

# Distributed Information Integration in Convolutional Neural Networks

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**Keywords:** Distributed Information Integration, Central Processor, Local Processor, Convolutional Neural Network, Filter Pyramid, Scale-invariance.

**Abstract:** A large body of physiological findings has suggested the vision system understands a scene in terms of its local features such as lines and curves. A highly notable computer algorithm developed that models such behaviour is the Convolutional Neural Network (CNN). Whilst recognising an object in various scales remains trivial for the human vision system, CNNs struggle to achieve the same behaviour. Recent physiological findings are suggesting two new paradigms. Firstly, the visual system uses both local and global features in its recognition function. Secondly, the brain uses a distributed processing architecture to learn information from multiple modalities. In this paper we combine these paradigms and propose a distributed information integration model called D-Net to improve scale-invariant classification of images. We use a CNN to extract local features and, inspired by Google's INCEPTION model, develop a trainable method using filter pyramids to extract global features called Filter Pyramid Convolutions (FPC). D-Net locally processes CNN and FPC features, fuses the outcomes and obtains a global estimate via the central processor. We test D-Net on classification of scaled images on benchmark datasets. Our results show D-Net's potential effectiveness towards classification of scaled images.

## 1 INTRODUCTION

Evolution has made our vision system a state-of-the-art biological object detector, recognition engine and classifier. This allows us to perform with ease several vision tasks such as object detection, classification and recognition. Even if the appearance of the object of interest in a scene has changed for example in terms of its relative size and position our visual system still achieves a high recognition accuracy. Making computer vision algorithms achieve biological vision-like behaviour has resulted in various techniques such as the Convolutional Neural Network (CNN) (LeCun et al., 1998). Since then CNNs have achieved great success in numerous computer vision tasks. However, the generalisation capability of CNN diminishes when classifying objects that are altered by transformations such as translations, scaling, rotation and reflection (Jaderberg et al., 2015; Kauderer-Abrams, 2017; Lenc and Vedaldi, 2015).

Recent physiological findings are suggesting two new paradigms. Firstly, the visual system uses both local and global features in its recognition function

(Huang et al., 2017; Su et al., 2009). Local feature information is used where global features cannot be determined. Here global features are not the same as global features obtained by aggregating local features from CNN models. Secondly instead of a dedicated multi-sensory integration brain area, there exists many multisensory brain areas that simultaneously process information from multiple modalities (Zhang et al., 2016b). This suggests our neural system uses a distributed information processing and integration architecture to learn information from different modalities. These paradigms provide the potential for improving transformation invariance problems in CNNs.

In this paper we combine these paradigms and propose a distributed information integration model for CNNs called D-Net. D-Net allows us to test these paradigms by locally processing local and global features of test images and then centrally processing the outcomes of local processors. We use a CNN to extract local features. In order to extract global features, we apply the concept of large filters (kernels) to spatially cover broader areas of an image (Peng et al., 2017). We achieve this by creating a convolution layer with pyramids of stacked filters (filter pyra-

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mids) of different sizes similar to Google's INCEPTION model (Szegedy et al., 2015). Through the process of convolution these filters generate multi-scale feature maps. These feature maps are down-sampled via pooling and used as global features. We use max pooling as research indicates max pooling help achieve some translation and rotation invariance (Xu et al., 2014) in CNNs. In our work we refer to this layer as Filter Pyramid Convolution (FPC) layer. We test D-Net on classification of scaled images on benchmark datasets. Our results show D-Net outperforms traditional CNN on raw train and test statistics. D-Net also shows promising results in classification of scaled images.

The main contributions of this paper are to improve CNNs towards classification of scaled images by showing the effectiveness of a) using both global and local features as different aspects of information for an image and b) applying the distributed processing architecture of the neural system in the artificial CNN.

The rest of the paper is organised as follows: Section 2 reviews related work while Section 3 introduces our model. Section 4 describes our experiment design and results are presented in Section 5. We summarise and point to future directions in Section 6.

## 2 BACKGROUND

Given our research is related to topics on global feature extraction using CNNs, the distributed information integration architecture of the biological neural system and filter and feature pyramid based design of CNNs, we cover review them briefly in the following sub-sections.

**Global Features:** Experiments on behaving monkeys by (Huang et al., 2017) showed detecting a distinction or change in the global feature (such as a hole in a circle) was faster than detecting a distinction or change in a local feature (solid shapes such as a circle). This means the visual system uses spatial and semantic information present in global features to identify objects prior to using local features (Park and Lee, 2016). In some studies, global features have been applied in CNNs but are limited to using feature descriptors such as histogram of gradients (HOG) (Zhang et al., 2016a). In another work, SIFT is combined with CNN (Zheng et al., 2017) but we note SIFT is classified as a local feature descriptor instead. An examination of how pre-trained Alex-Net and VGG-19 networks process local and global features is presented in (Zheng et al., 2018). These meth-

ods however have not been tested on how the network handles scaled images.

**Distributed Information Integration:** Anatomical evidence and experimental observations on the functioning of neural systems suggest the existence of dense clusters of neurons referred to as multisensory brain areas (Tononi and Edelman, 1998). To process different aspects of information about the same entity, a combined effort of several multisensory brain areas is needed (Zhang et al., 2016b; Ma and Pouget, 2008). Thus, the integration of information from multisensory brain areas form a reliable description of an underlying object of interest. (Zhang et al., 2016b) describe three principle architectures namely central, distributed and decentralised. We adopt the distributed architecture (Figure 1) in our work where we introduce multiple processing areas in the form of fully connected neural networks. We also show with some evidence the effectiveness of this design on classification of scaled images. Here our design contrasts with designs of most CNNs which use a dedicated multisensory integration area in the form of a single fully connected neural network.

A notable model to handle transformation invariance in CNNs is proposed by (Jaderberg et al., 2015) called Spatial Transformer networks. This model is built using 3 major components called a localisation network, grid generator and sampler to spatially transform feature maps. The localisation network in the model contains a feed-forward network which generates and learns the parameters of the spatial transformation that should be applied to the input feature map. A limitation of this technique is that it limits the number of objects that can be modelled in the feed-forward network. We refer to this work as another evidence of the use of small networks embedded with the CNN pipeline.

**Filter Pyramid:** Neuroscience models by (Poggio et al., 2014; Han et al., 2017; Dicarlo et al., 2012) essentially describe the vision system as having a conical neuronal architecture with increasing receptive field sizes in the form of an inverted pyramid of neurons. Visual stimuli processed by each horizontal slice of the neuronal pyramid allows the visual system to become robust to scale changes. Inspired by these models the approach of using differently sized convolutional filters in parallel to capture more context is increasingly being explored by researchers (Gong et al., 2014; Zagoruyko and Komodakis, 2015). Google's INCEPTION family of models uses this approach (Szegedy et al., 2015; Szegedy et al., 2016; Szegedy et al., 2017). Based on the INCEPTION model simi-

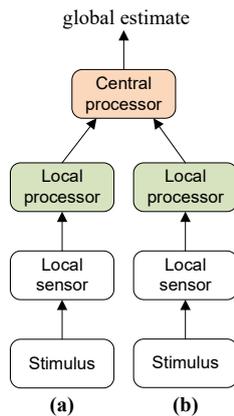


Figure 1: Distributed architecture adopted from (Zhang et al., 2016b). Dedicated local processors in each pipeline ((a) and (b)) compute local estimates which are then integrated by a central processor to obtain a global estimate.

lar models are proposed in (Liao and Carneiro, 2015; Wang et al., 2019). The FPC layer in D-Net adopts a similar approach as in the INCEPTION model. However what makes FPC different when compared to the original INCEPTION model (Szegedy et al., 2015) is a) FPC is uses much larger filters, b) is designed to operate on input images directly to capture global features and c) before filter concatenation, outputs from large filters are selectively maxpooled to generate uniform-sized feature maps. In a similar fashion, the use of maxpooling at the end of each parallel multi-scale pipeline makes FPC different when compared with competitive INCEPTION model and competitive multi-scale convolution model (Liao and Carneiro, 2015). In addition, FPC does not use Maxout (Goodfellow et al., 2013). Figure 2 shows the comparison of FPC with the INCEPTION family of models.

**Image and Feature Pyramid:** Pyramid based methods used to address scale-invariance in CNNs and can be categorised into image pyramids and feature map pyramids. For example, an image pyramid-based method is proposed by (Kanazawa et al., 2014) where they apply the same kernels on multi-scaled version of the target image. In another work (Xu et al., 2014) propose a scale-invariant CNN (SiCNN) by applying a similar process of convolving a filter on different image scales. (Lin et al., 2017) in their work develop lateral connections between the feature maps that are generated in deep convolutional networks through successive convolution and maxpooling operations. They argue connections between feature maps establish scale-invariance in the network as a change in an object’s scale is offset by shifting its level in the pyramid. (Kim et al., 2018; Zhao et al.,

2019; Kong et al., 2018; Yu et al., 2018) propose similar architectures. A commonality in these architectures is that features from different resolutions are fused by either concatenation or summation. What makes FPC different is that features from different resolutions are normalised by mandatory maxpooling operations except for the smallest-sized block of feature maps.

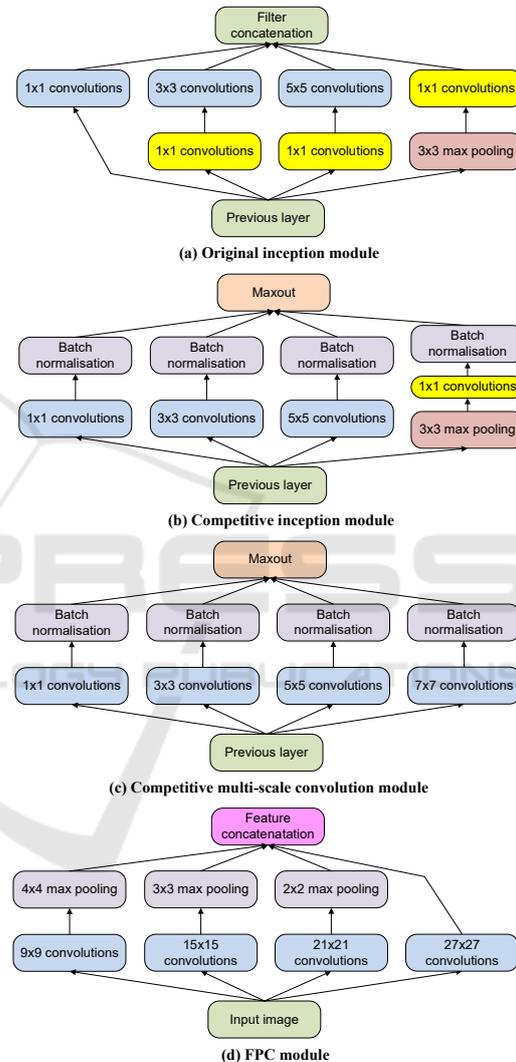


Figure 2: Comparison of FPC with INCEPTION family of models (Szegedy et al., 2015; Liao and Carneiro, 2015).

### 3 MODEL

In this section we propose a novel neural network model called D-Net that combines local features from CNN and global features from FPC. The design of D-Net is inspired by a) (Huang et al., 2017) who show that biological visual system utilizes global features

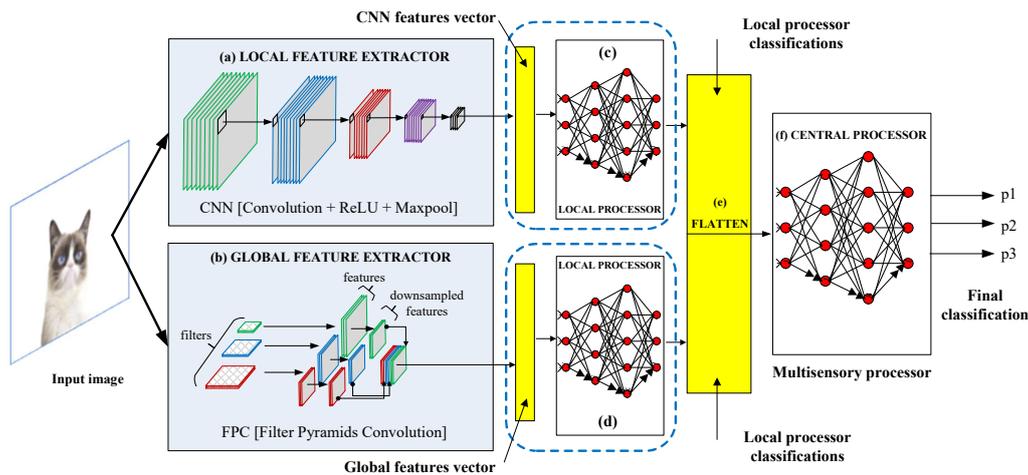


Figure 3: Architecture of D-Net which is explained in Section 3.

prior to local features in detection and recognition, b) (Poggio et al., 2014) who show the conical architecture of the visual system contains neurons packed in groups of different sizes in the form of an inverted pyramid of neurons and c) (Zhang et al., 2016b) who describe the distributed information integration architecture of the neural system. The ensemble D-Net model comprises of six main parts ((a)-(f)) as shown in Figure 3. They are explained in the following subsections.

### 3.1 Distributed Information Integration Model for CNNs (D-Net)

**Dual Pipeline Architecture:** The hallmark of D-Net is the dual channel pipeline in its architecture that enables integration of local processors and merging outputs in the central processor. The parallel pipelines are dedicated to extracting global and local features respectively. This design makes D-Net different from multi-scale parallel processing channels in CNNs such as in the INCEPTION family of models (Figure 2). Such models use a single linear feedforward processing channel despite the multi-scale channels. D-Net allows examination of input image data in two different aspects, in terms of its local and global features.

**Local Feature Extractor:** D-Net uses standard CNN as local feature extractor method. The operation of the CNN processes input image through several successive convolution, ReLU and maxpooling layers. The major advantage of CNN is the ability to process large datasets and extract features automatically, hence eliminating the need to manually extract features for learning. CNN uses lower layers to extract features such as lines and curves, while higher level

features may identify shapes relevant to the dataset such as actual digits, faces or natural objects. As such CNNs are widely used in image and video processing.

**Global Feature Extractor (FPC):** The FPC layer in D-Net contains multiple stacks of filters of varying sizes. This forms a pyramidal structure of stacked filters similar to the biological structure of the visual system proposed in (Poggio et al., 2014) and the INCEPTION model (Szegedy et al., 2015). The dimensions  $((k_h^0, k_w^0), (k_h^1, k_w^1), \dots, (k_h^n, k_w^n))$  of each filter in the stack is manually chosen where  $n$  is the number of filters in a stack and  $(k_h^0, k_w^0)$  is the largest filter. In addition, the size of each filter in the stack is determined by the output size of its resultant feature map  $((f_h^0, f_w^0), (f_h^1, f_w^1), \dots, (f_h^n, f_w^n))$  and where dimensions of feature maps  $(f^1, \dots, f^n)$  can become equal to  $f^0$  when pooled by an integer factor. Subsequently, sizes of other filters are identified using a similar process. For downscaling we use the technique of maxpooling.

**Local Processor:** In D-Net we use fully connected neural networks as local processors. The goal of local processor is to assimilate information flowing into it from each channel independently. In this way we can decentralise the learning of local and global features and obtain a reliable description for the underlying object of interest (image) in terms of information from the two modalities.

**Global Processor:** Information integration is facilitated by the central processor in D-Net. Here we represent the central processor by a fully connected neural network. Inputs in terms of local estimates from local processors feed into the central processor and are integrated to reach the final global estimate.

The probabilistic outputs from the central processor become the final classification results of D-Net.

### 3.2 D-Net Forward Propagation

Our goal is to combine extracted features from CNN and FPC for learning in distributed local processors and integrate the outcomes in the central processor. To achieve the forward pass function, an input image is processed in the local (CNN) and global feature extractor (FPC) pipelines respectively. The CNN part of the network obtains local-global features as output. Meanwhile in FPC, multi-scale filters produce multi-scale outputs. They are pooled to generate a set of uniform-sized downsampled feature maps which are concatenated and returned as final outputs of FPC. Both CNN and FPC outputs are then forward propagated through the respective local processors. Finally, *classification* outputs from local processors are combined and reshaped into a vector form in the flatten layer (Figure 3 (e)). This vector forms the input to fully connected neural network central processor in D-Net (Figure 3 (f))

### 3.3 D-Net Backward Propagation

Model loss is calculated on the outputs of the central processor. The backward function in the flatten layer receives gradients from the central processor. Since there are two pipelines in D-Net, the flatten layer returns two sets of gradients - CNN gradients and FPC gradients. The backward function in FPC layer takes the FPC gradients and updates the multi-scale filter weights in the respective filter pyramids. In a similar fashion CNN gradient are back propagated in the local feature extractor pipeline using chain rule derivative algorithm as well.

## 4 THE EXPERIMENTS

We describe the datasets, D-Net model component architectures and our experimental design in the following sub-sections.

### 4.1 Dataset Descriptions

We test D-Net on both color and grey-scale images. In practice color images are preferred, however we wish to ascertain the effectiveness of D-Net on both. For color images we use the CIFAR10 dataset (described in (Krizhevsky et al., 2009)). For grey-scale images we use the Fashion-MNIST dataset (FMNIST) (described in (Xiao et al., 2017)). Both datasets have 10

Table 1: Architecture of FPC in D-Net.

# of pyramids	16
# of filters in pyramid	4
<b>On CIFAR10 dataset</b>	
Sizes of filters in pyramid	(9x9), (15x15), (21x21), (27x27)
Final Output size	(64x6x6)
<b>On FMNIST dataset</b>	
Sizes of filters in pyramid	(5x5), (11x11), (17x17), (23x23)
Final Output size	(64x6x6)

classes and have equal distribution of samples in each class.

### 4.2 CNN and FPC Architectures

**CNN:** For benchmarking and local feature extractor part of D-Net we used LeNet5 CNN structure as proposed by (LeCun et al., 1998).

**FPC Parameters:** Table 1 describes the architecture of FPC in terms of filter sizes in each filter pyramid and the number of filter pyramids used. Since the dimensions of images in CIFAR10 and FMNIST dataset are different, filter sizes are adjusted accordingly.

**Local and Central Processor Networks:** Table 2 describes the layers present in our distributed processing modules. The fully connected neural networks comprise of two hidden layers. This is in line with suggestions by (Heaton, 2008) that a) two hidden layers can represent functions with any kind of shape and b) the optimal size of the hidden layer is recommended to be between the size of its input and output.

### 4.3 Training Process

End-to-end training was performed on all models. For networks trained on both CIFAR10 and FMNIST datasets we start with a warm-up strategy for 4 epochs with a learning rate of  $10^{-2}$ ,  $10^{-3}$  from epochs 5 – 50 and decreasing it to  $10^{-4}$  for the rest of training. Training on all models were stopped at 100 epochs. Stochastic gradient decent and cross-entropy were used as learning and loss function respectively. We use weight decay of  $10^{-4}$  and momentum of 0.9. For training we use batch size of 8 and 4 for testing. We implement our models using PyTorch version 1.2.0 on a Dell Optiplex i5 48GB RAM computer with Cuda support using NVIDIA GeForce GTX 1050 Ti 4GB graphics card.

Table 2: Layers in the distributed information processors.

Processor	Layers
Local (c)	(fc 480) $\rightarrow$ (relu) $\rightarrow$ (fc 84) $\rightarrow$ (relu)
Local (d)	(fc 2304) $\rightarrow$ (relu) $\rightarrow$ (fc 400) $\rightarrow$ (relu)
Central (f)	(fc 20) $\rightarrow$ (relu) $\rightarrow$ (fc 12) $\rightarrow$ (softmax)

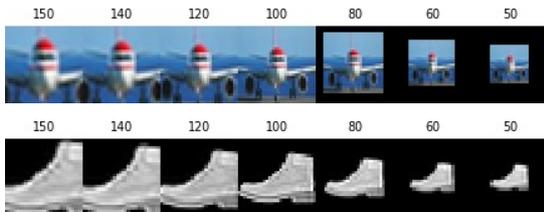


Figure 4: An example of scaled test image from datasets CIFAR10 - airplane (*top*) and FMNIST - ankle boot (*bottom*). The numbers indicate percentage image is scaled to. 100 indicates no scaling.

#### 4.4 Scaled Images for Testing

We establish 7 scale categories - [150, 140, 120, 100, 80, 60, 50] to test our models. The numbers indicate percentage an image is scaled to. In this paper we consider both reduction and enlargement of image size from the original. We select at random 100 images per class from the datasets. These images are scaled as per the scale category percentages. In this fashion for a single test image of a class we generate 7 scaled test images amounting to 1000 scaled images per scale category. We further combine images from all 7 scale categories into an *ensemble* scale dataset resulting in 7000 scaled images combined. We analyse our models on scaled images from each of these scale categories independently (Section 5.2) as well as on the ensemble dataset. Figure 4 shows an example image from each dataset and its corresponding scaled versions for testing.

#### 4.5 Evaluation Metrics

We use metrics *accuracy* to analyse results of D-Net on scale categories. Accuracy is an intuitive performance measure to simply evaluate the generalisation capability D-Net by finding out the total number of scaled images that were correctly classified in the respective scale categories.

## 5 RESULTS AND DISCUSSION

### 5.1 Comparing Train and Test Statistics on Regular Images

Table 3 compares the train losses and test accuracy for all networks used in our experiments on regular images from the test datasets. These are evaluations on images that have not been subjected to any form of scale transformations. Our ensemble D-Net model outperforms the traditional LeNet5 network on all train and test metrics (indicated in bold). We record lower train losses on D-Net networks on both datasets. The highest test accuracy increases of 5.3% is recorded on D-Net combining LeNet5 and FPC on CIFAR10 dataset. Similarly, we record a 1.0% increase in test accuracy on FMNIST dataset. These baseline results provide some evidence that combining global feature information in network training is useful in improving the overall generalisation capability of the models studied, more so on color images.

### 5.2 Improvements on Classification of Scaled Images

The classification results of our models on different scale categories and on different datasets can be viewed in Table 4. The column *hit-rate* indicates the number of scale categories D-Net outperformed the benchmark. For purposes of our study hit-rate of  $\geq 60\%$  is desirable, that is D-Net should at least perform better on 60% of the scale categories compared to the benchmark LeNet5 only network. Since the ensemble test dataset combines all scaled images in one batch it is excluded from this ratio. Classifications accuracies are obtained by testing the studied models on scaled images from each scale category. Our results show D-Net using LeNet5 with FPC performed better on most scale categories, where hit rate achieved is greater than 60% on both datasets. This means D-Net was able to identify a high number of samples from most scale bins in its correct class despite the images being scale transformed.

We compare accuracy scores of D-Net with LeNet5 on upscaled images (categories 150, 140, 120). For these categories on CIFAR10 dataset average D-Net accuracy score is 5.0% higher than LeNet5. A similar performance of D-Net over LeNet5 on FMNIST dataset is shown where average accuracy is 1.5% higher. Comparing accuracy scores on downscaled images (categories 80, 60, 50), we note promising performance of D-Net over LeNet5 on both datasets. Here average accuracy score is

Table 3: Train losses and test accuracy for all models used in our experiments.

Model	train loss CIFAR10	test acc CIFAR10	difference	train loss FMNIST	test acc FMNIST	difference
LeNet5	1.734	0.568		1.535	0.899	
D-Net	<b>1.692</b>	<b>0.621</b>	<b>-0.042 (loss)</b> <b>+5.3% (acc)</b>	<b>1.527</b>	<b>0.909</b>	<b>-0.008 (loss)</b> <b>+1.0% (acc)</b>

Table 4: Performance summarization (accuracy) of the studied models on all the scale categories.

Model	metric	scale categories								
		ensemble	150	140	120	100	80	60	50	hit rate
<b>CIFAR10 dataset</b>										
LeNet5	acc	0.381	0.449	0.478	0.531	0.577	0.265	0.217	0.149	
D-Net		<b>0.419</b>	<b>0.481</b>	<b>0.532</b>	<b>0.594</b>	<b>0.637</b>	<b>0.277</b>	0.214	<b>0.195</b>	0.857 (6/7)
<b>FMNIST dataset</b>										
LeNet5	acc	0.611	0.575	0.654	0.785	0.895	0.703	0.373	0.295	
D-Net		<b>0.629</b>	0.570	<b>0.685</b>	<b>0.804</b>	<b>0.922</b>	<b>0.712</b>	<b>0.410</b>	<b>0.303</b>	0.857 (6/7)

higher by 1.8% and 2.0% in favour of D-Net on CIFAR10 and FMNIST datasets respectively. Scale category 100 is where images are in their original state (unscaled). In this category test accuracy of D-Net surpasses benchmark LeNet5 by 6.0% on CIFAR10 dataset and by 2.7% on FMNIST dataset.

Further, higher D-Net accuracy scores over LeNet5 are recorded on all combined scaled images in the ensemble test dataset. In this the best D-Net performance is shown on CIFAR10 dataset where accuracy is higher by 3.8% than LeNet5. This equates to 266 more images classified correctly from the total 7000 samples in the ensemble dataset compared to LeNet5 only network.

From the above analysis we arrive at two observations. First, distributed information processing and integration has a positive impact on improving CNNs ability to classify scaled images. Second, we note in general accuracy scores of both D-Net and LeNet5 decline as images are blown-up as well as reduced in size. In other words, the classification accuracy of images closer to original image dimensions are higher. This shows CNN based architectures are task specific where they perform well when deviations in test images from the learnt samples are small.

## 6 CONCLUSION

In this paper we propose a novel model to improve classification of scaled images in CNNs by fusing global and local features in a distributed information integration neural network architecture called D-Net. We study the effects of using global features on image classification by combining FPC and CNN features and testing on scaled images. Our experimen-

tal results indicate using distributed information integration architecture with CNNs is an effective way to combine information from different modalities. We conclude adding global feature information in CNN models are beneficial in addressing scaled images.

Problems and opportunities that require further investigations are a) to evaluate other downsampling methods in FPC such as using interpolation instead of max pooling, b) test this technique to evaluate other forms of transformations such as rotations and translations, c) apply FPC layer with other benchmark network configurations using larger and more complex datasets and d) experiment distributed processors with other classifiers such as Support Vector Machines (SVM). Finally making CNNs learn features which are invariant to transformation remains a challenge and thus requires further investigation.

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