

Impact of Fully Connected Layers on Performance of Convolutional Neural Networks for Image Classification

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Abstract—The Convolutional Neural Networks (CNNs), in domains like computer vision, mostly reduced the need for handcrafted features due to its ability to learn the problem-specific features from the raw input data. However, the selection of dataset-specific CNN architecture, which mostly performed by either experience or expertise is a time-consuming and error-prone process. To automate the process of learning a CNN architecture, this letter attempts at finding the relationship between Fully Connected (FC) layers with some of the characteristics of the datasets. The CNN architectures, and recently data sets also, are categorized as deep, shallow, wide, etc. This letter tries to formalize these terms along with answering the following questions. (i) *What is the impact of deeper/shallow architectures on the performance of the CNN w.r.t FC layers?*, (ii) *How the deeper/wider datasets influence the performance of CNN w.r.t FC layers?*, and (iii) *Which kind of architecture (deeper/ shallower) is better suitable for which kind of (deeper/ wider) datasets.* To address these findings, we have performed experiments with three CNN architectures having different depths. The experiments are conducted by varying the number of FC layers. We used four widely used datasets including CIFAR-10, CIFAR-100, Tiny ImageNet, and CRCHistoPhenotypes to justify our findings in the context of the image classification problem. The source code of this research is available at <https://github.com/shabbeersh/Impact-of-FC-layers>.

I. INTRODUCTION

II. INTRODUCTION AND RELATED WORKS

The popularity of Convolutional Neural Networks (CNN) is growing significantly for various application domains related to computer vision, which include object detection [1], segmentation [2], localization [3], and many more in recent years. However, there is a limited amount of work carried-out to address many questions related to CNNs in the context of finding a suitable structure of the architecture specific to a dataset. In this letter, we have addressed some of the factors which impact the performance of the CNN w.r.t fully connected (FC) layers in the context of the image classification problem. We have also studied the possible interrelationship between the presence of the FC layers in the CNN, the depth of the CNN, and the depth of the dataset.

Deep neural networks generally provide better results in the field of machine learning and computer vision, compared to the handcrafted feature descriptors [1]. Krizhevsky *et al.* [4] proposed the first CNN called AlexNet consisting

of 5 convolutional (*Conv*) layers and 3 FC layers. The FC layers are placed after all the Conv layers. Zeiler and Fergus [5] made minimal changes to AlexNet with better hyper-parameter settings in order to generalize it over other datasets. This model is called ZFNet which also has 3 FC layers along with 5 convolution layers. Simonyan and Zisserman [6] further extended the AlexNet model to VGG-16 with 16 learnable layers including 3 FC layers towards the end of the architecture. Later on, many CNN models have been introduced with increasing number of learnable layers. Szegedy *et al.* [7] proposed a 22-layer architecture called GoogLeNet, which has a single FC (output) layer. In the same year, He *et al.* [8] introduced ResNet with 152 trainable layers where the last layer is fully connected. However, all the above CNN architectures are proposed for large-scale ImageNet dataset [9]. Recently, Basha *et al.* [10] proposed the RCCNet CNN model for routine colon cancer cell classification, which has 7 learnable layers including 3 FC layers. The FC layer is widely used in CNN models at least in the final layer to generate the class score. In a shallow CNN model, the features generated in the final convolutional layer corresponds to a portion of the input image as its receptive field does not cover the full spatial dimension. Thus, few FC layers in such scenario are mandatory. Despite their pervasiveness, the number of FC layers and number of neurons in FC layers required for a given problem is not explored.

A study by Bansal *et al.* [11] investigated the face recognition problem, where some crucial observations reported are, (i) Training CNN models on images and evaluating the models on videos leads to better performance, (ii) Deeper architectures are preferred over shallow architectures when training the model with deeper datasets, similarly shallow architectures perform better than deeper architectures while training the CNN models with wider datasets, and (iii) Adding label noise leads to better performance in deep neural networks. Some attempts have also been made to analyze the impact of label noise in the training set for deep neural networks [12], [13]. Recently, Ferrari *et al.* [14] performed the analysis over many aspects that affect the performance of CNN for face recognition. They have observed that different distance measures among the learned CNN features can provide meaningful information regarding the discriminative ability of the learned features. They have also found that the image normalization, as often believed, is not a crucial one in training the CNN.

In a typical deep neural network, the FC layers comprise

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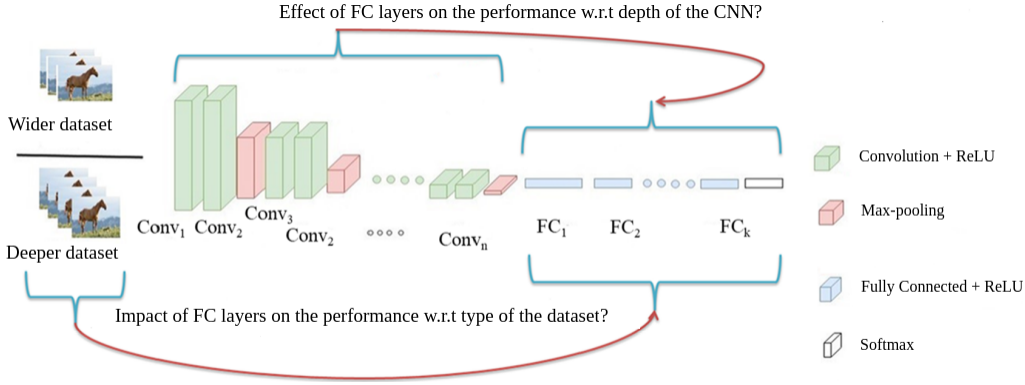


Fig. 1: The illustration of the effect of deeper/wider datasets and depth of CNN (i.e., the number of the Convolutional layers, n) over the number of FC layers (i.e., k). A typical plain CNN architecture has Convolutional (learnable), Max-pooling (non-learnable) and FC (learnable) layers.

most of the parameters of the network. AlexNet has 60 million parameters, out of which 58 million parameters correspond to the FC layers [4]. Similarly, VGGNet has a total of 135 million parameters, out of which 128 million parameters are from FC layers [6]. This huge number of parameters in FC layers is required to fit complex nonlinear discriminant functions in the feature space into which the input data elements are mapped. However, these large number of parameters may result in over-fitting the classifier. To reduce the amount of over-fitting Xu *et al.* [15] proposed a CNN architecture called SparseConnect where the connections between FC layers are sparsified.

Performance of a classifier may suffer because of the class imbalance problem (training set size differing significantly among the different classes), which is intrinsic to the dataset. Buda *et al.* [16] investigated the impact of the class imbalance problem in CNNs over MNIST [17], CIFAR-10 [18], and ImageNet [19] datasets. A study by Haixiang *et al.* [20] provides a detailed review and categorization of the existing application domains where class imbalance problem present. We have also experimented with a bio-medical dataset having the class imbalance problem to analyze the impact of FC layer.

To the best of our knowledge, no effort has been made in the literature to analyze the impact of FC layers in CNN for image classification. In this letter, we investigate the impact of FC layers on the performance of the CNN model with a rigorous analysis from various aspects. In brief, the contributions of this letter are summarized as follows,

- We conducted a systematic study to observe the effect deeper/shallow architectures on performance of CNN w.r.t FC layers in the context of image classification.
- We observed the effect of deeper/wider datasets on the performance of CNN w.r.t FC layers.
- We generalized one important finding of Bansal *et al.* [11] to choose the deeper or shallow architecture based on the depth of the dataset. They have reported the same in the context of face recognition. Whereas, we made a rigorous study to generalize this observation

TABLE I: The CNN-1 architecture having 5 *Conv* layers. The S , P , and BN denote stride, padding, and batch normalization, respectively. The output (FC) layer has 10, 100, 200, and 4 nodes in the case of CIFAR-10, CIFAR-100, Tiny ImageNet, and CRCHistoPhenotypes datasets, respectively.

Input:	Image dimension ($35 \times 35 \times 3$)
[layer 1]	Conv. (5, 5, 96), $S=1$, $P=0$; ReLU; BN;
[layer 2]	Conv. (5, 5, 256), $S=1$, $P=0$; ReLU; BN;
[layer 3]	Pool., $S=2$, $P=0$;
[layer 4]	Conv. (3, 3, 384), $S=1$, $P=1$; ReLU;
[layer 5]	Conv. (3, 3, 384), $S=1$, $P=1$; ReLU;
[layer 6]	Conv. (3, 3, 256), $S=1$, $P=1$; ReLU;
[layer 7]	Flatten; 43264;
Output:	(FC layer) Predicted Class Scores

over different kinds of datasets.

- To make the empirical justification of our findings, we have conducted the experiments on different modalities (i.e., natural and bio-medical images) of datasets like CIFAR-10 and CIFAR-100 [18], Tiny ImageNet [21], and CRCHistoPhenotypes [22].

Next, we illustrate the deep and shallow CNN architectures developed to conduct the experiments in Section III. Experimental setup including training details, datasets, etc., are discussed in Section IV. Section V presents a detailed study of the observations found in this letter. At last, Section VI concludes the letter.

III. DEVELOPED CNN ARCHITECTURES

The main objective of this letter is to analyze the impact of the number of FC layers and the number of neurons present in FC layers of CNN over the performance. Interdependency between the characteristics of both the datasets and the networks are explored w.r.t. FC layers as shown in Fig. 1. In order to conduct a rigorous experimental study, we have implemented three CNN models with varying depth in terms of the number of convolutional (*Conv*) layers before fully

connected (FC) layers. These models are termed as CNN-1, CNN-2, and CNN-3 having 5, 10, and 13 *Conv* layers, respectively. In this letter, a CNN model N_1 is considered as deep/shallow model w.r.t. a CNN model N_2 , if the number of learnable layers in N_1 is more/less as compared to N_2 .

A. CNN-1 Architecture

AlexNet [4] is well-known and first CNN architecture, which won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 [19] with a huge performance gain as compared to the best results of that time using handcrafted features. The original AlexNet architecture was proposed for the images of dimension $227 \times 227 \times 3$, we made minimal changes to the model to fit for low-resolution images. We name this model as CNN-1. Initially, the input image dimension is up-sampled from $32 \times 32 \times 3$ to $35 \times 35 \times 3$ in the case of CRCHistoPhenotypes [22], CIFAR-10, CIFAR-100 [18] datasets, whereas, it is down-sampled from $64 \times 64 \times 3$ to $35 \times 35 \times 3$ in the case of Tiny ImageNet [21] dataset. The 1st convolutional layer *Conv1* produces $31 \times 31 \times 96$ dimensional feature vector by applying 96 filters of dimension $5 \times 5 \times 3$. The *Conv1* layer is followed by another Convolution layer (*Conv2*), which produces $27 \times 27 \times 256$ dimensional feature map by convolving 256 filters of size $5 \times 5 \times 96$. The remaining layers of the CNN-1 model are similar to the original AlexNet [4]. The CNN-1 model with a single FC layer (i.e., the output FC layer) consists of following number of learnable parameters, 4,152,906 for CIFAR-10 dataset, 8,046,756 for CIFAR-100 dataset, 12,373,256 for Tiny ImageNet dataset, and 3,893,316 for CRCHistoPhenotypes dataset. Note that, the number of learnable parameters is different for each dataset due to the different number of classes present in the datasets which leads to the varying number of learnable parameters in the output FC layer. The detailed specifications of the CNN-1 model are given in Table I.

B. CNN-2 Architecture

Another CNN model is designed based on the CIFAR-VGG [23] model by eliminating some *Conv* layers from the model. We name this model as CNN-2. There are 6 blocks in this model, where first 5 blocks have two consecutive *Conv* layers followed by a *Pool* layer. Finally, the sixth block has FC (output) layer which generates the class scores. The input to this model is an image of dimension $32 \times 32 \times 3$. To meet this requirement, images of the Tiny ImageNet dataset are down-sampled from $64 \times 64 \times 3$ to $32 \times 32 \times 3$. The CNN-2 architecture corresponds to 9416010, 9462180, 9513480, and 9412932 learnable parameters in the case of CIFAR-10, CIFAR-100, Tiny ImageNet, and CRCHistoPhenotypes datasets, respectively. The CNN-2 model specifications are given in Table II.

C. CNN-3 Architecture

Most of the popular CNN models like AlexNet [4], VGG-16 [6], GoogLeNet [7], and many more were proposed for high dimensional image dataset called ImageNet [9]. On the

TABLE II: The CNN-2 model having 10-*Conv* layers. The S , P , BN , and DP_f denote the stride, padding, batch normalization, and dropout with a factor of f . The output layer has 10, 100, 200, and 4 nodes in the case of CIFAR-10, CIFAR-100, Tiny ImageNet, and CRCHistoPhenotypes datasets, respectively.

Input:	Image dimension ($32 \times 32 \times 3$)
[layer 1]	Conv. (3, 3, 64), S=1, P=1; ReLU; BN, DP _{0.3}
[layer 2]	Conv. (3, 3, 64), S=1, P=1; ReLU; BN;
[layer 3]	Pool., S=2, P=0;
[layer 4]	Conv. (3, 3, 128), S=1, P=1; ReLU; BN, DP _{0.4}
[layer 5]	Conv. (3, 3, 128), S=1, P=1; ReLU; BN;
[layer 6]	Pool., S=2, P=0;
[layer 7]	Conv. (3, 3, 256), S=1, P=1; ReLU; BN, DP _{0.4}
[layer 8]	Conv. (3, 3, 256), S=1, P=1; ReLU; BN;
[layer 9]	Pool., S=2, P=0;
[layer 10]	Conv. (3, 3, 512), S=1, P=1; ReLU; BN, DP _{0.4}
[layer 11]	Conv. (3, 3, 512), S=1, P=1; ReLU; BN;
[layer 12]	Pool., S=2, P=0;
[layer 13]	Conv. (3, 3, 512), S=1, P=1; ReLU; BN, DP _{0.4}
[layer 14]	Conv. (3, 3, 512), S=1, P=1; ReLU; BN;
[layer 15]	Pool., S=2, P=0;
[layer 16]	Flatten; 512;
Output:	(FC layer) Predicted Class Scores

other hand, the low dimensional image datasets like CIFAR-10/100 have rarely got benefited from the CNNs. Liu and Deng [23] have introduced the CIFAR-VGG architecture, which is basically a 16 layer deep CNN architecture proposed for CIFAR-10. We have utilized this CIFAR-VGG model as the third deep neural network to observe the impact of FC layers in CNN and named as CNN-3 in our experimentations. The input to this model is an image of dimension $32 \times 32 \times 3$. To meet this requirement, images of the Tiny ImageNet dataset are down-sampled from $64 \times 64 \times 3$ to $32 \times 32 \times 3$. The CNN-3 architecture with a single FC (output) layer corresponds to 14728266, 14774436, 14825736, and 14725188 trainable parameters in the case of CIFAR-10 [18], CIFAR-100 [18], Tiny ImageNet [21], and CRCHistoPhenotypes [22] datasets, respectively.

IV. EXPERIMENTAL SETUP

This section describes the experimental setup including the training details, datasets used for the experiments, and the evaluation criteria to judge the performance of the CNN models.

A. Training details

The classification experiments are conducted on different modalities of image datasets to provide the empirical justifications of our findings in this letter. The initial value of the learning rate is considered as 0.1 and it is decreased by a factor of 2 for every 20 epochs. The Rectified Linear Unit (*ReLU*) based non-linearity [4] is used as the activation function after every *Conv* and FC layer (except the output FC layer) in all the CNN models discussed in section III. The Batch Normalization (i.e., *BN*) [24] is employed after

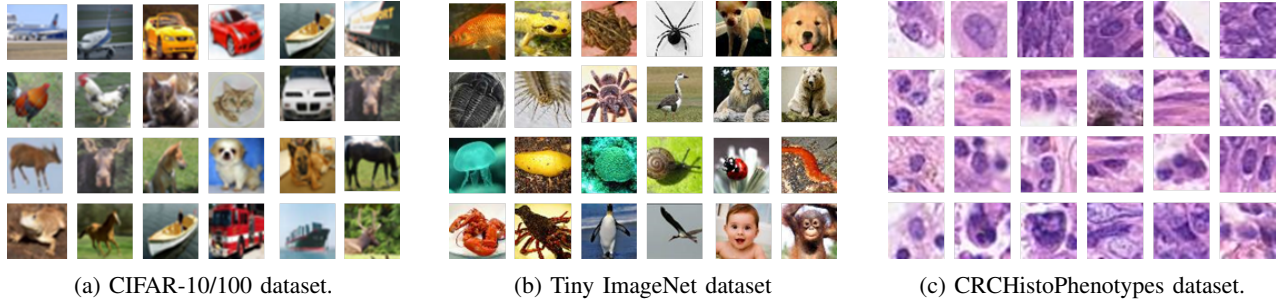


Fig. 2: (a) A few sample images from CIFAR-10/100 dataset [18]. (b) A random sample images from Tiny ImageNet dataset [21]. (c) Example images from CRCHistoPhenotypes dataset [22] with each row represents the images from one category.

ReLU of each *Conv* and FC layer, except final FC layer in CNN-2 and CNN-3 architectures. Whereas, in the case of CNN-1, the Batch Normalization is used only with first two *Conv* layers as mentioned in Table I. To reduce the amount of data over-fitting, we have used a popular regularization method called Dropout (i.e., *DP*) [25] after some Batch-Normalization layers as summarized in Table II for CNN-2. For CNN-3, the *DP* layers are used as per the CIFAR-VGG model [23]. In order to experiment the impact of fully connected (FC) layers, any added FC layer has the *ReLU*, *BN* and *DP* default. Along with dropout, various data augmentations techniques like rotation, horizontal flip, and vertical flip are also applied to reduce the amount of over-fitting. The implemented CNN architectures are trained for 250 epochs using Stochastic Gradient Descent (SGD) optimizer with a momentum of 0.9.

B. Evaluation criteria

To evaluate the performance of the developed CNN models (i.e., CNN-1, CNN-2, and CNN-3), we have considered the classification accuracy as the performance evaluation metric.

C. Datasets

To find out the empirical observations addressed in this letter, we have conducted the experiments on different modalities of datasets like CIFAR-10 [18], CIFAR-100 [18], Tiny ImageNet [21] (i.e., the natural image datasets), and CRCHistoPhenotypes [22] (i.e., the medical image dataset).

1) *CIFAR-10 [18]*: The CIFAR-10 [18] is the most popular tiny image dataset consists of 10 different categories of images, where each class has 6000 images. The dimension of each image is $32 \times 32 \times 3$. To train the deep neural networks, we have used the training set (i.e., 50000 images) of the CIFAR-10 dataset, and remaining data (i.e., 10000 images) is utilized to validate the performance of the models. A few samples of images from the CIFAR-10 dataset are shown in Fig. 2a.

2) *CIFAR-100 [18]*: The CIFAR-100 [18] dataset is similar to CIFAR-10, except that CIFAR-100 has 100 classes. In our experimental setting, the 50,000 images are used to train the CNN models and remaining 10,000 images are used to validate the performance of the models. Similar to CIFAR-10, the dimension of each image is $32 \times 32 \times 3$. The sample images are shown in Fig. 2a.

3) *Tiny ImageNet [21]*: The Tiny ImageNet dataset [21] consists a subset of ImageNet [9] images. This dataset has a total of 200 classes and each class has 500 training and 50 validation images. In other words, we have used 100000 images for training and 10000 images for validating the performance of the models. The dimension of each image is $64 \times 64 \times 3$. The example images of the Tiny ImageNet dataset are portrayed in Fig. 2b.

4) *CRCHistoPhenotypes [22]*: In order to generalize the observations reported in this letter, we have used a medical image dataset consists of routine colon cancer nuclei cells called “CRCHistoPhenotypes” [22], which is publicly available¹. This colon cancer dataset consists of the total 22444 nuclei patches that belong to the four different classes, namely, ‘Epithelial’, ‘Inflammatory’, ‘Fibroblast’, and ‘Miscellaneous’, respectively. In total, there are 7722 images belong to the ‘Epithelial’ class, 5712 images belong to the ‘Fibroblast’ class, 6971 images belong to the ‘Inflammatory’ class, and the remaining 2039 images belong to the ‘Miscellaneous’ class. The dimension of each image is $32 \times 32 \times 3$. For training the CNN models, 80% of entire data (i.e., 17955 images) is utilized and remaining 20% data (i.e., 4489 images) is used to validate the performance of the models. The sample images are displayed in Fig. 2c.

For any two datasets with roughly same number of images, one dataset is said to be deeper [11] than another dataset, if it has more number of images per class in the training set. The other dataset which has a lower number of images per subject in the training set is called the wider dataset. For example, CIFAR-10 and CIFAR-100 [18], both the datasets have 50000 images in the training set. The CIFAR-10 is a deeper dataset since it has 5000 images per class in the training set. On the other hand, the CIFAR-100 is wider dataset because it has only 500 images per subject.

V. RESULTS AND ANALYSIS

We have conducted extensive experiments to observe the useful practices in deep learning for the uses of plain Convolutional Neural Networks (CNNs). The three CNN models discussed in section III are implemented to perform the experiments on publicly available CIFAR-10/100, Tiny

¹<https://warwick.ac.uk/fac/sci/dcs/research/tia/data/crchistolabelednuclei>

ImageNet, and CRCHistoPhenotypes datasets. The results in terms of the classification accuracy are reported in this letter.

A. Impact of FC layers on the performance of the CNN model w.r.t to depth of the CNN

To observe the effect of deeper/wider architectures (i.e., the number of Convolution layers, *Conv*) on FC layers, initially, the CNN models are trained with a single FC (output) layer. Then another FC layer is added manually before the output (FC) layer to observe the gain/loss in the performance due to the addition of the new FC layer. The number of nodes is chosen (for newly added FC layer) starting from the number of classes to all multiples of 2 (i.e., powers of 2 such as 16, 32, etc.), which is greater than the number of classes and up to 4096. For example, in the case of CIFAR-10 dataset [18], the experiments are conducted by varying the number of nodes in the newly added FC layer with 10, 16, 32, 64, ..., 4096 number of nodes. In the next step, one more FC layer is added before the recently added FC layer. The number of nodes for newly added FC layer is chosen, ranging from the value for which best performance is obtained in the previous setting to 4096. Let us assume, we obtained the best performance using CNN-1 having two FC layers (with 512, 10 nodes in the case of CIFAR-10, [18]). Then, we observed the performance of the model by adding another FC layer by varying the number of nodes as 512, 1024, 2048, 4096. The details like the number of FC layers, number of nodes in each FC layer, best classification accuracies obtained for CIFAR-10 dataset using the three CNN models are shown in Table V. It is clearly observed from Table V that the deeper architectures (i.e., CNN-2 with 10 *Conv* layers and CNN-3 with 13 *Conv* layers) require relatively less number of nodes in FC layers compared to the shallow architecture (i.e., CNN-1 with 5 *Conv* layers) over the CIFAR-10 dataset. In order to generalize the above-mentioned observation, we have computed the results by varying the number of FC layers over other datasets also and reported the best performance in Table III. From Table III, the similar findings are noticed that the deeper architectures do not require more number of FC layers. In contrast, the shallow architecture requires more number of FC layers in order to obtain better performance for any dataset. The reasoning for such behavior is related to the type of features being learned by the *Conv* layers. In general, a CNN architecture learns the hierarchical features from raw image data. Zeiler and Fergus [5] have shown that the early layers learn the low-level features, whereas the deeper layers learn the high-level features. It means that the final *Conv* layer of shallow architecture produces less abstract features as compared to the deeper architecture. Thus, the number of FC layers needed for shallow architecture is more as compared to the deeper architecture.

B. Effect of FC layers on the performance of the CNN model w.r.t to different types of datasets

We have used two kinds of datasets (deeper and wider) to analyze the effect on FC layers. Table IV presents the

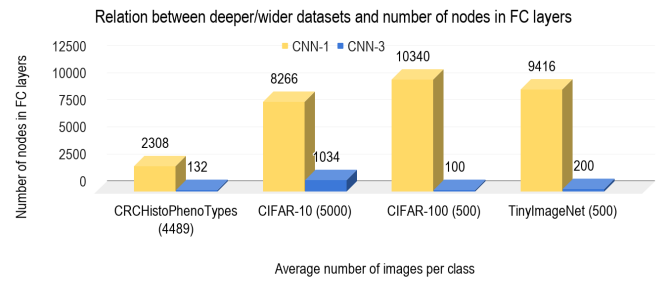


Fig. 3: The effect of deeper/wider datasets on FC layers of CNN. Deeper architectures CNN-3 require relatively less number of nodes in FC layers for the wider datasets compared to deeper datasets. In contrast, shallow architecture CNN-1 require relatively large number nodes in FC layers for wider datasets compared to deeper datasets.

characteristics like average number of images per class in the training set (N), number of classes (C), number of training images (Tr), and validation images (Va) of four datasets discussed in section IV-C. From Fig. 3, we can also observe that shallow architectures CNN-1 (shallow compared to CNN-3) require more number of nodes in FC layers for wider datasets compared to deeper datasets. On the other hand, deeper architecture CNN-3 (deeper than CNN-1) requires less number of nodes in FC layers for wider datasets compared to deeper datasets. A deeper CNN model such as CNN-3 with 13 *Conv* layers has more number of trainable parameters in *Conv* layers. Thus, a deeper dataset is required to learn the parameters of the network. Whereas, a shallow architecture such as CNN-1 with 5 *Conv* layers has less number of parameters for which a wider dataset is more suitable to train the model. A

C. Deeper/Shallow Architectures, Which are better?

Bansal *et al.* [11] have reported that the deeper architectures are preferred over shallow architectures while training the CNN models with deeper datasets. Whereas, for the wider datasets, the shallow architectures perform well compared to the deeper architectures. However, this observation is specific to face recognition problem as reported in [11]. In this letter, we made a rigorous study to generalize this finding by conducting extensive experiments on different modalities of datasets. For example, the CIFAR-10, CIFAR-100, and Tiny ImageNet datasets have the natural images and the CRCHistoPhenotypes dataset has the medical images. The results obtained through these experiments clearly indicate that the deeper architectures are always preferred over shallow architectures to train the CNN model using deeper datasets. In contrast, for the wider datasets, the shallow architectures perform better than the deeper CNN models.

From Table III, we can observe that training deeper architectures CNN-2 and CNN-3 (deeper than CNN-1) with deeper dataset produces 92.29% and 92.22% validation accuracies, respectively in the case of the CIFAR-10 dataset and 84.89% and 84.94%, respectively in the

TABLE III: The best validation accuracies obtained over CIFAR-10, CIFAR-100, Tiny ImageNet and CRCHistoPhenotypes datasets using three CNN models (i.e., CNN-1, CNN-2, and CNN-3). The results are presented in terms of the FC layer structures and validation accuracy.

S.No.	Dataset	Architecture		
		CNN-1 (5 Conv layers)	CNN-2 (10 Conv layers)	CNN-3 (13 Conv layers)
1	CIFAR-10	4096x4096x64x10 (90.77)	4096x256x10 (92.29)	1024 × 10 (92.22)
2	CIFAR-100	4096x4096x2048x100 (69.21)	4096x100 (62.28)	Single FC (output) layer (66.98)
3	Tiny ImageNet	4096x4096x1024x200 (50.1)	512x200, 1024x200 (41.84)	Single FC (output) layer (40.27)
4	CRCHistoPhenotypes	2048x256x4 (82.53)	512x4 (84.89)	128 × 4 (84.94)

TABLE IV: The characteristics of the datasets including CIFAR-10, CIFAR-100, Tiny ImageNet, and CRCHistoPhenotypes datasets are presented in this table. Here, N represents the average number of images per class in Training set, C represents the number of classes corresponding to a dataset, Tr and Va are the number of images in the Training and Validation sets, respectively.

Dataset	N	C	Tr	Va
CIFAR-10	5000	10	50,000	10,000
CIFAR-100	500	100	50,000	10,000
Tiny ImageNet	500	200	80,000	20,000
CRCHistoPhenotypes	4489	4	17955	4489

case of CRCHistoPhenotypes dataset. Whereas, in contrast, we obtained 90.77% and 82.53% validation accuracies for CIFAR-10 and CRCHistoPhenotypes datasets, respectively, when trained the deeper datasets with shallow architecture CNN-1 (shallow compared to CNN-2 and CNN-3). On the other hand, for the wider datasets like CIFAR-100 and Tiny ImageNet, better performance is obtained using the shallow architecture (CNN-1). From Table III, we can observe that the CNN-1 gives a validation accuracy of 69.21% for CIFAR-100 and 50.1% for Tiny ImageNet dataset. Whereas, the CNN-1 model performs relatively poor for deeper datasets.

This observation is very much useful while choosing a CNN architecture to train the model for a given dataset. The generalization of this finding intuitively makes sense because the deeper/shallow architectures have a more/less number of learnable parameters, in a typical CNN model which require more/less number of images per subject for the training.

VI. CONCLUSION

In this letter, we have analyzed the impact of certain decisions in terms of the FC layers of CNN for image classification. Careful selection of these decisions, not only improve the performance of the CNN models but also reduces the time required to choose among different architectures such as deeper and shallow. This letter is concluding the following guidelines that can be adopted while designing the deep/shallow convolutional neural networks to obtain the better performance. i) The shallow architectures require a large number of nodes to be presented in FC layers, whereas in the case of deeper architectures less number of nodes are required in FC layers irrespective of the type of the dataset. ii) The shallow models require a large number of nodes in FC

layers as well as more number of FC layers for wider datasets compared to deeper datasets and vice-versa. iii) Deeper architectures perform better than shallow architectures over deeper datasets. In contrast, shallow architectures perform better than deeper architectures for wider datasets. These observations can help the deep learning community while making a decision about the choice of deep/shallow CNN architectures.

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TABLE V: The effect of depth of the CNN models (i.e., CNN-1, CNN-2, and CNN-3) on FC layers for the CIFAR-10 dataset is shown in this table. The best and 2nd best accuracies are highlighted in bold and italic, respectively. For example, the CNN-2 model produces the best accuracy of 92.29% for three FC layers with 4096, 256, and 10 nodes and the 2nd best accuracy of 92.02% for two FC layers with 256 and 10 nodes.

S.No.	CNN-1	CNN-2	CNN-3
1	Single FC (output) layer (44.29)	Single FC (output) layer (91.46)	Single FC (output) layer (92.05)
2	10 × 10 (88.67)	10 × 10 (91.14)	10 × 10 (91.03)
3	16 × 10 (88.72)	16 × 10 (91.58)	16 × 10 (91.77)
4	32 × 10 (88.93)	32 × 10 (91.99)	32 × 10 (92.02)
5	64 × 10 (89.72)	64 × 10 (91.82)	64 × 10 (91.8)
6	128 × 10 (89.2)	128 × 10 (91.86)	128 × 10 (91.82)
7	256 × 10 (89.23)	256 × 10 (92.02)	256 × 10 (89.23)
8	512 × 10 (88.95)	512 × 10 (90.98)	512 × 10 (91.78)
9	1024 × 10 (89.56)	1024 × 10 (91.54)	1024 × 10 (92.22)
10	2048 × 10 (87.4)	2048 × 10 (91.27)	2048 × 10 (91.59)
11	4096 × 10 (86.27)	4096 × 10 (87.51)	4096 × 10 (90.68)
12	64 × 64 × 10 (89.35)	256 × 256 × 10 (91.97)	1024 × 1024 × 10 (91.27)
13	128 × 64 × 10 (89.71)	512 × 256 × 10 (91.92)	2048 × 1024 × 10 (91.43)
14	256 × 64 × 10 (89.79)	1024 × 256 × 10 (91.53)	4096 × 1024 × 10 (91.94)
15	512 × 64 × 10 (89.88)	2048 × 256 × 10 (91.95)	-
16	1024 × 64 × 10 (90)	4096 × 256 × 10 (92.29)	-
17	2048 × 64 × 10 (90.28)	4096 × 4096 × 256 × 10 (91.64)	-
18	4096 × 64 × 10 (90.59)	-	-
19	4096 × 4096 × 64 × 10 (90.77)	-	-
20	4096 × 4096 × 4096 × 64 × 10 (90.74)	-	-

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