Model fusion at score level for image classification

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Introduction

- Image classification is a fundamental task in computer vision.
- The goal is to classify & assign the image to a specific label or class.
- Convolutional Neural Networks (CNN) is a deep learning method used extensively in processing & classifying images for multiple applications like digital pathology, traffic image recognition, face recognition to name a few.



Traffic image recognition using computer vision

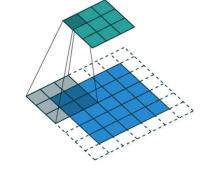
- Convolutional Neural Network (CNN) is the most classical multilayer neural network & the most common deep learning framework inspired by the visual perception mechanism of human beings.
- In 1990, LeCun et al. published a paper about a multi-layer neural network called LeNet-5 which could classify handwritten digits with little or no preprocessing using a backpropagation algorithm.
- Krizhevsky et al. developed a neural architecture, called AlexNet which was similar to LeNet-5 but had a deeper structure. It showed a significant improvement in the image classification task. With the success of AlexNet, many works have been done to increase performance like VGGNet, GoogleNet, ResNet, etc.
- With the advancement in neural networks a new machine learning method in which utilizing knowledge acquired from one task to solve related ones emerged known as Transfer Learning.
- Despite several advancements in neural networks & learning methods for image classification, robust & accurate classification of the target object in images remains unsolved because of difficulties posed by interclass & intraclass similarities, noisy images, etc. To overcome this difficulty a multimodal classification using fusion is used.
- This project aims to investigate the fusion of different models at the score level for the Fashion-MNIST dataset

Theoretical Background

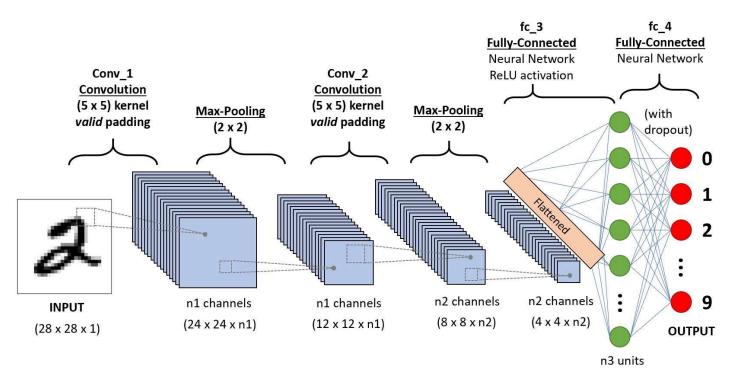
Image

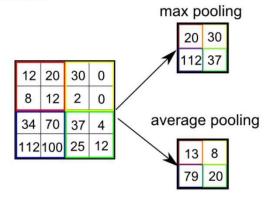
Convolved

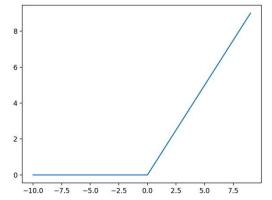
Feature



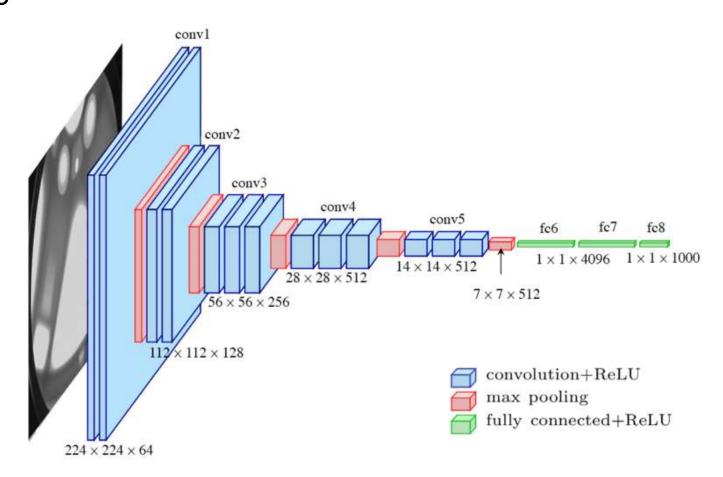
Convolutional Neural Network (CNN)



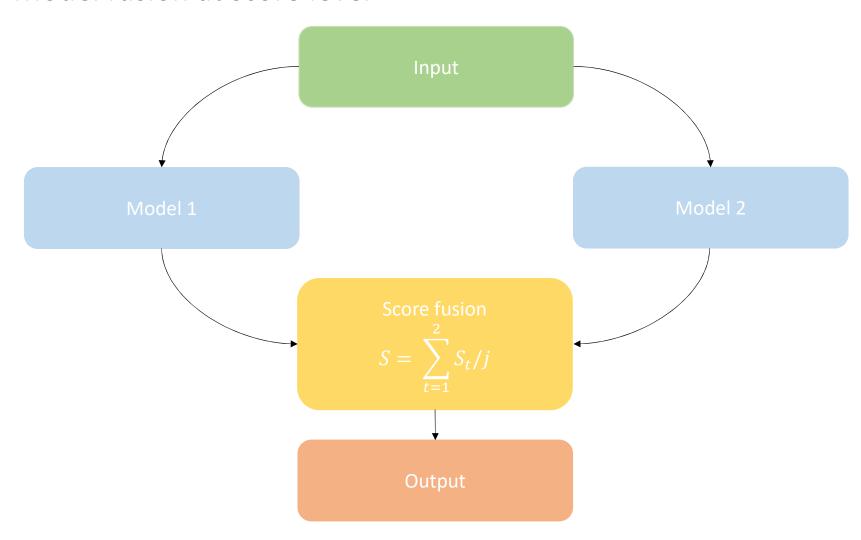




• VGG16



Model fusion at score level



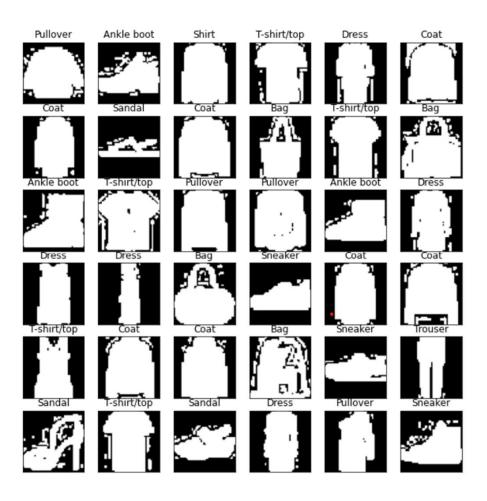
Methodology

- Understanding the dataset (Fashion-MNIST)
- Fashion-MNIST is a dataset of Zalando's article images.
- Training set: 60,000 examples; Test set: 10,000 examples.
- Each example is a 28x28 grayscale image, associated with a label from 10 classes.



• Data preparation & preprocessing

The images were resized from 28*28 to 48*48 & 3 channels as required for transfer learning



- Data normalization
- Converting labels to one-hot encoder

```
 \begin{bmatrix} [0. & 0. & 1. & \dots & 0. & 0. & 0. \\ [0. & 0. & 0. & \dots & 0. & 0. & 1. \\ [0. & 0. & 0. & \dots & 0. & 0. & 0. \\ ] \\ [0. & 0. & 0. & \dots & 0. & 1. & 0. \\ [0. & 0. & 0. & \dots & 0. & 1. & 0. \\ ] \\ [0. & 0. & 0. & \dots & 0. & 1. & 0. \\ ] \\ [1. & 0. & 0. & \dots & 0. & 0. & 0. \\ ] \\ [0. & 1. & 0. & \dots & 0. & 0. & 0. \\ ] \\ [0. & 0. & 0. & \dots & 0. & 1. & 0. \\ ] \\ [0. & 0. & 0. & \dots & 0. & 1. & 0. \\ ] \\ [0. & 0. & 0. & \dots & 0. & 1. & 0. \\ ] \\ [0. & 1. & 0. & \dots & 0. & 0. & 0. \\ ] \end{bmatrix}
```

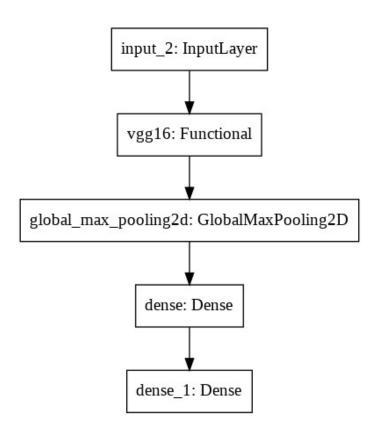
Splitting train data into training and validation data

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Train Validation

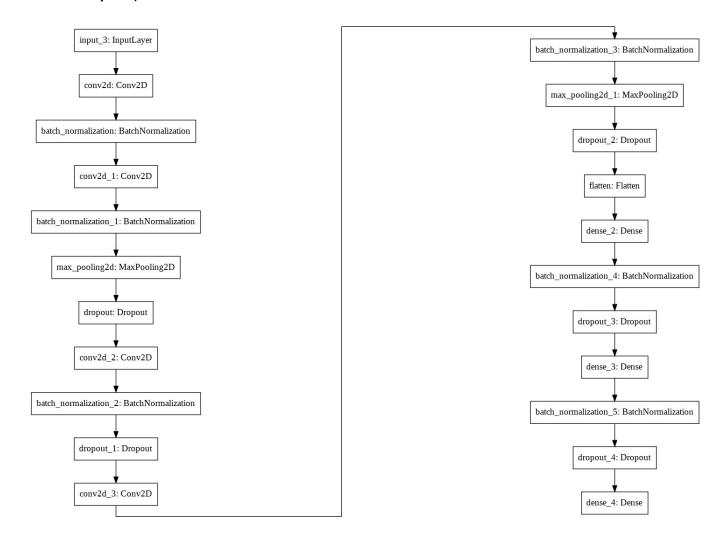
((57000, 48, 48, 3), (3000, 48, 48, 3))
```

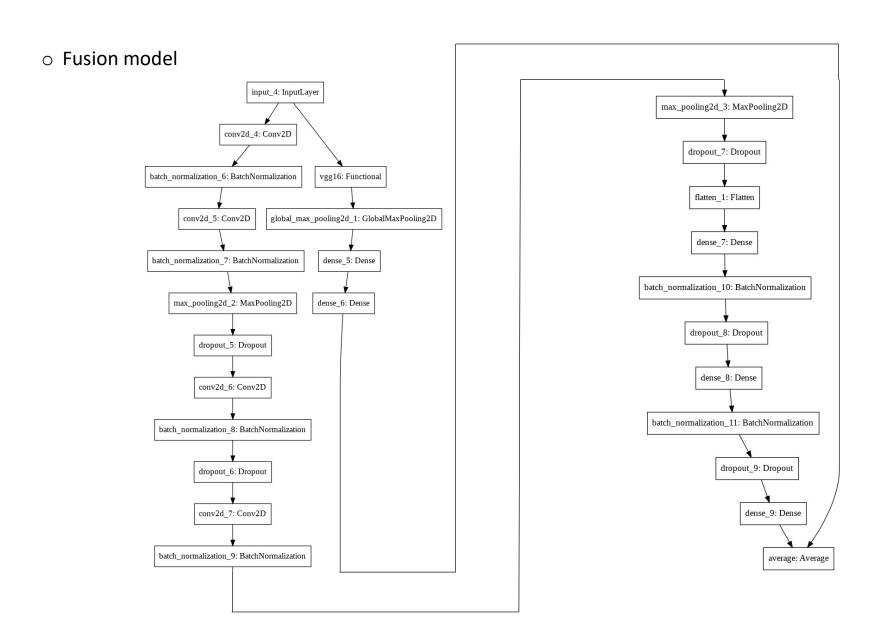
Model Definition

o Uni-model (Transfer learning model VGG16)



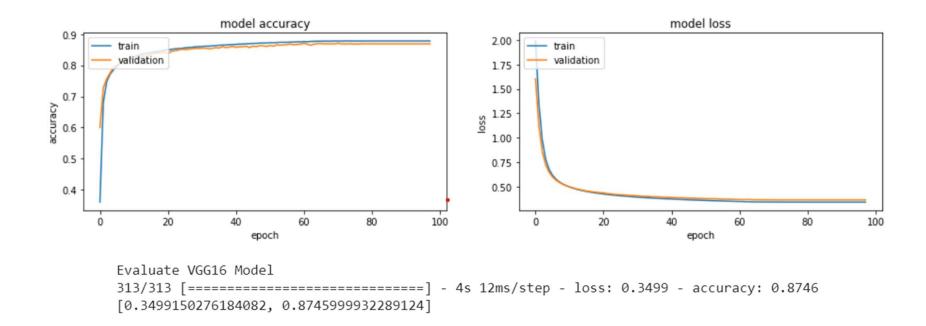
o Uni-model (CNN with 4 layers)



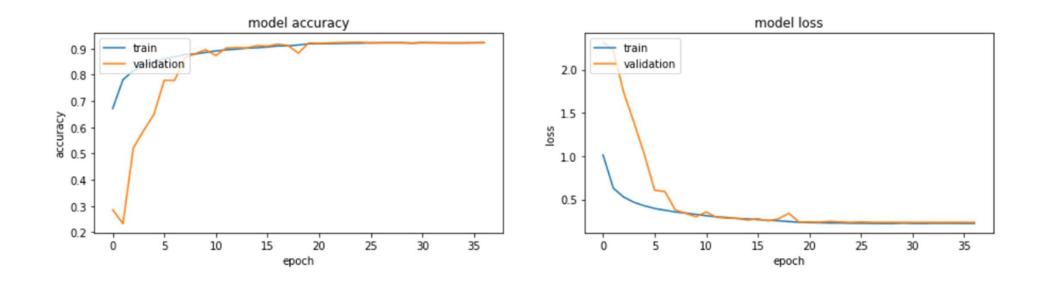


Results

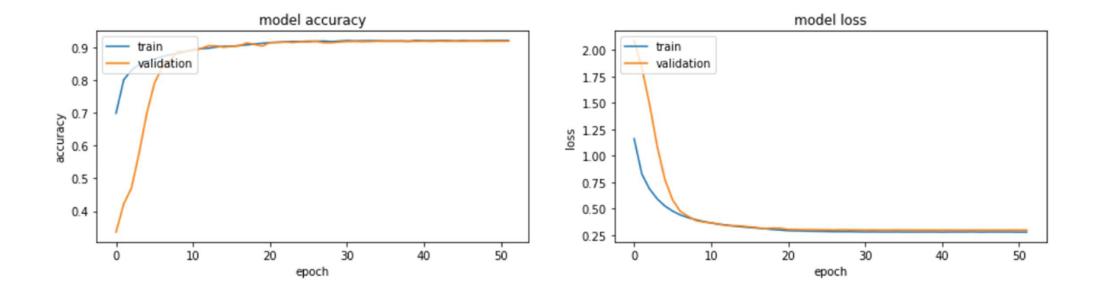
- Visualizing accuracy & loss
- Uni-model (Transfer learning model VGG16)



o Uni-model (CNN with 4 layers)

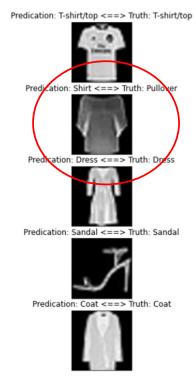


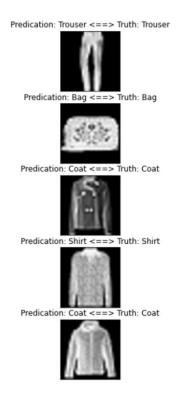
Fusion model

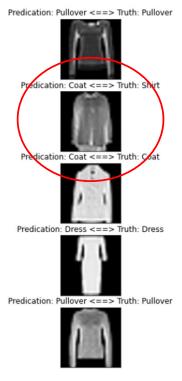


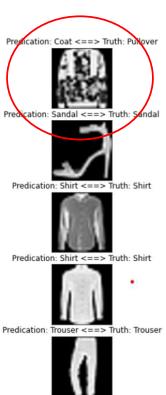
Model prediction

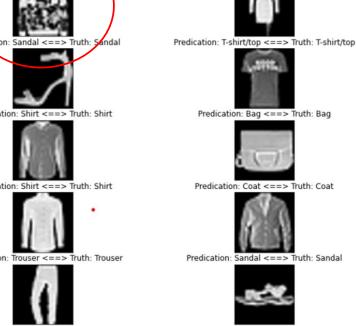
o Uni-model (Transfer learning model VGG16)





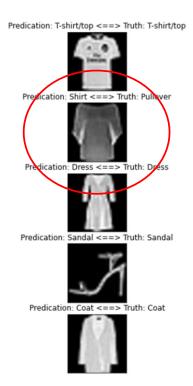


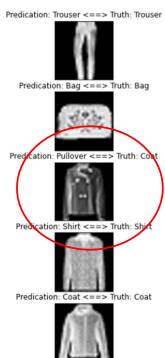




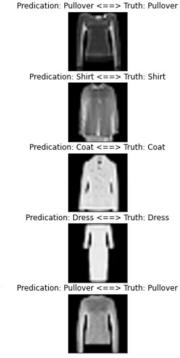
Predication: Dress <==> Truth: Dress

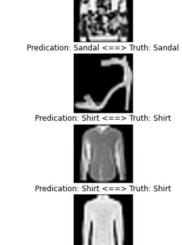
o Uni-model (CNN with 4 layers)

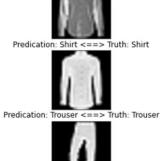












Predication: Pullover <==> Truth: Pullover











Fusion model

Predication: T-shirt/top <==> Truth: T-shirt/top



Predication: Dress <==> Truth: Dress



Predication: Sandal <==> Truth: Sandal



Predication: Coat <==> Truth: Coat



Predication: Trouser <==> Truth: Trouser



Predication: Bag <==> Truth: Bag



Predication: Pullover <==> Truth: coat



Predication: Shirt <==> Truth: Shirt



Predication: Coat <==> Truth: Coat



Predication: Pullover <==> Truth: Pullover



Predication: Shirt <==> Truth: Shirt



Predication: Coat <==> Truth: Coat



Predication: Dress <==> Truth: Dress



Predication: Pullover <==> Truth: Pullover



Predication: Shirt <==> Truth: Pullover



Predication: Sandal <==> Truth: Sandal



Predication: Shirt <==> Truth: Shirt



Predication: Shirt <==> Truth: Shirt



Predication: Trouser <==> Truth: Trouser



Predication: Dress <==> Truth: Dress



Predication: T-shirt/top <==> Truth: T-shirt/top



Predication: Bag <==> Truth: Bag



Predication: Coat <==> Truth: Coat

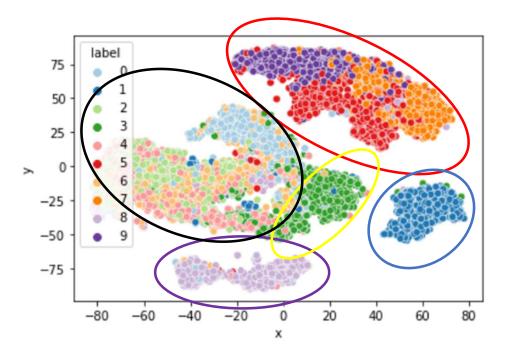


Predication: Sandal <==> Truth: Sandal



• t-SNE plot

index	0	1	2	3	4	5	6	7	8	9
Label	T- shirt/Top	Trouser	Pullover	Dress	Coat	Sandal	Shirt	Sneaker	Bag	Ankle Boot



Classes which can be classified distinctly:

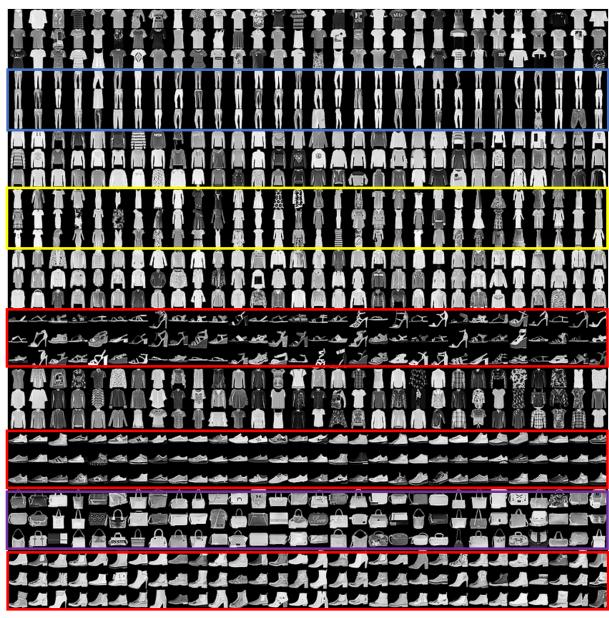
Sandal, Sneaker & Ankle Boot

Trouser

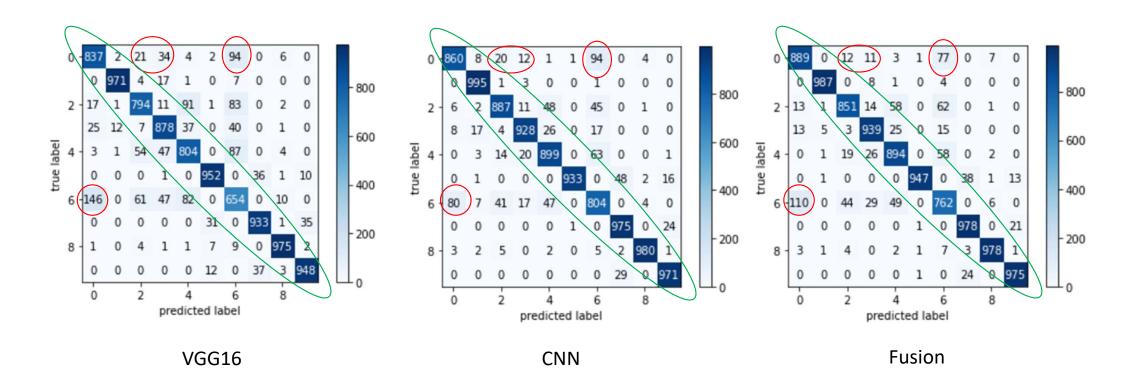
Bag

Dress

Classes which cannot be classified distinctly: T-shirt/Top, Pullover, Coat, Shirt



Confusion Matrix



Classification Report

													6.	
	precision	recall	f1-score	support		precision	recall	f1-score	support		precision	recall	f1-score	support
0 1 2 3 4 5 6 7 8	0.81 0.98 0.84 0.85 0.79 0.95 0.67 0.93	0.84 0.97 0.79 0.88 0.80 0.95 0.65 0.93	0.83 0.98 0.82 0.86 0.80 0.95 0.66 0.93 0.97	1000 1000 1000 1000 1000 1000 1000 100	0 1 2 3 4 5 6 7 8	0.90 0.96 0.91 0.94 0.88 1.00 0.78 0.93	0.86 0.99 0.89 0.93 0.90 0.93 0.80 0.97	0.88 0.98 0.90 0.93 0.89 0.96 0.79 0.95	1000 1000 1000 1000 1000 1000 1000 100	0 1 2 3 4 5 6 7 8	0.86 0.99 0.91 0.91 0.87 1.00 0.77 0.94 0.98	0.89 0.99 0.85 0.94 0.89 0.95 0.76 0.98	0.88 0.99 0.88 0.93 0.88 0.97 0.77 0.96 0.98	1000 1000 1000 1000 1000 1000 1000 100
9	0.95	0.95	0.95	1000	9	0.96	0.97	0.96	1000	9	0.97	0.97	0.97	1000
accuracy macro avg weighted avg	0.87 0.87	0.87 0.87	0.87 0.87 0.87	10000 10000 10000	accuracy macro avg weighted avg	0.92 0.92	0.92 0.92	0.92 0.92 0.92	10000 10000 10000	accuracy macro avg weighted avg	0.92 0.92	0.92 0.92	0.92 0.92 0.92	10000 10000 10000
VGG16						CI	Fusion							

Future Work

- This fusion method can be extended further with
 - Product rule

o Weight rule

$$S = \prod_{t=1}^{j} S_t$$

$$W = \sum_{t=1}^{j} acc_t$$

 $w_j = \frac{acc_j}{W}$, where j is the no of models

$$S = \sum_{t=1}^{j} w_t S_t$$

Conclusion

The proposed method of fusing two different models trained on same dataset seems promising. It takes into account both the positive and negative of both the models. From the experiment it is evident that the accuracy of fusion model is close to CNN model which compared to the VGG16 model is high. On further fine tuning of models & proper model selection with respect to data the score level fusion method can result in high accuracy.

Q/A

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