



# NOT VADAPAV

CS725/403 - Project

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# The Problem

We aim to **classify if a given image is that of a vadapav or not (binary classification task)**.

This can be used as a basis for a general food classification app, if we have training data for lots of different types of food items.

The challenge is to classify images which are taken in a natural setting, under different conditions of lighting and angles. Moreover, vadapavs look similar to burgers, and while burgers are commonly referred to as the American vadapav, we believe there is a huge difference.






# CNNs: Not Fake News

- ▮ **Convolutional Neural Networks (CNNs)** are a set of neural network architectures which are commonly used for image classification tasks.
- ▮ Have recently come to the forefront, as hardware has caught up.
- ▮ Architecture generally consists of many layers
  - ▮ **Convolution layers:** Applied convolution operation to input; emulates the response of an individual neuron to visual stimuli.
  - ▮ **Pooling layers:** Reduces size of convolution outputs
  - ▮ **Fully connected layers**
- ▮ Shared parameters at a given layer allow us to reduce number of parameters trained

# The Data

Images were sourced from the following:

-  **Vadapavs:** ~2000 pictures scraped from Instagram using #vadapav, **840 manually selected** as positive images in the dataset.
-  **Not Vadapav: 640 pictures** from Instagram, using #food & #fast food (includes pictures of people and non-food items)
-  **Burgers: 200 pictures** from Instagram, using #burger, 160 manually selected

Google Images did not yield images of good quality. Instagram gave **high quality natural images**, under **different conditions of lighting and angles**.

A script was developed for us to easily scroll through hundreds of pics and tag them easily.

# Approach I: Training Fully Connected Layers



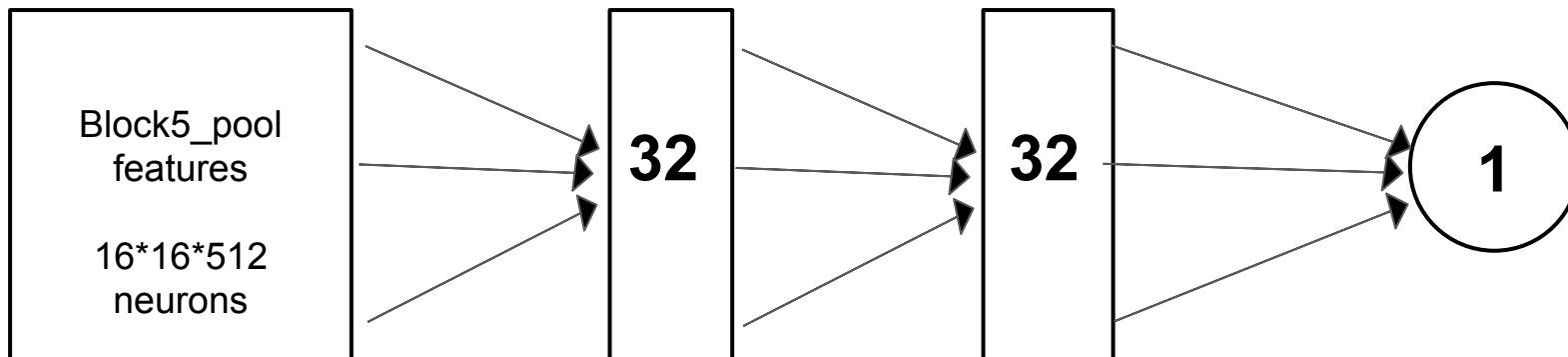
We used the **VGG19 architecture pre-trained weights** to extract convolution features for the images.



We extracted features after the **block5\_pool** layer.

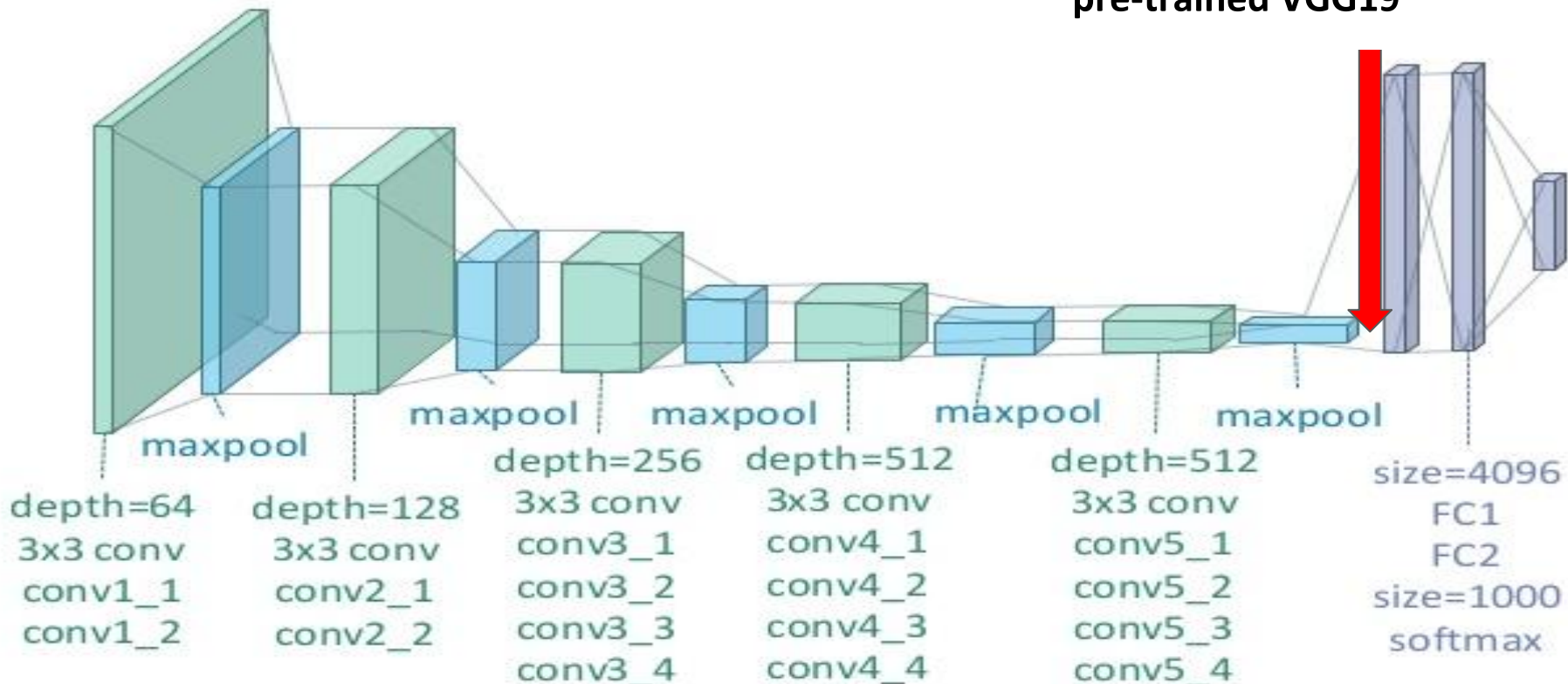


The extracted features were then flattened, and **3 fully connected layers** were trained. Adam optimizer was used, and training was for 10 epochs.



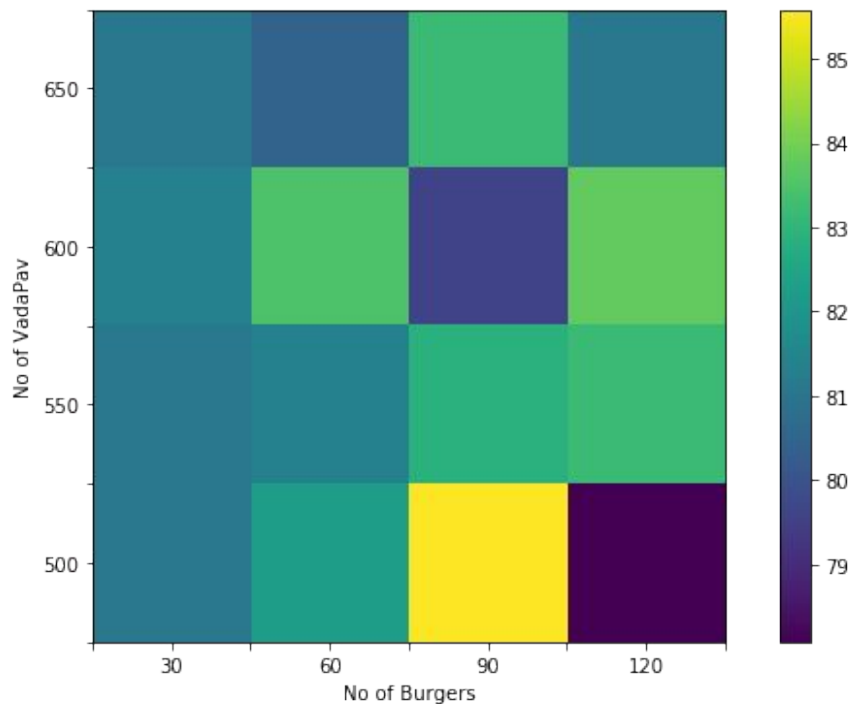
# VGG 19

Extraction point for  
block5\_pool features from  
pre-trained VGG19



# Results I: Training Fully Connected Layers

Accuracy variation for trained fully connected networks



# Results I: Training Fully Connected Layers

The best model was obtained from using 500 vadapavs and 90 burgers in the training. The confusion matrix on the test data was as follows

True label (->)	Not Vadapav	Vadapav	Burger
Predicted label	Not Vadapav	Vadapav	Burger
Not Vadapav	120	30	26
Vadapav	10	139	8



# Approaches II: Training Convolutional Layers



Extracted features after the **block4\_pool** layer of **VGG 19**.



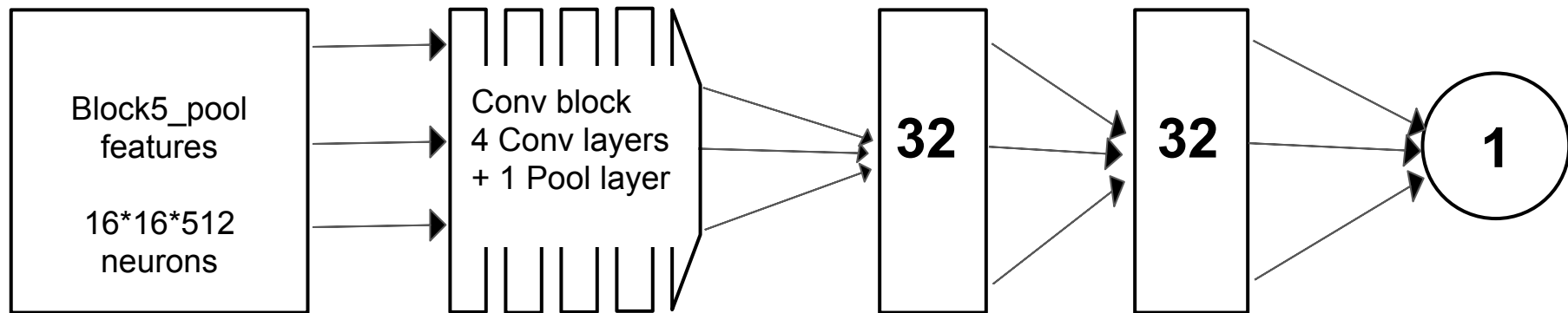
Features passed through our **convolutional network block**, then through 3 **fully connected** layers as before.



We **initialised the weights** of our 5th block to the **pre-trained imagenet weights** to improve accuracy.

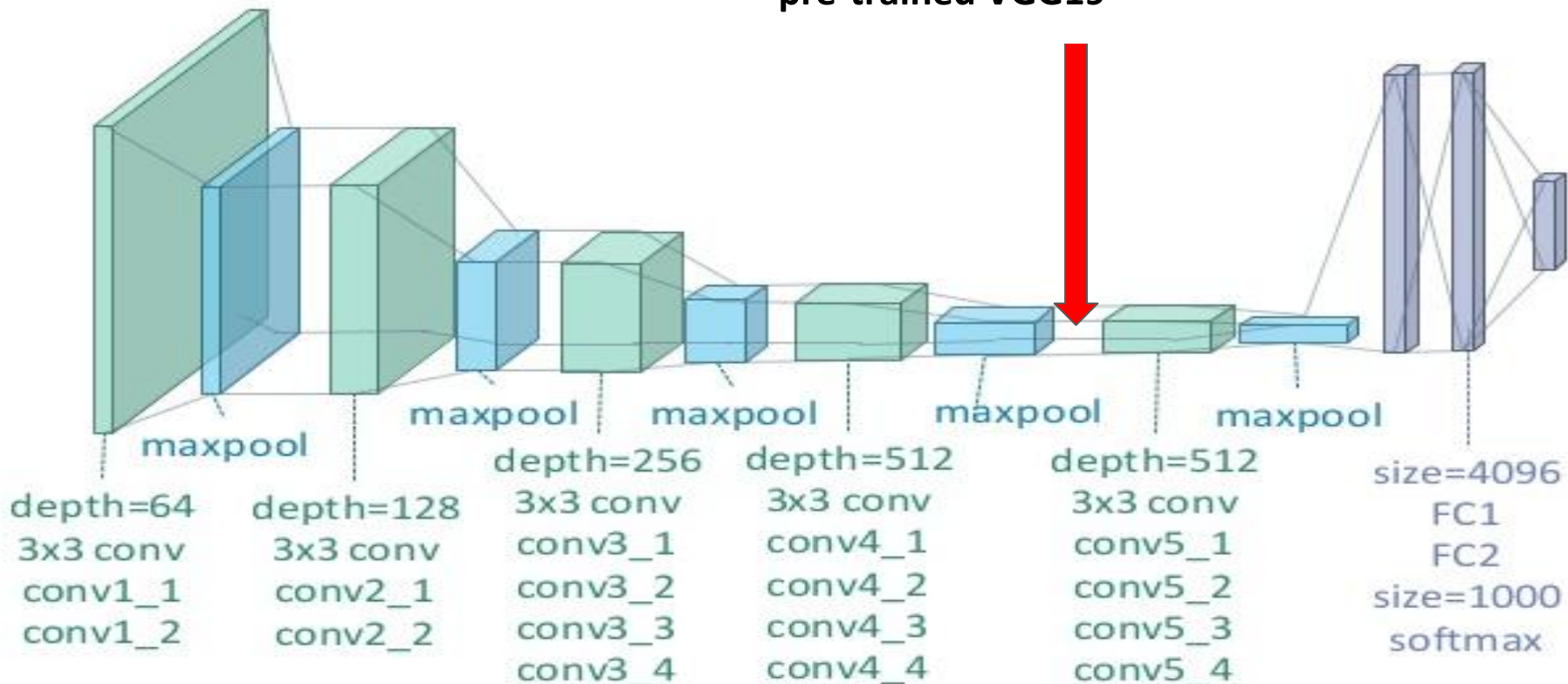


**SGD** used with no momentum, slight decay



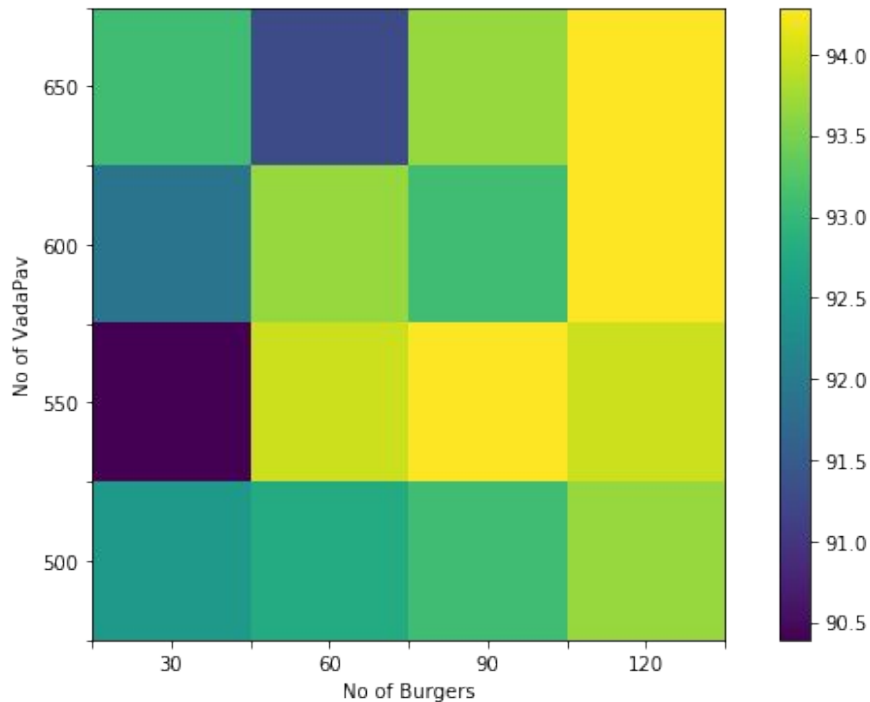
# VGG 19

Extraction point for  
block4\_pool features from  
pre-trained VGG19



# Results II: Training Convolutional Layers

Accuracy variation for trained fully connected + conv networks

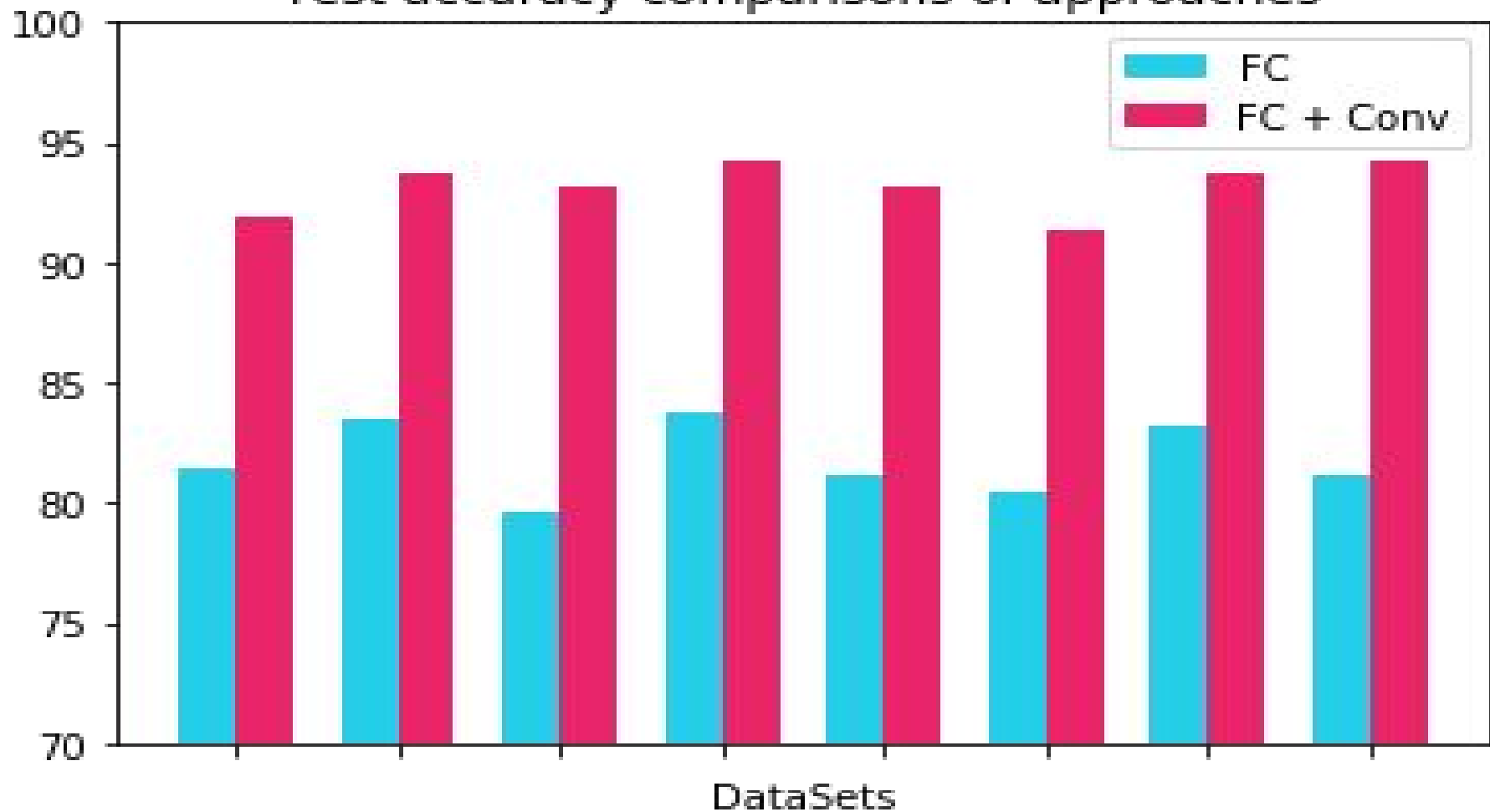


# Results II: Training Convolutional Layers

The best model was obtained from using 650 vadapavs and 120 burgers in the training. The confusion matrix on the test data was as follows

True label ( ->)	Not Vadapav	Vadapav	Burger
Predicted label	Not Vadapav	Vadapav	Burger
Not Vadapav	121	9	33
Vadapav	9	160	1

### Test accuracy comparisons of approaches



# The Demo

Now, if you would kindly turn your attention to the small screen...