



# Automatic Orange Fruit Classification Using Convolutional Neural Network

Ghassan Faisal Albaaji<sup>1</sup>, Vinod Chandra S. S<sup>2</sup>

## Abstract

One of the critical challenges across several industry sectors is fruit grading and classification. One of the most popular fruits in food products is the orange fruit because there are many value-added products produced from it. Due to the shared traits of the varieties with various tastes and uses, even in major markets, It would be challenging at times to instantly label numerous classifications of this fruit when there is a need for success. Three varieties of orange fruit that are currently popular in the Iraqi marketplace were studied in this research. We propose a fast and cost-effective way to automate the classification of this fruit, we suggest an effective classification framework system based on the most recent deep learning algorithms and clustering approaches. To determine the most effective model for classifying this fruit, we trained, evaluated, and contrasted the results within many deep-learning models. The accuracy was assessed to be 99.1%, indicating the reliability of the suggested method.

**Keywords:** Neural network, Deep learning, Orange classification, Efficient Net

التصنيف التلقائي لفاكهة البرتقال باستخدام الشبكات العصبية التلافيفية  
غسان فيصل البعاجي<sup>1</sup> ، فينود تشاندرا<sup>2</sup>

## المستخلص

تعتبر تصنيف الفاكهة هي احد التحديات الحاسمة التي تواجه قطاعات صناعة الاغذية. ان احد اشهر الفواكه التي تستخدم ضمن الصناعات الغذائية هي فاكهة البرتقال حيث ينتج من خلاله العديد من المنتجات ذات القيمة العالية نظرا للسمات المشتركة لاصناف هذه الفاكهة ذات المذاقات والاستخدامات المختلفة سيكون من الصعب احيانا تسمية وتحديد هذه التصنيفات حتى في الاسواق الرئيسية لضمان النجاح الانتاجي لهذه الصناعات. في هذا البحث تم تناول ثلاث اصناف من فاكهة البرتقال الاكثر استهلاكاً واستخداماً في السوق العراقي. نقدم في هذا البحث طريقة سريعة وفعالة من حيث التكلفة لأتمتة تصنيف هذه الفاكهة، ونقترح نظام إطار تصنيف فعال يعتمد على أحدث خوارزميات التعلم العميق ونهج التجميع. لتحديد النموذج الأكثر فعالية لتصنيف هذه الفاكهة، قمنا بتدريب وتقييم ومقارنة النتائج في العديد من نماذج التعلم العميق. تم تقييم الدقة بنسبة 99.1%، مما يشير إلى موثوقية الطريقة المقترحة.

الكلمات المفتاحية: الشبكات العصبية، التعلم العميق، تصنيف فاكهة البرتقال، EfficientNet

## Affiliation of Authors

<sup>1</sup> Machine Intelligence Research Lab, Department of Computer Science, University of Kerala, India, Thiruvananthapuram, 695581

<sup>2</sup> Directorate of Agriculture in Wasit Governorate, Iraq, Wasit, 52001

<sup>1</sup> [ghassan.albaaji88@gmail.com](mailto:ghassan.albaaji88@gmail.com)

<sup>2</sup> [vinod@keralauniversity.ac.in](mailto:vinod@keralauniversity.ac.in)

## <sup>1</sup> Corresponding Author

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## انتساب الباحثين

<sup>1</sup> مختبر أبحاث الذكاء الآلي، قسم علوم الحاسوب، جامعة كيرالا، الهند، ثيروفانانثابورام، 695581

<sup>2</sup> مديرية الزراعة في محافظة واسط، العراق، واسط، 52001

<sup>1</sup> [ghassan.albaaji88@gmail.com](mailto:ghassan.albaaji88@gmail.com)

<sup>2</sup> [vinod@keralauniversity.ac.in](mailto:vinod@keralauniversity.ac.in)

## <sup>1</sup> المؤلف المراسل

## معلومات البحث

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## Introduction

Many different types of communities all over the world have agricultural sectors that are extremely important to their economies [1]. One of the most important aspects of the agricultural industry is the cultivation and distribution of fresh fruits to various stores and marketplaces. It is an essential component not only for the study of it in academic settings, but also for its application in the industry as a whole. A structure like this one can serve as the foundation for a wide variety of important endeavors. The ability to act as a method for cashiers working in supermarkets is one of its primary functions. In order to arrive at an accurate price for the fruit a customer has purchased, the staff at the store needs to be able to identify both the species and the variety of the fruit. It is necessary to make use of a query table to store the price list. These classification-based apps might be able to automatically determine the purchase species of the customer and link it to the appropriate pricing. These problems with reading barcodes on packaged goods have been successfully solved by using barcode reading systems. Unfortunately, this method is not applicable to the purchase of fruit and vegetables because a customer must select each item separately when making their purchase at a store [2]. Several methodologies are being utilized currently in the process of fruit classification by using computer and machine vision techniques. Automatic identification is useful due to the variety of sizes and shapes that fruits can take, in addition to the fact that fruits are sensitive. In industrialized countries, worker-based systems for the administration and monitoring of agricultural commodities have been increasingly supplanted over the past few years by digital procedures such

as computer and machine vision. These digital procedures have the potential to improve efficiency and accuracy. The invention of classification tasks through the computer and machine vision systems has high resilience and repeatability at cheap prices [3], as well as high accuracy and speed capabilities to evaluate fruits and vegetables in adverse weather as well as in normal environmental circumstances [4]. The invention of classification tasks through the computer and machine vision systems has high accuracy and speed capabilities to evaluate fruits and vegetables in adverse weather as well as in normal environmental circumstances. In recent years, there has been an explosion in the use of machine learning techniques, which has opened the door to a wide variety of applications in a variety of fields. Machine learning algorithms attempt to learn on their own by modeling human learning processes in order to acquire information about the real world [5]. In this manner, machine learning systems are able to generalize from particular instances without the need for explicit coding. Because of this property, machine learning algorithms can be utilized in a wide variety of contexts [6]. The process of classifying fruits uses imaging characteristics such as texture, coloration, and form as inputs for computer vision and image processing techniques [7]. One of the most popular fruits, bananas come in a wide variety of flavors and look very similar to one another, making them a good candidate for automated classification. This is especially true when one takes into account the fact that different varieties have very distinct flavor profiles. The availability of a wide variety of orange flavors is the primary component in determining a customer's desire for selection. In this study, we propose a practical study to identify

three varieties of orange fruit by using EfficientNet as the basis for the classification and for capturing the key features of the image.

In this context, our research contributes:

1. Proposed classifying orange fruits that make use of futuristic deep learning techniques.
2. Examine and compare the suggested EfficientNet algorithm with the prior study.
3. Visual analysis of EfficientNet's crop classification tasks.

### Related Works

30–35% of the harvested fruit is wasted because there isn't enough skilled labor [8]. Again, fruit identification, identification, and grading are not made effective due to human perception subjectivity. The construction of an automated system to distinguish fruits based on their type, variety, maturity, and integrity has a significant amount of potential while using techniques for machine learning with adequate principles of image processing. In [9], the identification and ranking of a number of different fruits are proposed as an entirely automated process in this work. The fruiting area is extracted by using the split-and-merge method, and fuzzy segmentation is utilized in order to break it up into individual segments. The authors indicated in [10] the fruit-processing industry, computer vision has a wide range of applications that make it possible to automate various processes. It is essential to categorize and evaluate the quality of the fruit in order for the industrial product to deliver the highest quality finished food products and the highest quality raw fruits to be marketable in the marketplace. This can only be accomplished if the

quality of the fruit is appropriately categorized. The authors of this study [11] proposed a low-cost machine vision system that is based on deep learning for the purpose of classifying fruits according to their outward appearance or their level of freshness. Two different fruit data sets have been used for the purpose of training a wide variety of cutting-edge deep learning models and stacking ensemble deep learning models. The results of this research show that, in comparison to other deep learning models, EfficientNet CNN models and their stacked combinations have the highest accuracy in terms of scoring the actual samples and the test set. The classification and object detection problems have seen method to motivate due the machine learning and deep learning techniques. The core criterion for developing precise and trustworthy machine learning models for the real-time context is a tidy and neat data set [12]. The authors then proceed in [13] to demonstrate the concept of an intelligent artificial intelligence-based system that automatically sorts fruit according to grade by using spectrophotometry and computer vision. Utilizing a cloud computing platform to which access is provided by Microsoft Azure which allows for the accurate identification of fruit that is also fed into the suggested system. In addition, the quality of the fruit can be estimated through the use of spectroscopy and various forms of machine learning. [14] have been suggested as a technique for identifying diseases that can be found in apple fruit and for encouraging the prompt eradication of those diseases as a result of environmental factors. Deep learning, which has been shown to be effective in image processing and classification, is used to categorize pictures of apples. This is a relatively recent development. Deep neural

networks with varying numbers of neurons and convolution layers are evaluated and ranked by these experts. The authors [15] proposed to establish a structure with the objective of automatically classifying dates fruit without the need for time-consuming and difficult physical measurements. The stacking method that was developed by combining these two methods worked significantly more effectively. In the field of classification research, high-performance classification results have been achieved not only by utilizing traditional machine learning techniques, but also by utilizing cutting-edge stacking techniques, which are produced by merging two or more of these techniques. Stacking techniques have been shown to produce better results than traditional machine learning techniques.

## Materials and Methods

In the light of the fact that the data set for these cultivars was not easily obtainable, the images that were used for the data set were aggregated from a diversity of ways throughout the internet, incl Kaggle and other online platforms. An Agronomist specializing in horticulture proved each kind's variants (Samples from each type are represented in Figure 1). The aim of this study should be to provide proof to back up the assertion that oranges could well be classified by using convolution neural networks. Images of three classes of oranges most widely consumed in Iraqi marketplaces had been obtained from the Internet; they are bitter oranges (sour), navel oranges (Egyptian), and Valencia oranges (South Africa), and they are slightly similar in shape, but differ in taste and use (as their features are depicted in Table1).

**Table (1): Features of Orange Fruit**

Type	Features
<b>Bitter Orange</b>	<ul style="list-style-type: none"> <li>• Oval Shape.</li> <li>• Visibly rough dimpled.</li> <li>• Mostly one end is visible to the top and the other is concave.</li> <li>• The color sometimes tends to be greenish orange.</li> <li>• For use in food.</li> </ul>
<b>Navel Orange</b>	<ul style="list-style-type: none"> <li>• Round Shape.</li> <li>• Dimpled Skin.</li> <li>• Bright orange skin.</li> <li>• Its unique trait is that it has a navel that resembles a human navel.</li> <li>• For direct consumption</li> </ul>
<b>Valencia Orange</b>	<ul style="list-style-type: none"> <li>• Round to oval shape.</li> <li>• Thin rind skin.</li> <li>• Golden color.</li> <li>• For juice and industry</li> </ul>

**Reference: By The Authors**



Figure (1): Samples of Orange Fruit

The proposed work model will include image processing and data cleaning, as well as removing noise and inaccurate data. We deduced that adjusting the images to an appropriate dimension of 160 x 160 and a triple Color information scheme is the most efficient way to ensure training speed and model accuracy. The methodology for conducting the study that has been suggested (shown in Fig 2) comprises extraction data by using image sets to create feature vectors that are

grouped by each class and the area of each vector. Subsequently, to determine the peaks of the peel plus coloration, information on the morphological features in various parts of each of the three distinct varieties of orange fruit is acquired. While contrasted with other models in the use of convolutional neural networks, we asserted that the adoption of EfficientNet produced more factual and inspiring results than the other models [16].

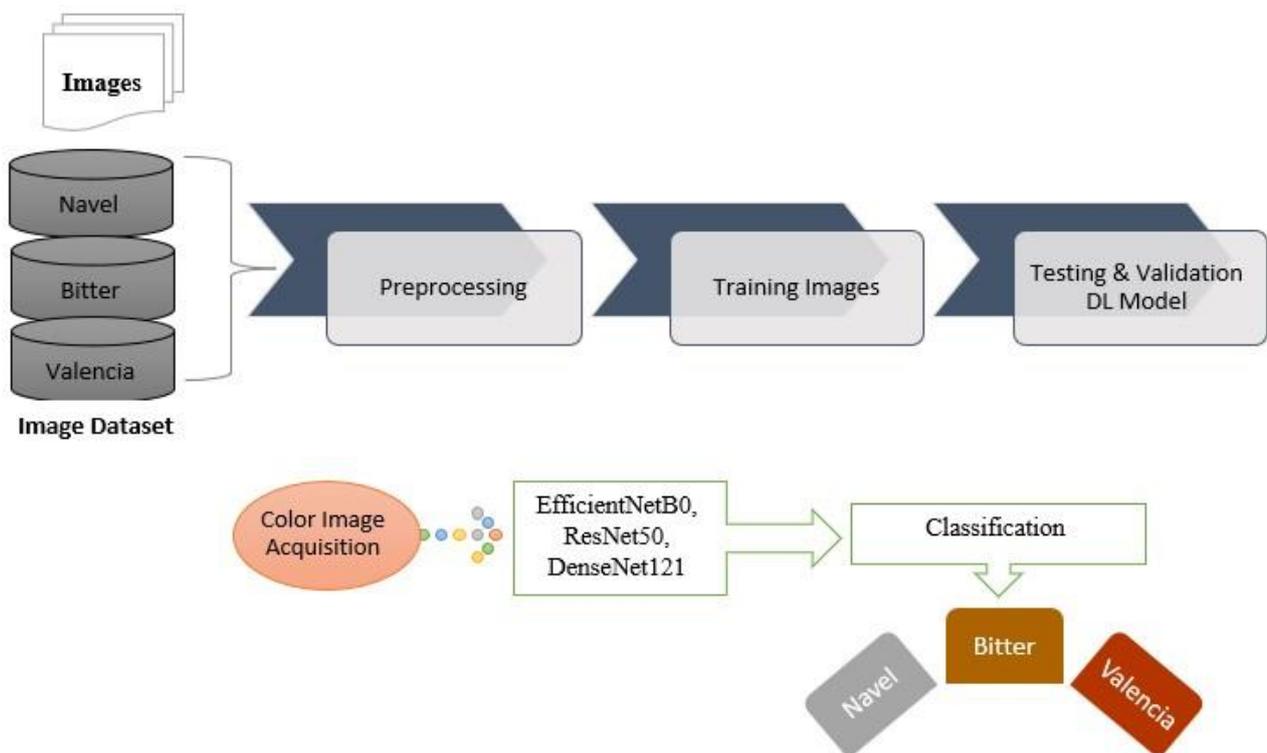


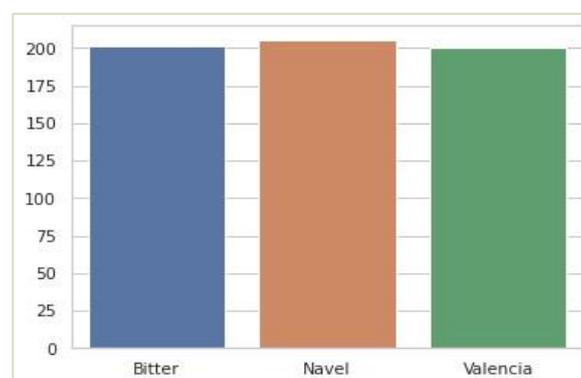
Figure (2): The Pipeline of The Proposed Method

For neural networks, it is necessary to acquire sufficient training data. However, such a criterion is difficult to meet in reality since labeled data can only be gathered via a time-consuming and error-prone manual method. To this purpose, transfer learning has been developed as a method for effectively transferring information from a mature source domain to a beginner target domain. Transfer learning enables the re-use of existing parameters, i.e., convolution weights, from a model learned on large datasets to train new models with a relatively smaller number of labeled pictures. In this study, we classified the dataset by using weights pre-trained on the ImageNet dataset, which comprised several fruit images and proved to be quite effective [17]. The low weight of EfficientNet-B0, in combination with its factor of 5.3m, represents one of its key traits. This model can be described as possessing a lower degree of complexity, and it has the further effect of giving for augmentation of the CNN network's depth by capturing higher unique features. It requires adequate quantities of memory and computational power [18].

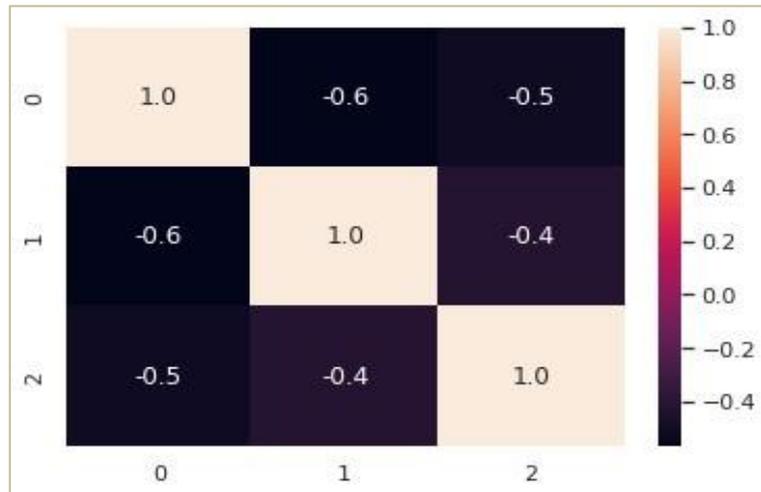
## Results and Discussion

We start our results analysis based on the fact that we identified. On the data set, evaluations

were performed on three different model parameters (EfficientNetB0, DenseNet121, and ResNet50). 635 images (as shown in Fig 3) were collected from the dataset so they could be tested (Figure 2 reveals the variation in the number of shots between the three types). Image augmentation was adapted because our key aim is to increase the size of the training zone. In order to conduct an evaluation of the results, the models were trained in Google Colab for a total of 15 epochs each. In the climax, the research led to the conclusion that the proportion of accuracy was obtained for each of the three models that were used, bearing in mind the time that was spent in training. (The details of each model are shown in Table 2). During whole midst of training by using the three models that we had mentioned previously, we highlighted the fact that EfficientNetB0 has the highest test accuracy among the other models, which is 99.1% with 27 minutes for a training session (Figure 4 indicates to confusion matrix) (Figure 5 and Figure 6 explain the ACC and Loss plots for each learning epoch), while the ResNet50 model gives a test accuracy of 97.2% with 84 minutes time for practice, and DenseNet121



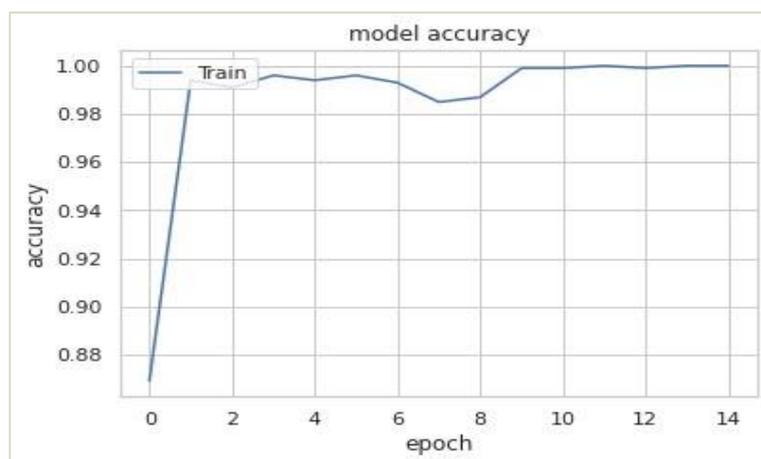
**FIGURE (3): The Number of Shots for Each Type Of Orange.**



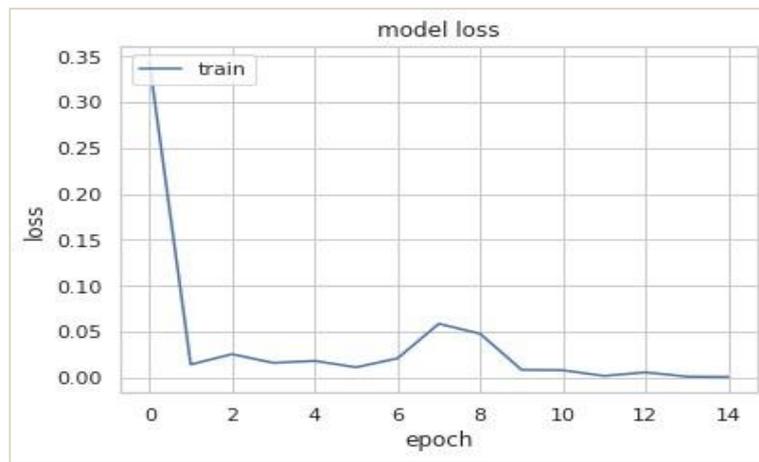
**Figure (4): Confusion Matrix of Efficientnet-B0 Model.**

was unable to achieve good results; It resulted in a 71.1% accuracy rate and required 57 minutes of total training time. conversely, It is attainable to point out that the achievements of the experiments carried out on the first and second models, to some extent, be comparable with one another in regard to the accuracy of the test. ResNet50, on the other hand, takes a longer time to be trained, which it

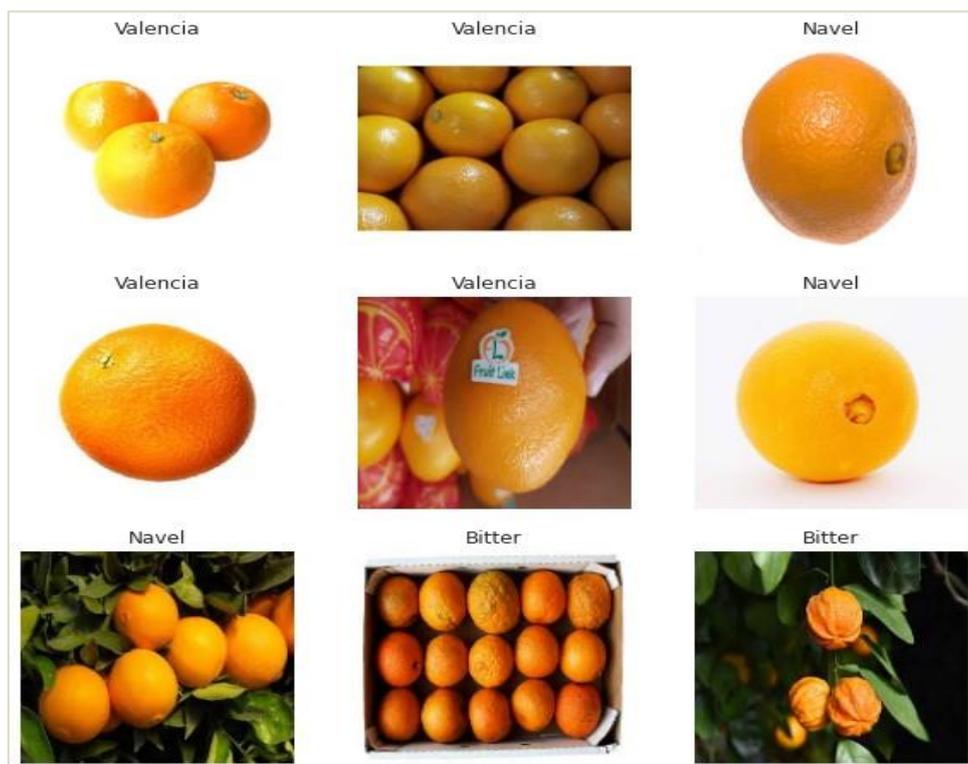
needs remarkably more potent memory as well as constitutes processing resources for a prolonged period. This is entirely at odds with direct, which aims at obtaining the highest accuracy rate at the lowest possible cost in terms of the quantity of time required to attain improvement (Figure 7 gives samples for prediction output).



**Figure (5): Accuracy Plot for Learning Epochs.**



**Figure (6): Loss Plot for Learning Epochs.**



**Figure (7): Prediction Output of Orange Fruit.**

**Conclusion**

In this work, we proposed a low-cost deep learning-based machine vision technique to classify orange fruits based on their morphological characteristics. The classification was facilitated by embracing well-defined classifiers developed

from neural networks, and the scheme’s ability was substantiated by using a real-world data set consisting of orange fruits. The research results of the experiments indicate that the EfficientNetB0 use of the data set that was being analyzed did lead to a significant improvement in the accuracy of the

overall prediction. We drove actions to ensure that transfer learning is appropriate to the classification of orange fruits. We intend to include further images of other versions of this fruit in the near future. In addition, we highly advise classifying fruits according to their weight as a prospective work by creating an opportunity to do so initially. To develop a precise forecast of the actual weight of this fruit in order to ensure that the model would be economically viable in the processes involved in the selling of the crop harvested from orange orchards.

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