

Notably, in order to further accelerate the convergence and improve the model accuracy, the batch normalization (BN) is applied before the ReLU function, given by [19–21]

$$\begin{aligned}\mu_B &\leftarrow \frac{1}{m} \sum_{i=1}^m x_i, \\ \sigma_B^2 &\leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_B)^2, \\ \widehat{x}_i &\leftarrow \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}, \\ y_i &\leftarrow \gamma \widehat{x}_i + \beta,\end{aligned}\quad (3)$$

where x is the input feature, y is the output of BN, and ϵ is a slight noise. Notations γ and β are learnable parameters [22, 23]. Moreover, pooling layers are followed and used to downsample the feature map. The architecture of used network architecture is composed of a sequence of convolutional layers, pooling layers as well the full connected networks are followed the last layers to output prediction. The softmax function is used to map the output into probabilistic representation [24],

$$\Pr(i) = \text{Softmax}(z^{(i)}) = \frac{e^{z^{(i)}}}{\sum_{j=0}^n e^{z^{(j)}}}. \quad (4)$$

The whole network architecture is shown in Table. 2.

2.3. Training strategies

For data classification in the knowledge management based power system, we use the cross entropy based loss function to evaluate the distance between the prediction and label, given by [25, 26]

$$\text{Loss} = \frac{1}{N} \sum_{i=0}^N \left(- \sum_{c=1}^n y_{i,c} \log p_{i,c} \right). \quad (5)$$

We adapt the Adam optimizer to update the weights, and the cosine annealing learning rate is applied in this paper, given by [27, 28]

$$\gamma_t = \gamma_{\min} + \frac{1}{2}(\gamma_{\max} - \gamma_{\min}) \left(1 + \cos \left(\frac{t - T_w}{T - T_w} \pi \right) \right), \quad (6)$$

where γ_t is the learning rate at the t -th round, and T_w and T are the number of warm up epochs and total epochs, respectively. In this paper, T_w and T are set to 5 and 50, respectively.

3. Experiment

Table 1. Comparison of test accuracy for the knowledge management based power system.

	Baseline	BN	BN+Ag
Test Accuracy	72.48	77.68	78.92

Table 2. Comparison of test accuracy of several network architectures for the knowledge management based power system.

	FLOPs	Param	ACC
2-MLP	3.15M	3150K	63.06
3-MLP	3.67M	3670K	63.75
2-CNN	1.68M	17.50K	76.50
3-CNN	1.97M	27.17K	78.92
4-CNN	2.27M	100K	76.64

3.1. Dataset

For the knowledge management based power system, a total of 10028 samples are collected and divided into training set, validation set and test dataset. The training set in the knowledge management based power system is used to train the deep model, and the model with the best performance in the validation set is used to evaluate in the test dataset. It is worth noting that samples of the test and validation sets do not overlap with the training set.

3.2. Numerical results

Fig 3. illustrate the accuracy versus training epoch for the knowledge management based power system, where the red curve is the result of using BN technology, and the black curve represents the result without BN. We can find from the figure that the curve with BN technology increases rapidly, and shows the stability in the training processing. In contrast, the curve without BN has obvious jitter in the training process and is difficult to converge. This is because that if batch normalization is not used, the trained data distribution of each layer is different, and the network needs more overhead to learn the new distribution, which makes the network model more complicated and slow down the convergence.

Table. 1 shows the test accuracy of three methods for the knowledge management based power system, where we refer the CNN without using BN to “baseline”, “BN” denotes the CNN with BN technology and “BN+Ag” means that both BN and data augment are used. From the table, we can find that “BN+Ag” achieves a better accuracy gain of 1.24% and 6.44% compared to “BN” and baseline, respectively. These results indicate that the effectiveness of adding BN and data augment in the training processing.

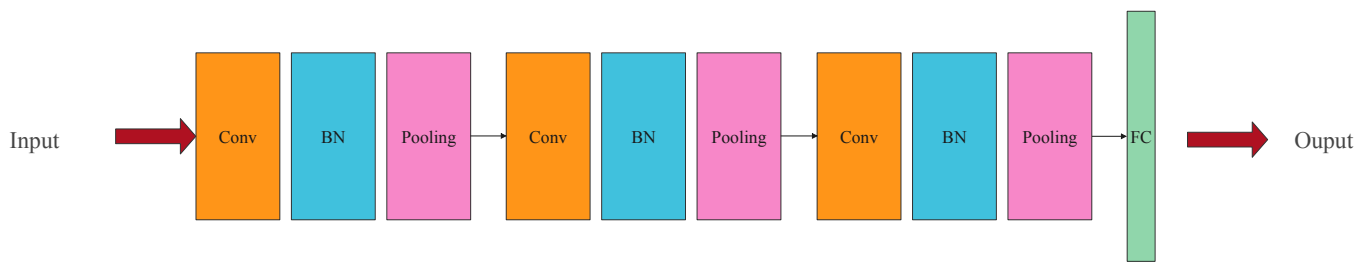


Figure 2. Network architecture for the knowledge management based power system.

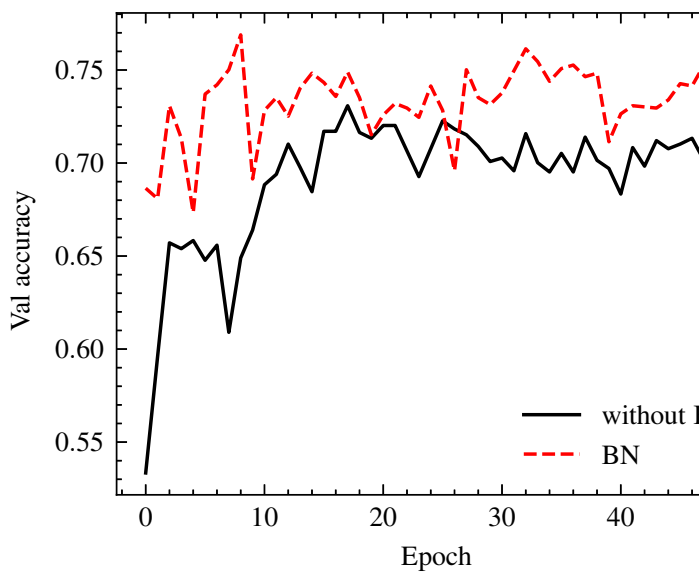


Figure 3. Accuracy on validation set versus training epoch for the knowledge management based power system.

Table 2 compares the performance and complexities of several network architectures including multilayer perception (MLP) and CNN with different depths, for the knowledge management based power system. Specifically, the MLP is set to 2 and 3 layer, and we also test the CNN with 2, 3, and 4 layers. From the table, we can find that the CNN architectures show the superiority over the MLP model, with accuracy gain up to 25%. In addition, the number of floating point operations (FLOPs) and parameters of CNN architectures are significantly less than those of MLP. These indicate that the stacked convolution kernel can still extract features in rich spatial space and reduce the number of parameters required for calculation to reduce the possibility of overfitting. Regarding to the CNN architectures, we can find that the model complexity increases with the model depth. However, the accuracy does not increase with model depth. In particular, the 3-layer CNN achieves the best accuracy. This is because that the 2-layer CNN lacks of adequate receptive field, and can not extract enough non-local

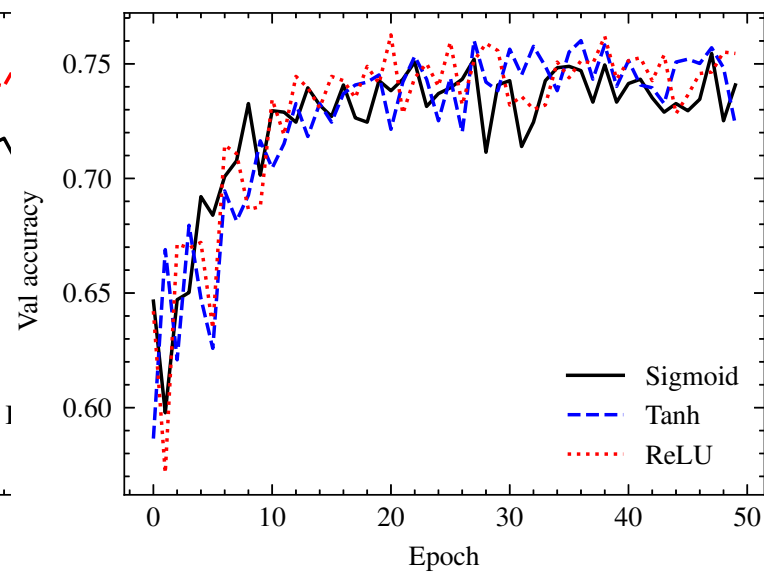


Figure 4. Accuracy on validation set versus training epoch with several activated functions for the knowledge management based power system.

Table 3. Accuracy on the test dataset versus training epoch with several activated functions for the knowledge management based power system.

	Sigmoid	Tanh	ReLU
Test Accuracy	75.78	77.98	78.92

features. In addition, the 3-CNN is enough for the task, and increasing an additional layer will cause the occurrence of overfitting.

Fig. 4 shows the accuracy on validation set versus the training epoch of three activated functions for the knowledge management based power system. We can find that the three activated function can work successfully in the training processing. However, the ReLU can reach the highest accuracy performance, which demonstrates its ability of non-linear transformation. The same situation can be found in Table 3, where the test dataset is used. In particular, the model with

ReLU function achieves the accuracy gain of 3% and 1%, compared to that of sigmoid and tanh, respectively.

4. Conclusions

With the rapid development of information technology, the power system had been developed and applied rapidly. In the power system, fault detection was very important and was one of the key means to ensure the system operation. How to effectively improve the ability of fault detection was the most important issue in the research of power system. Traditional fault detection mainly relied on manual daily inspection, and the power must be cut off during maintenance, which affected the normal operation of the power grid. In case of emergency, the equipment could not be powered off, which may lead to missed test and bury potential safety hazards. To solve these issues, in this paper, we studied the knowledge management based power system by employing the deep learning technique. Specifically, we firstly introduced the data augmentation in the knowledge management based power system and the associated activated functions. We then developed the deep network architecture to extract the local spatial features among the data of the knowledge management based power system. We further provided several training strategies for the data classification in the knowledge management based power system, where the cross entropy based loss function was used. Finally, some experimental results were demonstrated to show the effectiveness of the proposed studies for the knowledge management based power system.

4.1. Data Availability Statement

The data of this work can be obtained through the email to the authors: Zhengping Lin (zhengping_lin@hotmail.com), Jiaxin Lin (jiaxinlincsg@hotmail.com). As to this work, the authors would like to sincerely thank the following researchers for the meaningful discussions: Xiazhi Lai (xiazhilai@hotmail.com), Bowen Lu (bwlu@ieee.org), and Yinghao Guo (yinghaoguo@ieee.org).

4.2. Copyright

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