# APPLICATION OF UNSUPERVISED LEARNING AND IMAGE PROCESSING INTO CLASSIFICATION OF DESIGNS TO BE FABRICATED WITH ADDITIVE OR TRADITIONAL MANUFACTURING

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## ABSTRACT

Manufacturing process (MP) selection systems require a large amount of labelled data, typically not provided as design outputs. This issue is made more severe with the continuous development of Additive Manufacturing systems, which can be increasingly used to substitute traditional manufacturing technologies. The objective of this paper is to investigate the application of image processing for classifying MPs in an unsupervised approach. To this scope, k-means and hierarchical clustering algorithms are applied to an unlabelled image dataset. The input dataset is constructed from freely accessible web databases and consists of twenty randomly selected CAD models and corresponding images of machine elements: 35% additively manufactured parts and 65% manufactured with traditional manufacturing technologies. The input images are pre-processed to have the same colour and size. The k-means and hierarchical clustering algorithms reported 65% and 60% accuracy, respectively. The algorithms show comparable performance, however, the k-means algorithm failed to predict the correct subdivisions. The research shows promising potential for MP classification and image processing applications.

**Keywords**: Computer Aided Design (CAD), Machine learning, Additive Manufacturing, Image Processing, Unsupervised Learning

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# 1 INTRODUCTION

Advancements in the manufacturing industry and product development create competition among designers that lead to producing increasingly complex and advanced products (Hoefer and Frank, 2018). In this context, one of the most critical tasks is manufacturing process selection. Selecting the most appropriate manufacturing process in the early stages of design can be advantageous since it can reduce production costs (Hernández-Castellano et al., 2019).

Manufacturing process selection was traditionally carried out in two ways: using experts that were available inside the company or relying upon other companies' expertise. Because of the mentioned growth of product complexity, the exploitation of internal and external knowledge is expensive and the manufacturing process selection turns to be increasingly time-consuming and resource-inefficient. In particular, due to industrial progress, selecting the most suitable manufacturing process has become challenging for designers since process selection involves a careful investigation of a wide range of aspects such as material type, cost, part quality, application area, and production performance (Ördek et al., 2022; Zhang et al., 2014).

Machine learning (ML) applications have been introduced in the manufacturing industry with this main purpose (Hoefer and Frank, 2018). Overall, ML applications have been used to support manufacturing and design operations in various applications: material selection (Pilania et al., 2013), product design for additive manufacturing (AM) (Liu et al., 2020), production monitoring (Zhang et al., 2022), and process selection (Dohale et al., 2021). These applications usually include supervised and unsupervised learning algorithms that use labeled and unlabeled data, respectively (Paturi and Cheruku, 2021).

Applications of unsupervised ML started to become more popular since these applications do not require labeled data for finding patterns or clusters within the input data (Ashenden et al., 2021; McCue, 2015). K-means clustering, hierarchical clustering, and principal component analysis (PCA) are some of the unsupervised learning methods that can be used to cluster sustainability indicators in the manufacturing of a product (Mukherjee, 2017), defects (Grasso et al., 2017), and material properties (Wang et al., 2022).

Recent industrial developments, such as cyber-physical systems, sensor networks, and the internet of things, generated an enormous amount of unlabelled data in the context of increased digitalization of product design and management practices. The analysis and labelling of such a large amount of data require advanced systems and Artificial Intelligence (AI). The data uncertainty increases in parallel with the amount, speed, and variety of data (Hariri et al., 2019). Thus, as mentioned before, the introduction of AI into data processing is necessary in order to label the data faster and cheaper. In addition, the majority of ML applications in manufacturing contain supervised learning that works with large labelled datasets (Dogan and Birant, 2021). Despite the success of supervised learning applications, heavy reliance on labelled data generates some problems: the high cost of gathering and manually labelling data and the overfitting problem for purely supervised algorithms (Liu et al., 2022).

In design, images are widely used to improve products, hence they are largely available kinds of (oftentimes, unlabelled) data. Based on the visual basis of human perception of the world, an image is a way of observing, interpreting, and transmitting knowledge, while image processing is the transformation of two-dimensional data into information (Zhang et al., 2022). Image processing includes image enhancement, image restoration, image compression, face detection, character recognition, signature verification, and biometrics applications (Kuruvilla et al., 2016). Image processing is used in various applications such as the medical field (Bhattacharya et al., 2021), the construction field (Choi et al., 2017), the manufacturing industry (García-Moreno et al., 2020), and the food industry (Pouladzadeh et al., 2014). In the last decade, image processing started to be used in design and manufacturing industries for distinguishing materials (Maree et al., 2009), monitoring tool conditions (Martínez-Arellano et al., 2019), defect detection (Grasso et al., 2017), spot weld design (Gerlach and Eggink, 2021), and design for AM (Jiang et al., 2022).

Given the mentioned abundance of images of designed parts and the limitations concerning manufacturing process selection, the main objective of this research is to explore the capabilities of unsupervised learning and image processing to distinguish the major families of manufacturing processes. K-means and hierarchical clustering algorithms were applied to this scope. The ideal outcome of such application is the distinction of images into two or three different clusters:



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1. products prone to be manufactured with AM,
2. products prone to be manufactured with traditional technologies,
3. as a potential additional option, products suitable for both AM and traditional manufacturing technologies, and/or a combination of the two options.

The rest of the paper is organized as follows. Section 2 presents the background and literature regarding ML and image processing. Section 3 describes the methodology that was followed to achieve the objective of this research. In Section 4, the clustering results are presented and discussed. Finally, in Section 5, conclusions are drawn and future work is presented.

## 2 BACKGROUND

The literature has evidenced significant interest in investigating the criteria and methodologies of manufacturing process selection for traditional and AM technologies. For example, multi-criteria decision-making (MCDM) methodologies were proposed in several articles for manufacturing process selection (Kek et al., 2016; Schneberger et al., 2019; Wang et al., 2018; Zaman et al., 2018). Another methodology used preliminary design properties, design requirements, and cost calculations to select the AM technology in (Tavcar and Nordin, 2021). The scholars proposed a multi-criteria AM function that analysed the effect of processing of AM technologies and design requirements on product cost (Tavcar and Nordin, 2021). In another research (Algunaid and Liu, 2022), scholars proposed an approach for optimising the selection of the most suitable AM process among large-scale options. The AM selection procedure followed four steps: AM technology suitability, initial screening, ranking AM service options, and selection from top-ranked options (Algunaid and Liu, 2022). Salobir et al., (2019) proposed a software application named 3D-advise that was used to provide information on the most appropriate 3D printing technology by reducing the cost and design time of a product. The software used seven parameters as inputs from the user in order to propose the most appropriate AM technology (Salobir et al., 2019). An MCDM-based approach was proposed for AM process selection (Qin et al., 2020). The methodology was based on fuzzy Archimedean weighted power Bonferroni mean operator. In this research, process performance and user preference were assessed to rank the AM processes (Qin et al., 2020).
In addition to the aforementioned methodologies, ML-based decision-making was also used in the literature for manufacturing process selection. For example, manufacturing process selection was achieved by using heat kernel signature (HKS) and convolutional neural networks (CNN) for specified processes: laser-cut, three-axis machining, injection-moulding, and turning (Wang and Rosen, 2022). In the research, the scholars applied the HKS methodology to 3D CAD models and used HKS data for training the CNN (Wang and Rosen, 2022). Hoefer and Frank (2018) generated an ML approach used to decide between two manufacturing options: machining or cast-then-machining. A three-metric group was used as input for the decision trees and random forest algorithms. This research focused on selecting the manufacturing process for a product's conceptual design (Hoefer and Frank, 2018). In another research, scholars (Venkataraman et al., 2015) suggested an artificial neural network to classify the inputs into six manufacturing technologies: planing, rolling, shaving, shaping, hobbing, and milling. These technologies were ranked based on several manufacturing criteria. Finally, the highest-ranked manufacturing process was selected (Venkataraman et al., 2015).

CAD model classification was also foreseen in several methodologies. For example, hierarchical clustering and support vector machine algorithms were used to propose a hybrid (unsupervised and supervised learning) ML approach to recommend design features for AM technologies (Qin et al., 2014). CAD model classification was also applied to identify a thin part or discover the thin section of a part (Pernot et al., 2015). Clustering algorithm was applied into a CAD model dataset by (Jayanti et al., 2009) to classify different shapes. Hierarchical clustering and support vector machines algorithms were used in a hybrid (combination of supervised and unsupervised learning) manner to identify the final cluster containing recommended AM design features. (Yao et al., 2017).

## 3 METHODOLOGY

In this section, the methodology behind image processing and unsupervised learning is explained and the necessary equations are displayed. The workflow of the current research follows three steps illustrated in Figure 1: image pre-processing, feature extraction, and clustering.



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In order to extract information from an image, pre-processing is needed since feature extraction requires the images to have the same colour and size (Bhattacharyya, 2011). Thus, the subsequent actions are followed regarding pre-processing:

1. All images were converted into grayscale.
2. Grayscale images were then resized in order to equate the number of features in each image.

Pre-processed images are then introduced to a feature extraction methodology called Histogram of Oriented Gradients (HOG). The HOG methodology was initially used for pedestrian detection (Zhou et al., 2020). Its working principle includes counting the number of occurrences of gradient orientation in an image (Zhou et al., 2020). HOG is good for detecting features related to the orientation and direction of the edges of an image. In short, it is a basic version of the original image that contains only the most important information (Manikonda and Gaonkar, 2020). Hence, due to having good performance for extracting and detecting the orientation of long edges and circular patterns, it can also be implemented into machine elements. Figure 2 shows the results of the HOG feature extraction algorithm.

The last step of the workflow for this research includes clustering, which is an unsupervised learning methodology. In this research, k-means and hierarchical clustering algorithms are used as preliminary tentative options to distinguish the major families of manufacturing processes.

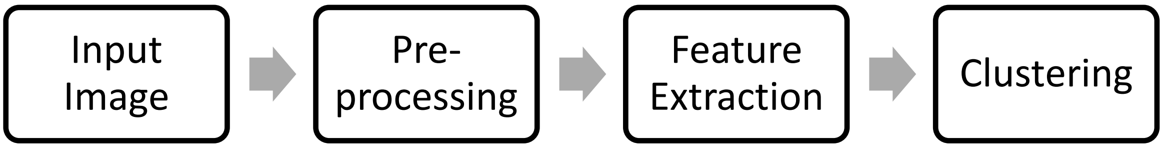


*Figure 1. The workflow for image processing and clustering*

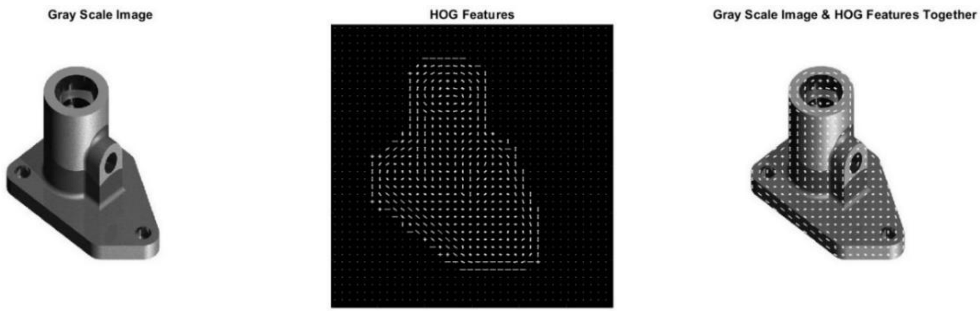


*Figure 2. Demonstration of the HOG feature extraction*

The k-means clustering algorithm utilizes partitional clusters to organize the data into k mutually selected clusters. The main aim of this algorithm is to minimize the variance in every cluster (Garza-Ulloa, 2018). The first and second principal components (PC) of each data point are calculated and clustered based on these PCs. Moreover, hierarchical clustering is an unsupervised methodology that seeks to classify the data into a hierarchy of clusters. The main objective of this method is to investigate the grouping of the data across a variety of scales simultaneously. The output of this algorithm is usually presented via a dendrogram (Garza-Ulloa, 2018). Hierarchical clustering is conducted in three steps:

- Determining the distances between each point within the data. There are various methods to calculate the distances and these methods affect the shape of the generated clusters.
  - The first method is called Euclidean Distance, based on the straight-line distance between two points. It is calculated with Equation 1 (Garza-Ulloa, 2018).

$$||a - b||_2 = \sqrt{\sum_i^n (a_i - b_i)^2} \quad (1)$$

where a and b are two subsequent points within the data.

  - Another method is called Manhattan distance, which is the distance between two points in the sum of the absolute differences of the Cartesian coordinates. It is shown in Equation 2 (Garza-Ulloa, 2018).

$$\mathrm{a} - \mathrm{b} = \sum_i^n |a_i - b_i| \quad (2)$$


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- Maximum distance can be calculated by using Equation 3 (Garza-Ulloa, 2018).

$$a - b_{\infty} = \max_{i} |a_i - b_i| \tag{3}$$

- Mahalanobis distance is the distance between a point and a distribution. It can be calculated with Equation 4 (Garza-Ulloa, 2018).

$$M = \sqrt{(a - b)' \cdot S^{-1} \cdot (a - b)} \tag{4}$$

where M is the Mahalanobis distance, S is the covariance matrix, and a, and b are two subsequent points within the data.

- The second step is called linkage, which consists in grouping the data points into a binary hierarchical tree. The most common method to be applied here is to calculate the distances between sets of data as a function of the pairwise distances among the data points (See Equation 5) (Garza-Ulloa, 2018).

$$\min \{(a, b): a \in A, b \in B\} \tag{5}$$

- The last step is dividing the hierarchical tree into clusters. Then, the hierarchical tree is cut to analyse the clusters (Garza-Ulloa, 2018).

The input dataset used in this research is a sample of convenience built with the constraints that follow. It was supposed to comprise twenty machine elements' and parts' CAD models and corresponding pictures (already available) taken from online freely accessible databases. The CAD models were selected with the sole requirement that 35% of them were from a sub-dataset of parts to be preferably fabricated by means of AM technologies (images named with capital letters N to T in the English alphabet). The images had to have sufficient quality (already available images from online freely accessible databases) and show the part accurately through an axonometric view. The authors evaluated that the rest were best produced through traditional manufacturing technologies (images A to M). The images were all in the fashion of axonometric projections or views capable of showing different dimensions of the parts. The dataset is used to develop the ML algorithms. All calculations and algorithms were generated by using the 2022b version of MATLAB software and ran on Intel core i5 10210U, 2.11 GHz CPU.

## 4 RESULTS AND DISCUSSIONS

In this section, the results of the unsupervised learning algorithms are presented and discussed.
The performance of the k-means algorithm is evaluated based on the Silhouette evaluation criterion, which is used to determine the optimal number of clusters. The result of the Silhouette evaluation is presented in Figure 3 and the result shows that the optimal number of clusters for the input dataset is two, in line with the paper's objectives. An ideal outcome would be then to distinguish AM-ed and traditionally manufactured parts.

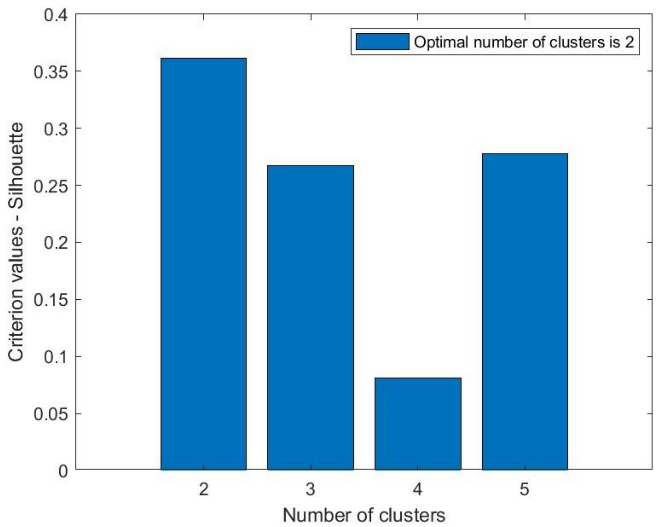


*Figure 3. Silhouette evaluation chart*



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The Silhouette score of the k-means clustering algorithm with two clusters is approximately 0.35, which suggests that the data points are slightly in the correct cluster (Shahapure and Nicholas, 2020). This score represents the correctness of the cluster distribution shown in Figure 4. There are ten data points in each cluster, while the ideal results should be two clusters with thirteen and seven points, respectively. The performance of the categorisation, i.e. the fraction of correctly clustered points according to the expected subdivision of AM-ed and other parts, is 65% and this is represented in Figure 4; the correct classifications are shown with green colour whereas the incorrect ones are shown with red colour (See Figure 4).

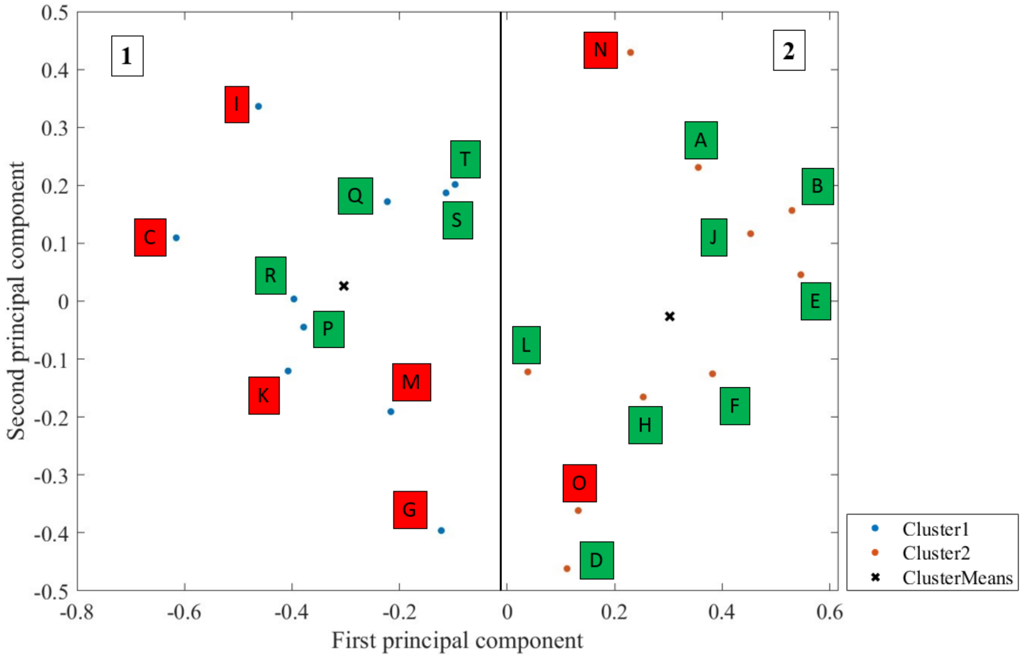


*Figure 4. Results of the k-means clustering algorithm*

Figure 5 shows instead the results of the hierarchical clustering algorithm as a dendrogram, where the dataset is divided into two clusters of the expected quantity of data points. Actually, cluster 1 in Figure 5 is mostly representative of products more prone to be produced by AM technologies are found in; the ones to be produced by traditional manufacturing technologies better comply with cluster 2 in Figure 5. It emerges that the subdivision does not mirror the ideal results, because the expected quantity of points in the two clusters is swapped. Inconsistencies can be noticed also thanks to the letters indicating the parts for each cluster, which are also reported in Figure 5, where black letters show discrepancies with expectations. Figure 6 shows illustrative examples of compliant and incompliant parts for both clusters and both algorithms. In the current state, the performance of the proposed methodology is 60% which is acceptable if compared to other image clustering methodologies found in the literature that used different input datasets (Ji et al., 2018; Yu and Shi, 2003; Zelnik-manor and Perona, 2004).

According to the results presented in Figures 4 and 5, both clustering algorithms categorised the input dataset into two clusters; however, these clusters are not identical. Based on the performance comparison between the two algorithms, the k-means clustering methodology performed better than the hierarchical clustering algorithm. Hence, the two algorithms show similar performance and applicable into image clustering; however, k-means algorithm separated the two clusters wrongly.

The fact that two major clusters emerged in all cases has both positive and negative aspects. On the one hand, the authors' expectations was the subdivision of pictures into "families" of AM and traditionally manufactured parts. On the other hand, the recognition of two clusters can be indicative that the model had learned simple trends and not the underlying causes, as geometry is very complex and it could not be captured properly. In this regard, retesting the algorithm with a wider set of examples is a priority follow-up study.



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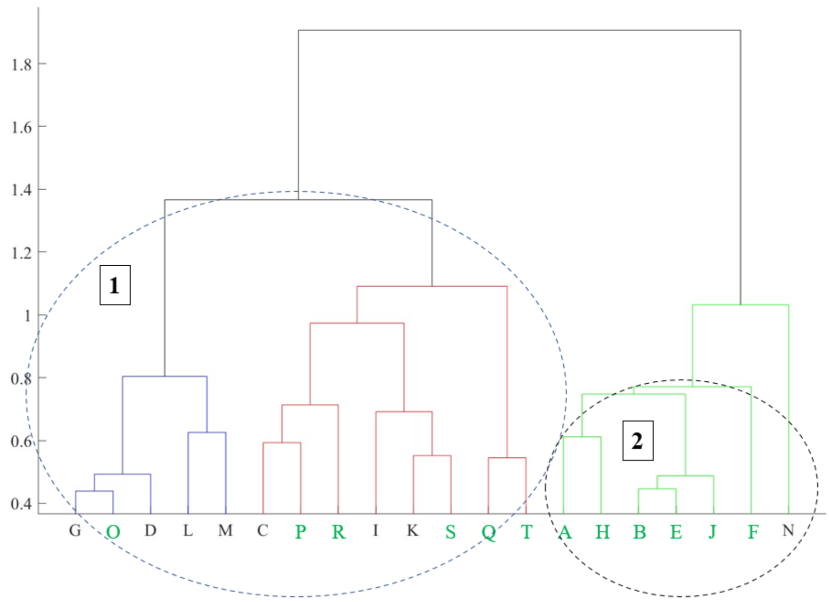


*Figure 5. Results of hierarchical clustering represented as a dendrogram*


*Figure 6. Input images that are clustered correctly and incorrectly with two algorithms*

## 5 CONCLUSIONS AND FUTURE WORK

This preliminary research tested the potential use of unsupervised learning and image processing for classifying the major families of manufacturing processes. This line of research is particularly relevant for companies handling a large number of designs willing to reconsider used manufacturing processes, especially for refurbishing of spare parts or small batches, where AM is an increasingly reliable alternative.

In the present study, the input dataset comprised twenty 3D CAD models along with their distinguishing images, which were actually used to feed unsupervised learning algorithms. Image pre-processing is applied to the dataset in order to extract features easily. Then, the HOG feature extraction methodology is used to complete the image processing operations. After pre-processing and feature extraction, the k-means and hierarchical clustering algorithms are applied in order to classify the input dataset. Inputs are separated into two clusters, which partially distinguish products more prone to be produced with AM and with traditional manufacturing technologies. Finally, each algorithm was evaluated according to a specific method. The k-means clustering algorithm is



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evaluated with the Silhouette criterion, having a score of 0.35, which is considered a fairly successful clustering operation. The hierarchical clustering algorithm divided the input dataset into two clusters with 60% accuracy whereas k-means clustering algorithm has a 65% accuracy. Hence, both algorithms show similar performance and applicable into 3D CAD and image clustering, however, k-means algorithm wrongly divided the two clusters. The current results show similarities with the research conducted in image clustering applications. Nevertheless, the system's accuracy should be improved since it is a relatively low for industrial applications, which highlights the limitations of the proposed methodology. Based on the results, the following research activities are planned to fine-tune the unsupervised learning algorithm and achieve more impacting results:

- Using a larger dataset.
- Introducing other feature extraction methodologies, e.g., Local binary pattern features or speeded-up robust features.
- Testing other clustering methodologies, (e.g., self-organizing maps, or gaussian mixture model).
- Increasing the quality of the input images and making them more homogeneous, as different hues could have affected the accuracy.

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