Meta-learning of Pooling Layers for Character Recognition

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Abstract. In convolutional neural network-based character recognition, pooling layers play an important role in dimensionality reduction and deformation compensation. However, their kernel shapes and pooling operations are empirically predetermined; typically, a fixed-size square kernel shape and max pooling operation are used. In this paper, we propose a meta-learning framework for pooling layers. As part of our framework, a parameterized pooling layer is proposed in which the kernel shape and pooling operation are trainable using two parameters, thereby allowing flexible pooling of the input data. We also propose a meta-learning algorithm for the parameterized pooling layer, which allows us to acquire a suitable pooling layer across multiple tasks. In the experiment, we applied the proposed meta-learning framework to character recognition tasks. The results demonstrate that a pooling layer that is suitable across character recognition tasks was obtained via meta-learning, and the obtained pooling layer improved the performance of the model in both few-shot character recognition and noisy image recognition tasks.

Keywords: Convolutional neural network · Pooling layer · Meta-learning · Character recognition · Few-shot learning.

1 Introduction

In convolutional neural network (CNN)-based character recognition, pooling layers play an important role in dimensionality reduction and deformation compensation. In particular, the max and average pooling layers, as illustrated in Figs. 1(a) and (b), respectively, are widely used in CNNs. These pooling operations are effective in absorbing the deformations that occur in character images. Even if the convolutional features undergo local changes owing to the deformation of the character image, the dimensionally-reduced feature map is invariant to such changes. As a result, a CNN with pooling layers is robust to character image deformation.

Nevertheless, typical pooling layers have a limitation in that the kernel shape and pooling operation should be determined empirically and manually. In the pooling layers,
pooling operations are performed by sliding a fixed-size kernel, and the kernel size is predetermined as a hyperparameter. In two-dimensional pooling, the shape of the kernel is fixed to a square generally. Although various pooling operations have been proposed [20, 12, 25, 32, 23], the type of pooling operation is chosen manually, and the same operation is performed in the layer.

The purpose of this study is to determine a pooling layer suitable for character recognition tasks in a data-driven approach. Although max and average pooling layers with fixed-size square kernels are generally used in tasks using character images, it is unknown whether this is in fact appropriate. If we can obtain a suitable pooling layer across multiple tasks using character images, we can apply it to subsequent new tasks using character images, thereby leading to improvements in recognition accuracy.

For this purpose, we utilize meta-learning. Meta-learning aims to improve the learning performance of a machine learning model by providing datasets of multiple tasks and then acquiring knowledge shared among the tasks. Specifically, hyperparameters, such as a learning rate and initial weights, that are suitable across all the tasks are obtained via meta-learning. As a result, the meta-learned model can improve its learning efficiency when a new task is given.

In this paper, we propose a meta-learning framework for pooling layers. As part of the framework, a parameterized pooling layer is proposed in which the kernel shape
and pooling operation can be trained using two parameters, thereby allowing flexible pooling of the data. We also propose a meta-learning algorithm for the parameterized pooling layer, which allows us to acquire a suitable pooling layer across multiple tasks.

Fig. 1 illustrates an example of a pooling layer obtained under our framework, alongside its comparison with max and average pooling layers. In the traditional max and average pooling layers shown in Figs. 1(a) and (b), respectively, fixed-size square kernels are used, and the same operation is performed in each kernel. In contrast, in the pooling layer meta-learned in our framework, flexible kernel shapes are used. Furthermore, the operation in each kernel is defined based on $L_p$ pooling [27], which means various types of operations, including max and average pooling, can be realized depending on the value of $p$.

In the experiments, we reveal what pooling layer is suitable for character recognition tasks in a data-driven approach and demonstrate that the obtained pooling layer improves the learning performance of a CNN for a subsequent new task. Fig. 2 shows the flow of the proposed method applied to the meta-learning of character image recognition. First, we prepare a meta-dataset containing a large number of character recognition tasks and apply the proposed meta-learning framework to a pooling layer in a CNN, as shown in Fig. 2(a). In this step, a pooling layer suitable for multiple character recognition tasks can be obtained. Then, the CNN with the meta-learned pooling layer is adapted to a new task (Fig. 2(b)).

The main contributions of this study can be summarized as follows:

- We propose a meta-learning framework for pooling layers. As part of the proposed framework, a parameterized pooling layer is proposed to make the kernel shape and pooling operation trainable. A meta-learning algorithm for the parameterized pooling layer is also presented.
- We reveal a pooling layer suitable for character recognition tasks in a data-driven manner. We prepare a large number of character image recognition tasks using the Omniglot dataset [17] and then apply the proposed meta-learning framework to these tasks. After meta-learning, we analyze the obtained kernel shapes and pooling operations by visualizing the meta-parameters of the parameterized pooling layer. The results demonstrate that the meta-learned pooling layer applies max pooling around the character region in an annular shape.
- We demonstrate the effectiveness of the meta-learned pooling layer for few-shot character image recognition and noisy character image recognition tasks. The meta-learned pooling layer is effective in improving accuracy for one-shot character image recognition compared to max and average pooling layers. The robustness to noisy images is also remarkably improved by the proposed method.

2 Related Work

2.1 Pooling Layers

In recent years, many pooling methods have been proposed and have demonstrated remarkable performance in specific tasks. Gao et al. [10] proposed a global second-order pooling (GSoP) block which can be used to calculate the second-order information in
Fig. 2: Meta-learning flow. The flow of the proposed framework is divided into two steps: (a) First, the kernel shapes and pooling operations of the parameterized pooling layer are trained via meta-learning. By learning the pooling layer from a large number of tasks, we can acquire knowledge across all tasks. At this time, the parameters of the other layers are updated once for each task batch, and their gradients are used in the meta-learning of the parameterized pooling layer, whereas the updates of the other layers themselves are not used in the subsequent step. (b) Then, the meta-learned pooling layer is adapted to a new task. In this step, with the meta-learned pooling fixed, the parameters of the remaining layers are trained using the training dataset of the new task. Next, with all parameters fixed, the trained model is adapted to the new task by classifying the test data.
but narrow kernel. They demonstrated that short-range and long-range dependencies among different locations can be captured simultaneously by combining a strip pooling module with a pyramid pooling module (PPM) \cite{34} in semantic segmentation tasks.

Instead of utilizing a specific pooling operation, some trials have been aimed to generalize pooling operations for global use. A representative example is $L_p$ pooling \cite{27, 2}, which calculates an $L_p$-norm over the input elements. Consequently, $L_p$ pooling involves average pooling when $p = 1$ and max pooling when $p \to \infty$, and it can perform pooling operations between average and max pooling using $1 < p < \infty$ without completely eliminating the influence of input elements with small values. Another example is generalized mean pooling (GeM) \cite{5, 29, 2}, which is a generalization of average pooling and consequently has a similar operation to $L_p$ pooling. A pooling method that can automatically enhance important features by learning has also been proposed \cite{33, 17}.

The proposed method is inspired by the attempts to generalize pooling operations. In particular, the formulation of the proposed method is an expansion of $L_p$ pooling. The proposed method differs from $L_p$ pooling in that the kernel shape is trainable. Another difference from conventional trainable pooling methods is that the proposed method learns suitable pooling across multiple tasks, instead of a single task, based on meta-learning.

2.2 Meta-learning

Meta-learning aims to learn knowledge shared across multiple tasks to adapt the model to another subsequent task given with a small amount of training data or few learning steps. According to Baik et al. \cite{1}, meta-learning algorithms can be divided into three categories: network-based, metric-based, and optimization-based. Network-based methods learn a fast adaptation strategy using auxiliary networks \cite{26, 21}. Metric-based methods learn the relationships between inputs in the task spaces and acquire object metrics or distance functions to facilitate problem solving \cite{3, 30, 28}. Optimization-based methods adjust the optimization algorithm so that the model can be adapted to several tasks \cite{8, 1, 24, 35}.

Among existing optimization-based meta-learning algorithms, model-agnostic meta-learning (MAML) \cite{8} has attracted much attention because of its simplicity and generality. MAML encodes prior knowledge so that the model can perform well across tasks and learn new tasks rapidly. Some studies have aimed to improve the performance of MAML while maintaining simplicity and generality. Rusu et al. \cite{24} proposed an approach that learns an embedding of the model parameters into a low-dimensional space and conducts meta-learning in that space, achieving more efficient adaptation. Baik et al. \cite{11} improved the MAML-based framework by attenuating the conflicts among tasks and layers, thereby improving its performance in few-shot learning. Some researchers have attempted to extend MAML. Zhou et al. \cite{35} introduced a method called meta-learning symmetries by reparameterization (MSR) for meta-learning neural network architectures. They showed that MSR can learn symmetries shared among tasks from data based on meta-learning and reparameterization of network weights.

Although the algorithm of the proposed method is inspired by MAML and MSR, the proposed algorithm differs from the above optimization-based meta-learning algorithms
in that meta-learning is applied to the pooling layer while considering the gradients of other layers. To the best of our knowledge, this is the first attempt in adopting meta-learning in the pooling layer. Another unique feature of the proposed algorithm is that the kernel shape matrix is learned with a constraint to be binary.

3 Meta-learning of Pooling Layers

In this section, we present our meta-learning framework for pooling layers. To make pooling layers trainable, we first introduce a parameterized pooling layer, wherein the shape and operation of each kernel are trained individually. We then describe the meta-learning algorithm of the parameterized pooling layer.

3.1 Parameterized Pooling Layer

The purpose of the proposed method is to acquire the knowledge shared across multiple tasks, thereby developing a pooling layer that can be efficiently applied to new tasks. By parameterizing the pooling layer and making it trainable, flexible determination of kernel shapes and pooling operations can be achieved.

The parameterized pooling layer has two (meta-)parameters that are trained via meta-learning. One is a kernel shape matrix, $W$, with binary elements that determines the area in which the pooling operation is applied. By multiplying $W$ with the input vector/image, various types of kernel locations and shapes can be realized, including the sliding square kernels of ordinary pooling. The other is an operation parameter, $p$. The parameterized pooling layer is based on $L_p$ pooling, where the pooling operation in each kernel is defined by the $L_p$ norm. Incidentally, $L_p$ pooling is a generalization of pooling operations that includes max pooling (when $p \to \infty$) and average pooling (when $p = 1$). Whereas the value of $p$ in $L_p$ pooling is determined empirically, the value of $p$ in the proposed method is automatically determined via meta-learning.

Given an input vector $x \in \mathbb{R}_+^J$, the parameterized pooling layer $f : \mathbb{R}_+^J \to \mathbb{R}_I^1$ ($J \geq I$) is defined as follows:

$$f_i(x) = \left( \frac{1}{J} \sum_{j=1}^{J} W_{ij} x_j^p \right)^{1/p}, \quad i = 1, \ldots, I,$$  

(1)

where $W \in \{0, 1\}^{I \times J}$ is the kernel shape matrix, $p \in \mathbb{R}_+^I$ is the operation parameter, and $J$ and $I$ are the input and output dimensions, respectively. Although the assumption that the input elements are positive is relatively strong, in practice, it can be satisfied by applying a rectified linear unit (ReLU) activation function to the previous layer.

The parameterized pooling layer can also be applied to an image input, as with conventional pooling layers. One simple method is to vectorize the image input by raster scanning before inputting the data to the parameterized pooling layer. Another method is to combine equation (1) and sliding windows. Taking a small window in the input image, we vectorize the pixels in the window and prepare independent $W$ and $p$ for each window. Then, we apply equation (1) to the entire image while shifting the window...
Meta-learning of Pooling Layers for Character Recognition

Algorithm 1 Meta-learning of the parameterized pooling layer

Inputs: \( \{\tau_j\}_{j=1}^N \sim \rho(\tau) \): Meta-learning tasks
Inputs: \( \{W, p\} \): Randomly or arbitrarily initialized meta-parameters
Inputs: \( \theta \): Randomly initialized weights of other layers
Inputs: \( \alpha, \eta \): Learning rates for the inner and outer loops

while not done do
    Sample minibatch \( \{\tau_i'\}_{i=1}^n \sim \{\tau_j\}_{j=1}^N \)
    for \( \tau_i' \in \{\tau_i'\}_{i=1}^n \) do
        \( \{D_{tr}^i, D_{val}^i\} \leftarrow \tau_i' \); // task data
        \( \delta_i \leftarrow \nabla_\theta L(W, p, \theta, D_{tr}^i) \);
        \( \theta' \leftarrow \theta - \alpha \delta_i \); // inner step
        \( G^w_i \leftarrow \frac{\partial}{\partial W} L(W, p, \theta', D_{val}^i) \), \( G^p_i \leftarrow \nabla_p L(W, p, \theta', D_{val}^i) \);
    end for
    \( W \leftarrow W - \eta \sum_i G^w_i \), \( p \leftarrow p - \eta \sum_i G^p_i \);
end while

across the image. In practice, the latter method is computationally advantageous; therefore, we employed it in our experiments using image inputs, as reported in Sections 4 and 5.

To maintain the binariness of \( W \) and positiveness of \( p \), we employ the following variable transformation:

\[
W_{ij} = \begin{cases} 
\text{Sigmoid}((\bar{W}_{ij} - 0.5)/T) & \text{during meta-learning} \\
\text{Step}(\bar{W}_{ij} - 0.5) & \text{otherwise} 
\end{cases}, \quad (2)
\]

\[
p_i = \exp(\bar{p}_i), \quad (3)
\]

where \( \text{Sigmoid}(\cdot) \) is the sigmoid function, \( T \) is a temperature parameter, \( \text{Step}(\cdot) \) is the unit step function, which returns 0 for a negative input and 1 otherwise, and \( \bar{W}_{ij}, \bar{p}_i \in \mathbb{R} \) are auxiliary variables. The step function is used to make \( W \) binary, but it is not differentiable; therefore, the sigmoid function is used as an approximation during meta-learning to enable gradient calculation. For \( p \), the exponential function is used to satisfy \( p_i > 0 \). In the meta-learning algorithm described below, the gradients are calculated with respect to the auxiliary variables \( \bar{W}_{ij} \) and \( \bar{p}_i \). However, in the following sections, we will explain as if we deal directly with \( W_{ij} \) and \( p_i \) instead of \( \bar{W}_{ij} \) and \( \bar{p}_i \) for simplicity.

3.2 Meta-learning Algorithm

The aim of the meta-learning of pooling is to learn and exploit a pooling layer that is suitable for multiple tasks. Given a task distribution \( \rho(\tau) \), we assume that there is an optimal pooling layer that is shared across \( \rho(\tau) \), and we estimate it by learning meta-parameters \( W \) and \( p \) through meta-learning.

Algorithm 1 shows the meta-learning algorithm of the parameterized pooling layer. The algorithm is a gradient-based meta-learning algorithm similar to MSR [35] and
MAML algorithms. Assuming that we have a neural network with a parameterized pooling layer as well as other layers with weights $\theta$, the meta-parameters $W$ and $p$ are updated during the meta-learning algorithm. Note that even if there are multiple parameterized pooling layers in a neural network, we can independently apply this algorithm to each one.

This algorithm consists of inner and outer loops. The inner loop calculates gradients and is nested in the outer loop, which updates the meta-parameters. In the outer loop, a task minibatch $\{\tau'_i\}_{i=1}^n$ is first sampled from the task set $\{\tau_j\}_{j=1}^N$, where $n$ and $N$ are the minibatch size and number of tasks, respectively. The task minibatch is then split into training and validation data $\{D_{tr}^{i}, D_{val}^{i}\}$ for any $\tau'_i$. Proceeding to the inner loop, the parameters of other layers $\theta$ are updated as

$$
\theta' \leftarrow \theta - \alpha \nabla_{\theta} L(W, p, \theta, D_{tr}^{i}),
$$

where $L(\cdot)$ is the loss function and $\alpha$ is the learning rate for the inner loop. After calculating the gradients with respect to the meta-parameters using the updated $\theta'$ and validation data, the meta-parameters are updated in the outer loop as follows:

$$
W \leftarrow W - \eta \sum_i \frac{d}{dW} L(W, p, \theta', D_{val}^{i}),
$$

and

$$
p \leftarrow p - \eta \sum_i \nabla_{p} L(W, p, \theta', D_{val}^{i}),
$$

where $\eta$ is the learning rate for the outer loop.

### 4 Experiment on Artificial Data

To verify the validity of the proposed method, we conducted an experiment using artificially generated data. The goal of this experiment is to verify whether the proposed method can meta-learn the kernel shapes and pooling operations from a task set that is generated by passing random vectors or images through a certain pooling layer.

Fig. 3 outlines the data generation process for this experiment. We prepared datasets for one-dimensional and two-dimensional cases. For the one-dimensional case (Fig. 3(a)), we generated sets of inputs and outputs by passing random input vectors, whose elements were generated from a uniform distribution over $[0, 1]$, through a 1D pooling layer with a filter size of 2 and a stride of 2. For the two-dimensional case (Fig. 3(b)), we generated sets of inputs and outputs by passing a random image, in which each pixel value was generated from a uniform distribution over $[0, 1]$, through a 2D pooling layer with a filter size of $2 \times 1$ (vertical rectangle) and a stride of 2. Here, the pooling layer consisted of max pooling for the first half and average pooling for the second half. Each task contains 20 sets of input and output vectors/images, and we generated 8,000 training tasks. We set the dimensions of the input and output data to 60 and 30 in the one-dimensional case, and $28 \times 28$ and $14 \times 14$ in the two-dimensional case, respectively.

In the meta-learning, we used a neural network with only a single parameterized pooling layer. We set the task batch size to 32 and the number of epochs in the outer loop to 10,000, which was sufficient to converge the training. The data in each task were split into 1 training sample and 19 validation samples. In the outer loop, we used...
Fig. 3: Data generation process for the experiment using artificial data. (a) In the one-dimensional case, a set of input and output data was generated by passing a random vector through a 1D pooling layer with a kernel size of 2 and stride of 2. (b) In the two-dimensional case, a random image was passed through a 2D pooling layer with a kernel size of $2 \times 1$ and stride of 2, i.e., pooling with a vertical rectangular kernel was performed for every other column. In both cases, max pooling was used in the first half, and average pooling was used in the second half.

The Adam [16] optimizer with a learning rate of 0.001. The temperature parameter $T$ was set to 0.2. In the inner loop, $W$ and $p$ themselves were updated only once instead of $\theta$ because the network used in this experiment did not have any layer other than pooling, and the stochastic gradient descent (SGD) optimizer with a learning rate of 0.1 was used. We used the mean squared error as the loss function. After meta-learning, we observed the learned meta-parameters $W$ and $p$.

Figs. 4 and 5 show the learned meta-parameters $W$ and $p$ for the one-dimensional and two-dimensional artificial data, respectively. In Fig. 4(a), higher values are concentrated on the diagonal parts of $W$, demonstrating that the parameterized pooling layer successfully learned the kernel shape with a size of 2 and stride of 2. It can also be confirmed that $p$ takes large values in the first half and approximates 1 in the second half, meaning that the max and average pooling operations are also learned approximately. In Fig. 5(a), the pooling pattern with a kernel size of $2 \times 1$ and stride of 2 was reproduced. The pooling operations with max pooling in the first half and average pooling in the second half were also correctly estimated as shown in Fig. 5(b).

These results demonstrate that the proposed method can learn the kernel shapes and pooling operations in a data-driven manner. In this experiment, we used a network with only a parameterized pooling layer for simplicity. We have also confirmed that the parameterized pooling layer can be meta-learned in a network that includes other layers, such as convolutional and fully connected layers, but these results are omitted due to page limitations. In the next section, we describe experiments using character images with a network that includes other layers besides a parameterized pooling layer.
Fig. 4: Learned meta-parameters $W$ and $p$ in the simulation experiment on one-dimensional artificial data. In (a), the black and white pixels represent 0 and 1, respectively. The numbers of columns and rows correspond to the input and output dimensions, respectively.

5 Experiment on Character Datasets

To evaluate the effectiveness of the proposed method on real-world datasets, we conducted a character image recognition experiment. The aim of this experiment is twofold: One is to determine a pooling layer suitable for character recognition tasks in a data-driven manner, and the other is to evaluate the generalization capability of the meta-learned pooling for new tasks. For the former, we first prepared a CNN that includes a parameterized pooling layer. Then, we meta-learned the parameterized pooling layer using multiple character recognition tasks. After that, we analyzed the learned meta-parameters of the pooling layer, which can be regarded as the kernel shapes and pooling operations that are suitable across multiple tasks. For the latter, we evaluated the model using tasks that were not given during the meta-training. Based on the assumption that the proposed meta-learning of pooling can obtain the knowledge shared across multiple datasets, meta-learned pooling will improve the generalization capability of the model for subsequent new tasks. Therefore, we evaluated the model with the meta-learned pooling layer based on few-shot image recognition and noisy image recognition tasks. Fixing the meta-parameters, we trained the weights of the remaining layers and evaluated the entire model.

5.1 Dataset

We used the Omniglot dataset [17], which is a standard benchmark dataset of handwritten character images. Examples from the Omniglot dataset are shown in Fig. 6. In particular, this dataset is frequently used in few-shot learning tasks [30] [6] [13]. In this study, we used this dataset to meta-learn a suitable pooling layer for multiple character recognition tasks and evaluate the meta-learned pooling in few-shot and noisy image recognition tasks. The Omniglot dataset consists of 20 instances of 1,623 characters.
Fig. 5: Learned meta-parameters \( W \) and \( p \) in the simulation experiment on two-dimensional artificial data. In (a), the black and white pixels represent 0 and 1, respectively.

Fig. 6: Example images from the Omniglot dataset. Pixel colors were inverted from the original images.

From 50 different alphabets, and each instance was depicted by a different person. In this experiment, we randomly selected 1,200 characters for meta-learning regardless of the alphabet, and used the remaining 423 characters for few-shot and noisy image recognition tasks. We used the images after inverting pixel colors. We applied data augmentation by rotating the images by 90, 180, or 270 degrees.

5.2 Experimental Setups

Through the experiment, we used the same network architecture. The network consisted of a \( 3 \times 3 \) convolutional layer with 64 filters, batch normalization \([14]\), ReLU activation functions, a \( 2 \times 2 \) parameterized pooling layer, and a fully connected layer with a softmax activation function. In the parameterized pooling layer, sliding windows with a size of \( 2 \times 2 \) and a stride of 2, i.e., no overlap between windows, were used. The temperature parameter \( T \) was set to 0.2.

After meta-learning, we conducted few-shot recognition and noisy image recognition tasks. In the few-shot recognition task, the model classified images into one of five classes (five-way recognition) given either one or five images as the training data (one-shot or five-shot, respectively). Among the 423 character classes that were not used in the meta-learning, five classes were randomly sampled 100 times with duplication to
generate 100 five-way recognition tasks. In each task, one or five images were used to
train the weights of the convolutional and fully connected layers, and the remaining
images were used as test data to evaluate the recognition accuracy. In the noisy image
recognition task, we reused the network weights obtained in the few-shot recognition
tasks and evaluated the recognition accuracy by adding salt-and-pepper noise to the test
data. We varied the noise ratio in the interval of 10–60%.

In the meta-learning, the number of task batches was set to 32, and the images in
each batch were split into 1 for training and 19 for validation in the one-shot setting
and 5 for training and 15 for validation in the five-shot setting. We used the Adam
optimizer with a learning rate of 0.001 for the outer loop and the SGD optimizer with
a learning rate of 0.1 for the inner loop. The numbers of epochs for inner and outer
loops were set to 1 and 10,000, respectively. The initial weights of the convolutional
and fully connected layers were determined based on the MAML algorithm [8] using
the meta-learning dataset.

For comparison, we prepared two networks with the parameterized pooling layer
replaced with either a max or average pooling layer. The results of the few-shot recog-
nition and noisy image recognition tasks were compared to those of the prepared net-
works. The initial weights of these networks were also determined based on the MAML
algorithm.

5.3 Results

The learned meta-parameters \( W \) and \( p \) are shown in Fig. 7. According to the kernel
shape matrix \( W \), the proposed pooling layer learned to extract the annular-shaped area
around the region where the character is written. Surprisingly, it did not focus on the
center of the image. From the result of \( p \), max pooling was applied around the character
region, whereas average pooling was used in other regions. The annular shape observed
in both \( W \) and \( p \) occurred because the character was not always written in the exact
center of the image in the Omniglot dataset, and the essential information existed in
somewhat peripheral regions. Furthermore, the white annulus in \( W \) was thicker than
the red annulus in \( p \), indicating that max pooling was learned at the outer edge of the
annulus to distinguish the character from the background, and average pooling was
used in the area near the character to mitigate the effect of noise in the same manner as
a linear filter.

Table 1 lists the recognition accuracies for each pooling method in the one-shot
and five-shot settings. As can be seen, the proposed meta-learned pooling showed the
best performance in the one-shot setting, whereas max pooling outperformed ours in
the five-shot setting. These results indicate that the proposed method is particularly
effective when the training data are extremely limited.

The results of noisy image recognition are presented in Fig. 8. The figures show the
accuracy of each method with varying noise ratio. The proposed method outperformed
max and average pooling when the noise ratio was large. Fig. 9 exhibits the pooling
features for each pooling operation when the noise ratio was 10%. The figures display
a randomly selected channel out of 64 channels for five examples of test images. It was
confirmed that the max pooling features excessively emphasized noise, and the average
pooling produced blurred features due to noise. In contrast, the proposed method could
Fig. 7: Learned meta-parameters on the Omniglot dataset. (a) Kernel shape matrix $W$ and (b) operation parameter $p$. In (a), the black and white pixels represent 0 and 1, respectively. These meta-parameters were learned using non-overlapping sliding windows with a size of $2 \times 2$ and a stride of 2. These figures were depicted by placing the learned parameters at the corresponding positions.

Table 1: Accuracies in the few-shot character recognition task.

| Pooling Operation          | Accuracy (%) |
|----------------------------|--------------|
|                            | One-shot  | Five-shot |
| Max pooling                | 90.52 ± 0.68 | **97.3 ± 0.92** |
| Average pooling            | 90.25 ± 0.81 | 97.0 ± 0.93 |
| Meta-pooling (proposed)    | **93.16 ± 0.83** | 96.5 ± 0.69 |

acquire relatively clean pooling features that preserved the strokes of the characters. These results suggest that the proposed method can learn a pooling layer with a high generalization capability, thus resulting in robustness to noise.

6 Conclusion

In this paper, we proposed a meta-learning method for pooling layers. As part of our meta-learning framework, we proposed a parameterized pooling layer in which the kernel shape and pooling operation are trainable using two parameters, thereby allowing flexible pooling of the input data. We also proposed a meta-learning algorithm for the parameterized pooling layer, which allows us to acquire an appropriate pooling layer across the distribution of tasks. In the experiment, we applied the proposed meta-learning framework to character recognition tasks. The results demonstrated that a pooling layer that is suitable across multiple character recognition tasks was obtained via meta-learning, and the obtained pooling layer improved the performance of the model for new tasks of few-shot character image recognition and noisy character image recognition.

In future work, we will conduct a further comparison with other pooling methods since we only compared the proposed method with max pooling and average pooling. A detailed analysis of the computational complexity will also be performed.
Fig. 8: Accuracy in the noisy image recognition task.

Fig. 9: Pooling features for images with noise (noise ratio: 10%): (a) input image with noise, (b) max pooling, (c) average pooling, and (d) meta-learned pooling.

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