniques have shown the ability to enhance the depiction of visual characteristics, enabling the model to identify common waste patterns in different environmental circumstances dynamically. The findings of this study make a substantial contribution to enhancing the precision of waste identification, reducing misclassification, and facilitating more effective waste management. The utilization of CNN and transfer learning methodologies in visual waste detection presents significant opportunities to enhance the sustainability of waste management across diverse environmental settings. Hence, this research demonstrates the crucial role of this technology in enhancing efficient and precise waste management procedures.

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* Corresponding author



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