Layered Batch Inference Optimization Method for Convolutional Neural Networks Based on CPU

Hongzhi Zhao[1], Xun Liu[1], Jingzhen Zheng[2] and Jingjing He[1]
[1]*School of Computer and Information Technology, Beijing Jiaotong University, Beijing, China*
[2]*Zhejiang Scientific Research Institute of Transport, Hangzhou, China*

Keywords: Convolutional Neural Network, Batch Processing, Inference Task Scheduling Optimization, CPU.

Abstract: In recent years, CPU is still the most widely used computing system. And in CNN inference applications, batching is an essential technique utilized on many platforms. The arrival time and the sample number of the convolutional neural network inference requests are unpredictable, and the inference with the small batch size cannot make full use of the computation resources of the multi-threading in CPU. In this paper, we propose a layered batch inference optimization method for CNN based on CPU (LBCI). This method implements "layer-to-layer" optimal scheduling for being-processed and to-be-processed CNN inference tasks under the constraints of the user preference delay in a single batch. It conducts the dynamic batch inference by "layer-to-layer" optimal scheduling during the processing. The experimental results show that for the request with a single-sample inference task, LBCI reduces the inference time by 10.43%-52.43% compared with the traditional method; for the request with a multi-sample inference task, LBCI reduces the inference time by 4.32%-22.76% compared with the traditional method.

1 INTRODUCTION

Convolutional neural network (CNN) is often used in the field of computer vision. In practice, since computer vision tasks such as face recognition (F. Boutros, 2022), (Kim, 2022) and image classification (D. Landa-Silva, 2008), (Li, 2023) are widely applied, the number of CNN deployments are also showing an increasing trend year by year. CNN models are deployed on CPU platforms such as servers, clients, and edge devices for the needs of some practical applications (Mittal, 2022). In recent years, CPU is still the most widely used computing system, and CPU manufacturers continue to launch CPU products for deep learning applications (Daghaghi, 2021).

In the cloud server providing the services, the cloud inference server will process inference requests sent by users to obtain prediction results. In most scenarios, a user inference request carries only one inference sample, which is called a single-sample inference task; in a small number of application scenarios, a user inference request carries multiple inference sample, which is called a multi-sample inference task (AMAZON, 2018). Some traditional inference servers can only process one inference request at a time; some set the maximum allowed batch size and a batching time window that is the maximum period time of waiting for incoming requests to form a batch (Choi, 2021). With these methods, the server can only process the tasks in the order of the arrivals. And we call them as the "end-to-end" coarse-grained inference method. The "end-to-end" coarse-grained inference method will produce the good effect under the strict condition that the batch size of the running inference tasks is just fit. Actually, the arrival time and the sample number of the inference requests are unpredictable. It is hard to form a batch with a fit batch size all the time for the inference. And it is also unreasonable to blindly wait the arrival of the new inference requests to form a batch with a fit batch size. The running inference tasks with the small batch size can’t fully utilize the computation resources of the multi-threading in CPU. After the running inference tasks are finished, the server needs to reload the weight data to process the new inference task. Accessing memory too frequently will reduce the CPU processing efficiency. Therefore, the "end-to-end" coarse-grained inference method is only a suboptimal solution for CPU platforms.

The related works didn’t provide a solution that optimizing the inference on CPU while the batch size is smaller than the ideal value. Based on the

Zhao, H., Liu, X., Zheng, J. and He, J.
Layered Batch Inference Optimization Method for Convolutional Neural Networks Based on CPU.
DOI: 10.5220/0012277100003807

In *Proceedings of the 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (ANIT 2023)*, pages 182-189
ISBN: 978-989-758-677-4

above, we propose a layered batch inference optimization method for convolutional neural networks based on CPU referred to as LBCI. This is a fine-grained inference method, which converts the traditional "end-to-end" inference method into a "layer-to-layer" inference method. The user preference delay on the server is the most significant constriction for processing the inference requests. Hence, LBCI will schedule the to-be-processed inference task samples to be batching processed with the being-processed inference task samples in a running thread within the user preference delay, while the batch size of the being-processed inference task samples is smaller than the ideal value. LBCI can make full use of the parallel capability of the CPU and improve the average throughput of the inference server within the user preference delay.
Our contributions can be summarized as follows.

•Our study indicates that the batch process schedule of the CNN inference on CPU can be optimized at the level of the layers, not only at the level of the model. And we design a novel strategy for predicting the running time with the new batch size by using the running time ratio lookup table of the computed sub-models.

•We propose a layered batch inference optimization method for convolutional neural networks based on CPU referred to as LBCI which makes full use of the parallel capability of the CPU and improve the average throughput of the inference server within the user preference delay.

2 RELATED WORK

2.1 Optimizing CNN Inference Task Scheduling

On homogeneous devices, the focus of scheduling optimization is fully utilizing resources on the device; while on heterogeneous devices, the focus of scheduling optimization is often the division of computing tasks and communication between heterogeneous devices. Here we only focus on research work on scheduling optimization of CNN inference requests on homogeneous devices. Choi et al. (Choi, 2021) proposed a batch processing system LazyBatching that supports SLA (service level agreement) on the NPU simulator. It performs scheduling and batch processing at the level of nodes in the graph, rather than at the level of the entire graph, and improves the throughput of batch processing on the NPU simulator. But this work is based on the NPU simulator, not the CPU platform. Zhang et al. (Y. Zhang, 2022) proposed a CNN task scheduling paradigm, "One-Instance-Per-x-Core", which improved the throughput of multi-core CPU batch processing on DNN training and inference tasks. Since ParaX works mainly for DNN model training, they mainly consider the impact of the batch size in each instance on the accuracy of the training results, not on the delay and throughput of multi-core CPUs. Wu et al. (X. Wu, 2020) proposed Irinan online scheduling optimization strategy on the GPU platform for multiple different DNN models' inference, which reduces delays under unpredictable workloads, effectively shares GPU resources and minimizes average inference delays. Irina focuses on scheduling optimization between different DNN model inference tasks.

2.2 Using CPU Multithreading to Calculate CNN Inference Tasks

The CPU computing modules in mainstream deep learning frameworks such as PyTorch already support multi-threading technology. The PyTorch deep learning framework can achieve multiple levels of parallelism on the CPU platform (Pytorch, 2019). Liu et al. (Liu, 2019) pointed out that high-performance kernel libraries (such as Intel MKL-DNN (INTEL, 2022) and OpenBlas (Zhang, 2016) are usually used to obtain the high performance of CNN operations. In the convolution calculation, the parallel instructions of OpenMP (Openmp] are used to realize multi-threaded parallel operations at the same time, making full use of hardware resources and greatly reduce computing time. Amazon (Daghaghi, 2021) pointed out that the inference time per unit image shows a decreasing trend as the number increases using the MXNet framework on the CPU platform for CNN inference when the number of input images is within a certain range.

2.3 Optimizing Batch Processing of DNN Inference Tasks

Batch research on the inference process of DNN began in 2018, and Gao et al. (Gao, 2018) firstly studied the inference process of RNN. The traditional CNN batch inference method is image-wise batch processing. Wang et al. (Wang, 2020) proposed a layer-wise scheduling method on a CPU processor without parallel optimization. With the layer-wise scheduling method, the images in one batch use the weights of one layer at the same time, reducing the memory accesses and the access delays. In view of the different weight data and memory usage of each layer in a CNN model, Choudhury et al. (A. R. Choudhury, *2020*] proposed a strategy which used dynamic programming to set the optimal batch size of each layer of the CNN model on the GPU platform, making full use of the computational parallelism of the GPU and speeding up the inference execution speed.

3 METHOD

3.1 Overview of LBCI

LBCI consists of four functional modules as shown in Fig 1: an initialization setting module (IS), a buffer data storage module (DS), a buffer data detection module (DD), and a CNN computing module (CNNC).

Initialization Setting Module: First, LBCI will run the initialization setting module (IS) on the corresponding CPU platform to initialize two key variables and preprocess the CNN model. The key variables are the user preference delay t_{opt} and the optimal number N_{opt} of the batch size for the model inference. The user preference delay t_{opt} is a hyperparameter provided by the CPU server. We propose an strategy to calculate the optimal number N_{opt} with which the running time of the batch inference must satisfy the constraint of t_{opt}. The strategy is described in the section B.

The IS prepocesses the CNN model at the level of the layers. As shown in Fig. 2, the IS refers several sequential convolutional layers as a sub-model and the whole CNN model can be referred to as a combination of the sub-models. The preprocess won't change the results of the original model.

Based on the sub-models of the CNN model, the IS runs the model inference to record the running time of each sub-model. The input data are a batch of samples and the batch size b is an integer ranging from 1 to N. The model inference is performed for N times with the different batch sizes. Then the IS builds the running time ratio lookup table of the computed sub-models as shown in Fig. 3. The running time ratio of the computed sub-models $r_{p,\,q}$ is:

$$r_{p,\,q} = \sum t_{p,\,i} \div t_p,\ (i = 1, 2, \ldots, q) \tag{1}$$

where p is the batch size of the input data, q is the number of the computed sub-models, $t_{p,i}$ is the running time of the sub-model$i$ with the batch size b of p and t_p is the total running time of the model with the batch size b of p.

Buffer Data Storage Module: After the initialization, LBCI uses a thread to independently run the buffer data storage module (DS) which receives and stores CNN inference tasks' samples in the memory. We define a state variable f for marking a sample at the being-processed or to-be-processed state. f = 0 indicates to-be-processed while f = 1 indicates being-processed. The DS maintains a queue of the samples, in which saves the data, the arriving time and the state variable f of each sample. The DS will check all the state variables in the queue while the new samples arrive, and delete the samples with f = 1 in the queue. The state variable f of each new arriving sample is referred to as 0 by default.

CNN Computing Module: The CNN computing module (CNNC) loads the preprocessed model which contains several sub-models. The CNNC with the certain input data is an instance for the model inference. One instance needs an individual thread. Please note that the threads separately running the different CNNC instances can exist at the same time.

Assuming that the number of the to-be-processed samples in the queue is N_{st}. If $N_{\mathrm{st}} \geq N_{\mathrm{opt}}$, the CNNC instance will read $N_{\mathrm{d}} = N_{\mathrm{opt}}$ to-be-processed samples from the head of the sample queue and set f = 1. N_{d} is the batch size of the CNNC instance input samples. And we will not optimize the instance later in the computing process. If $N_{\mathrm{st}} < N_{\mathrm{opt}}$, the CNNC instance will read $N_{\mathrm{d}} = N_{\mathrm{st}}$ to-be-processed samples and set f = 1. For the condition, the above CNNC instance can be optimized in the computing process. Since the batch size of the instance input data is smaller than N_{opt}, the purpose of the optimization is increasing the batch size with the constraint of t_{opt}. The CNNC instance calls the buffer data detection module (DD) to detect whether it can be optimized or not, when the calculations of each sub-model are completed as shown in Fig. 1. Based on the DD's feedback, if the CNNC can be optimized, it will continually be processed in the rest of the sub-models with the "layer-to-layer" optimal scheduling which is described in the section D. Once a CNNC instance is optimized, it will not call the DD and be optimized again.

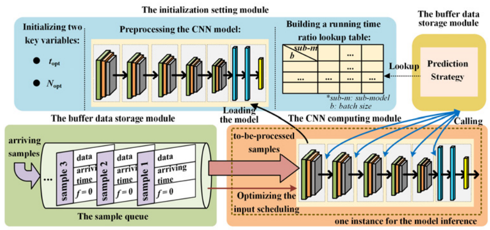


Figure 1: The overview of LBCI.

Buffer Data Detection Module: The buffer data detection module (DD) will count the number N_{st} of the to-be-processed samples in the queue after being called by a CNNC instance. If $N_{st} = 0$, the DD will return 0 to the instance, which means that no to-be-processed sample in the queue. The instance can't be optimized at the moment. If $N_{st} > 0$, the instance can be optimized. Then the DD utilizes the prediction strategy to predict how many (N_{add}) to-be-processed samples can be added to the instance while keeping the total running time will not over t_{opt}. And the DD will return N_{add} to the instance. The prediction strategy is explained in the section C. If $N_{add} = 0$, the CNNC instance can't be optimized now and later, and will never call the DD again. If $N_{add} > 0$, the CNNC instance will schedule N_{add} to-be-processed inference task samples to be batching processed with N_d being-processed samples.

3.2 Strategy for Calculating the Optimal Number N_{opt}

The strategy calculates N_{opt} on the basis of the test data coming from the multiple inference tests. The key steps of the strategy are explained as follows.

•The IS runs the model inference for N times with the different input data batch size b ($1 \le b \le N$) and obtains a set of the average running time per sample $T = \{t_b\}$ where t_b is the average running time per sample while the batch size is b. Then fitting a function $T = g(b)$.

•For each batch size b, the inference is performed for n times. The IS gets a running time set $\{t_j|1 \le j \le n\}$ and the average running time t_{avg} of n inferences where $t_{avg} = \sum t_j \div n$. And calculating the average fluctuation ratio r_b of the running time per sample by (2):

$$r_b = [\sum (|t_j - t_{avg}| \div t_{avg})] \div n. \quad (2)$$

Then we obtain the average fluctuation ratio set $\{r_b|1 \le b \le N\}$ and find the maximal ratio r_{max} in the set. Let $t_{OPT} = t_{opt} \times r_{max}$ where t_{OPT} is the strict user preference delay.

•With the strict user preference delay t_{OPT}, let $T = t_{OPT}$ and substitut in $T = g(b)$. Then b is obtained which is the optimal number N_{opt} of the batch size for inference.

3.3 Prediction Strategy of Buffer Data Detection Module

The prediction strategy produces N_{add} being return to the CNNC instance. Assuming that the CNN model has x sub-models. The key of the prediction strategy is that (3) should be valid while N_{add} is as large as possible:

$$t_{all} = t_{wait} + t_{done} + t_{add} + t_{k+1} \text{ and } t_{all} < t_{opt}, \quad (3)$$

where t_{all} is the predicted total time, t_{wait} is the waiting time for N_{add} to-be-processed samples lining up in the queue, t_{done} is the elapsed running time of N_d being-processed samples in the thread, t_{add} is the predicted running time of N_{add} to-be-processed samples from the sub-model$_1$ to the sub-model$_k$ ($1 < k < x$) and t_{k+1} is the predicted running time of (N_d + N_{add}) samples from the sub-model$_{k+1}$ to the sub-model$_x$. The key steps of the strategy are explained as follows.

•Initializing $N_{add} = 1$ by default. Since we recorded the arriving time of the samples in the queue, the DD can directly calculate t_{wait}. And t_{done} can be obtained from the thread running time by calling some system functions.

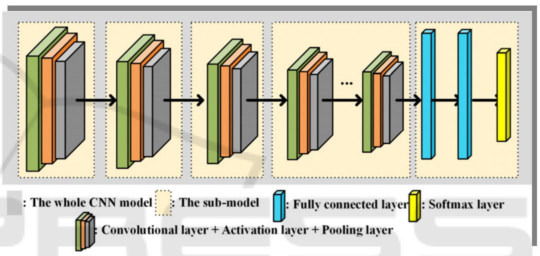


Figure 2: The IS refers several sequential convolutional layers as a sub-model.

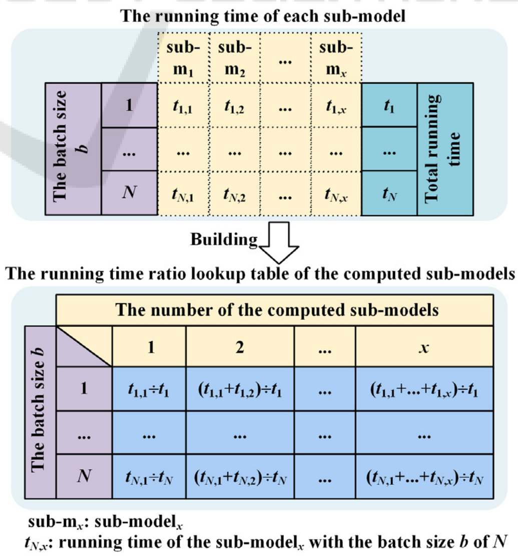


Figure 3: The IS builds the running time ratio lookup table of the computed sub-models.

•Let batch size $b = N_{add}$ and substitut in $T = g(b)$, predicting average running time per sample for b =

N_{add}. In the running time ratio lookup table of the computed sub-models, the DD finds $r_{p,q}$, ($p = N_{add}$, $q = k$). t_{add} can be predicted by (4):

$$t_{add} = N_{add} \times g(N_{add}) \times r_{p,q} \quad (4)$$

•Let batch size $b = N_d + N_{add}$ and substitut in $T = g(b)$, predicting average running time per sample for $b = N_{add}$. In the running time ratio lookup table of the computed sub-models, the DD finds $r_{p,q}$, ($p = N_d + N_{add}$, $q = k+1$). t_{k+1} can be predicted by (5):

$$t_{k+1} = (N_d + N_{add}) \times g(N_d + N_{add}) \times (1 - r_{p,q}) \quad (5)$$

•Then the DD calculates t_{all} by (3). If $t_{all} < t_{opt}$, $N_{add} = N_{add} + 1$ and going back to the step 2. If $t_{all} \geq t_{opt}$, it means that the DD finds the final N_{add} at the sub-model$_k$ and ends the prediction. At last, the DD will return $N_{add} = N_{add} - 1$ to the CNNC instance.

3.4 "Layer-to-Layer" Optimal Scheduling

Assuming that the CNNC instance calls the DD when the calculations of the sub-model$_k$ are completed. After getting the DD feedback, the CNNC instance is aware of that N_{add} ($N_{add} > 0$) to-be-processed samples can be added to the instance while keeping the total running time will not over t_{opt}. The specific steps of "layer-to-layer" optimal scheduling are described as follows.

•The batch processing of N_d being-processed samples in the instance are paused before the sub-model$_{k+1}$ calculations begin. The instance stores N_d outputs produced by the sub-model$_k$ in the memory.

•The CNNC instance reads N_{add} to-be-processed samples from the head of the queue maintained by the DS and modifies the state variable f of these samples to 1. Then the instance processes these N_{add} samples in batch from the sub-model$_1$ to the sub-model$_k$ and generates N_{add} outputs.

•Then the instance loads N_d outputs from the memory and concatenates (N_d + N_{add}) outputs produced by the sub-model$_k$ as a new batch. The new batch will be calculated by the rest of the sub-models until outputting (N_d + N_{add}) results in the CNNC instance.

4 EVALUATION

We verify the effectiveness of LBCI in two perspectives: the effectiveness of strategy for calculating the optimal number N_{opt} and the comparison with two typical batching inference methods on the time and throughput. The verification experiments use AlexNet (Krizhevsky, 2017) as the inference model with the test dataset ImageNet-2012. We deploy AlexNet by "web server" method, which is implemented with the lightweight web framework Flask of Python. The web page sends the inference requests, and the backend server receives and responses the requests. The inference platform is a multi-core CPU platform with Intel(R) Core (TM) i7-8700 CPU and L1 384KB, L2 1.5MB, L3 12MB.

4.1 Effectiveness of Strategy for Calculating the Optimal Number N_{opt}

The IS runs the AlexNet inference for $N = 256$ times with the different input data batch size b ($1 \leq b \leq 256$) and obtains a set of the average running time per sample $T = \{ t_b \}$ where tb is the average running time per sample while the batch size is b. We consider that the four-parameter equation fits best. Then the fitting four-parameter function is:

$$g(b) = b \times [(z1 - z2) \div (1 + (b \div z3)^{z4}) + z2], \quad (6)$$

where $z1$, $z2$, $z3$ and $z4$ are the parameters of the fitting function.

Then we rerun the AlexNet inference for 100 times with the different input data batch size b ($1 \leq b \leq 100$) and record the real running time per samples of each time. The real time and the predicted time calculated by (6) are close as shown in Fig. 4(a), which preliminarily verifies the effectiveness of (6).

And we calculate the strict user preference delay t_{OPT} and the optimal batch size N_{opt} with (6) on the basis of the strategy. The running time of performing the AlexNet inference with $b = N_{opt}$ for 100 times is shown in Fig. 4(b). The blue line denotes that the user preference delay t_{opt} = 500ms. Only 1% of the inference running time are larger than t_{opt}, which verifies the effectiveness of the strategy for calculating the optimal number N_{opt}.

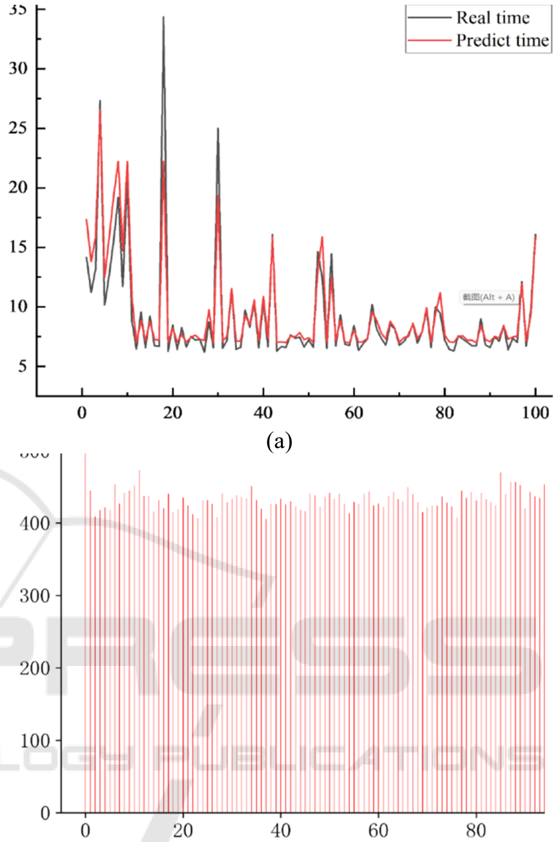
4.2 Time and Throughput Comparison

We use two typical batching inference methods to comprise with LBCI: (1) sequential processing one task at a time like Amazon Rekognitio inference server (AMAZON, 2022) referred to as Serial. (2) Batch processing by setting the maximum allowed batch size m and a batching time window (Choi, 2021) referred to as Batchsize(m). The web page sends the requests per second to the backend server producing four traffics (20/s, 40/s, 60/s and 80/s).

1)The single-sample inference task: The request with a single-sample inference task is the most common. The average delay time per batch for LBCI is always below Serial and Batchsize(10) as shown in Fig. 5(a). At the low traffic (20/s), the average delay time per batch for Serial and LBCI is much less than Batchsize(10). At the medium, high and heavy traffics (40/s, 60/s and 80/s), since the poor efficiency of Serial the sequential processing, many requests are waiting, which causes the larger increasing of the average delay time per batch for Serial. With Batchsize(10), the backend server always processes a batch of the requests after collecting 10 requests. Therefore, the average delay time per batch for Batchsize(10) is relatively stable at four traffics (20/s, 40/s, 60/s and 80/s).

The throughput of LBCI is higher than Serial and Batchsize(10) at the low, medium and high traffics (20/s, 40/s and 60/s) as shown in Fig. 5(b). LBCI sacrifices the throughput for the lower average delay time per batch at the heavy traffic (80/s). But the throughput at the heavy traffic (80/s) is still higher than that at the 20/s and 40/s. At the low traffic (20/s), LBCI reduces the average delay time per batch by 26.12% and improves the throughput per second by 20.3% compared with Serial. At the medium and high traffics (40/s and 60/s), LBCI reduces the average delay time per batch by 52.43% and 19.43%, and improves the throughput per second by 16.96% and 9.56% compared with Batchsize(10). Since the average delay time per batch hardly exceeds the user preference delay t_{opt}, we only assess the timeout ratio at the high traffic (60/s), as shown in Fig. 6. The probability for the average delay time per batch of LBCI exceeding the user preference delay t_{opt} is 11.67% at t_{opt} = 500, which is much lower than Serial and Batchsize(10).

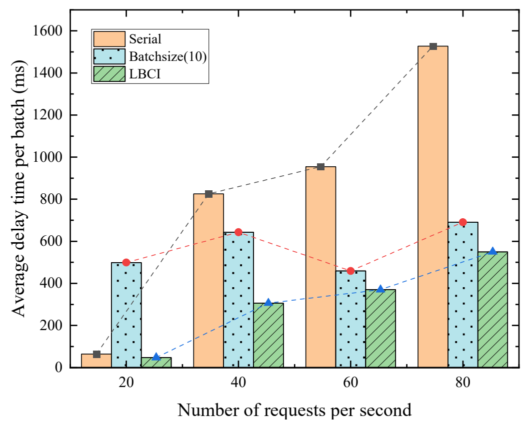
2)The multi-sample inference task: For the request with a multi-sample inference task, since Batchsize(m) may divide a request to form a batch of m samples, it loses the original advantage. Hence, we compare LBCI with Serial. The web page sends the requests with *num* samples per request to backend server per 100 ms for 10 times. We respectively conduct three tests to process the *num* samples and record the running time of each test. For each test, *num* is randomly generated from the different ranges. The range of [1, 10] means the small data; [1, 25] means the medium data; [1, 50] means the big data. As shown in Fig. 7, compared with Serial, LBCI reduces the running time per test by 22.76% at the small data, 10.08% at the medium data and 4.32% at the big data. And the average delay time per batch of LBCI and Serial is always below the user preference delay t_{opt} at the small data and the medium data. At the big data, the average delay time per batch of LBCI occasionally exceeds t_{opt}, which can be accepted. From the analysis results, LBCI is more suitable for the inference requests



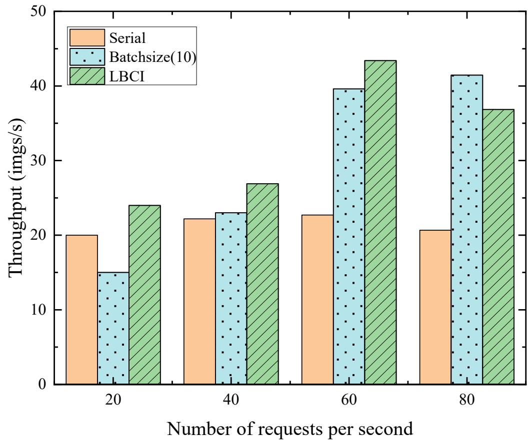
(a)

(b)

Figure 4: (a) Comparison between real time and predicted time. (b) The running time of performing the AlexNet inference with $b = N_{opt}$ for 100 times.



(a)



(b)

Figure 5: Comparison between LBCI, Serial and Batchsize (10) on average delay time per batch and throughput per second at four traffics (20/s, 40/s, 60/s and 80/s).

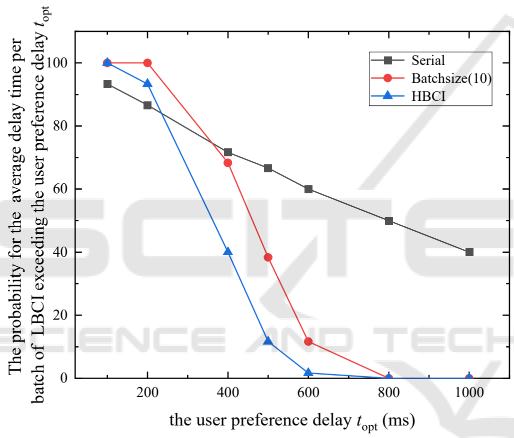


Figure 6: The probability for the average delay time per batch of LBCI exceeding the user preference delay t_{opt}. of the small data and medium data.

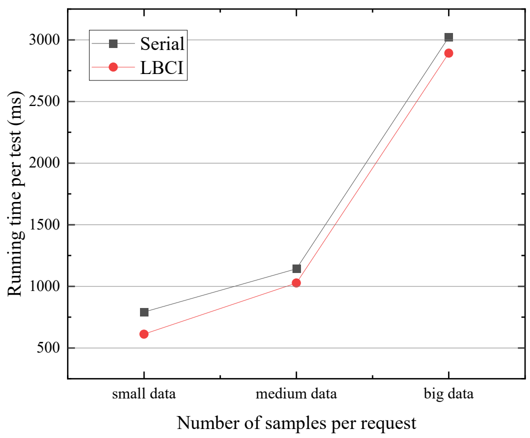


Figure 7: The running time of tests for the small/medium/big data.

5 CONCLUSION

In the cloud server providing the services, the arrival time and the sample number of the inference requests are unpredictable. And the running inference tasks with the small batch size can't fully utilize the computation resources of the multi-threading in CPU. Based on the mentioned above, we propose a layered batch inference optimization method for CNN based on CPU (LBCI). LBCI executes "layer-to-layer" optimal scheduling for being-processed and to-be-processed CNN inference tasks. It conducts the dynamic batch inference by "layer-to-layer" optimal scheduling during the processing. The experimental results show that for the request with a single-sample inference task, LBCI reduces the inference time by 10.43%-52.43% compared with the traditional method; for the request with a multi-sample inference task, LBCI reduces the inference time by 4.32%-22.76% compared with the traditional method.

ACKNOWLEDGMENTS

This work was financially supported by Research and Development Center of Transport Industry of New Generation of Artificial Intelligence Technology (202207H).

REFERENCES

F. Boutros, N. Damer, F. Kirchbuchner and A. Kuijper, ElasticFace: Elastic margin loss for deep face recognition[C]. *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, New Orleans, LA, USA, 2022, 1577-1586. https://doi.org/10.1109/CVPRW56347.2022.00164.

M. Kim, A. K. Jain and X. Liu, AdaFace: Quality Adaptive Margin for Face Recognition[C]. *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, New Orleans, LA, USA, 2022, 18729-18738. https://doi.org/10.1109/CVPR52688.2022.01819.

D. Landa-Silva, K. N. Le, A simple evolutionary algorithm with self-adaptation for multi-objective nurse scheduling[J]. *Adaptive and multilevel metaheuristics*, 2008, 133-155. https://doi.org/10.1007/978-3-540-79438-7_7.

Y. Li, W. Liu. Deep learning-based garbage image recognition algorithm[J]. *Applied Nanoscience*, vol. 13, No. 2, 2023, 13(2): 1415-1424. https://doi.org/10.1007/s13204-021-02068-z.

S. Mittal, P. Rajput and S. Subramoney, A survey of deep learning on cpus: Opportunities and co-optimizations[J]. *IEEE Transactions on Neural Networks and Learning Systems*, Oct. 2022, 33(10): 5095-5115. https://doi.org/10.1109/TNNLS.2021.3071762.

S. Daghaghi, N. Meisburger, M. Zhao, A. Shrivastava, Accelerating slide deep learning on modern cpus: Vectorization, quantizations, memory optimizations, and more[J]. *arXiv preprint arXiv:2103.10891*, 2021. https://doi.org/10.48550/arXiv.2103.10891.

AMAZON, Accelerating apache mxnet with the nnpack library. 2018. Available online. https://aws.amazon.com/cn/blogs/china/speeding-up-apache-mxnet-using-the-nnpack-library/.

Y. Choi, Y. Kim and M. Rhu, Lazy batching: An sla-aware batching system for cloud machine learning inference[C]. *2021 IEEE International Symposium on High-Performance Computer Architecture (HPCA)*, Seoul, Korea (South), 2021, 493-506. https://doi.org/10.1109/HPCA51647.2021.00049

A. Krizhevsky, I. Sutskever, G. E. Hinton, ImageNet classification with deep convolutional neural networks[J]. *Communications of the ACM*, 2017, 60(6): 84-90. https://doi.org/10.1145/3065386

Y. Zhang, L. Yin, D. Li, Y. Peng and K. Lu, ParaX: Bandwidth-Efficient Instance Assignment for DL on Multi-NUMA Many-Core CPUs[J]. *IEEE Transactions on Computers*, Nov. 2022, 71(11): 3032-3046. https://doi.org/10.1109/TC.2022.3145164.

X. Wu, H. Xu, Y. Wang, Irina: Accelerating dnn inference with efficient online scheduling[C]. *4th Asia-Pacific Workshop on Networking*, 2020, 36-43. https://doi.org/10.1145/3411029.3411035

Pytorch, Pytorch chinese tutorial & documentation. 2019. Available online. https://pytorch.apachecn.org/#/.

Y. Liu, Y. Wang, R. Yu, M. Li, V. Sharma, and Y. Wang, Optimizing CNN model inference on CPUs[C]. *In Proceedings of the 2019 USENIX Conference on Usenix Annual Technical Conference (USENIX ATC '19)*. 2019, 1025–1040. https://dl.acm.org/doi/10.5555/3358807.3358895.

INTEL, Intel math kernel library for deep neural networks (intel mkl-dnn). Available online. https://oneapi-src.github.io/oneDNN/v0/index.html.

X. Y. Zhang, Q. Wang, W. Saar, et al. Openblas: An optimized blas library. In Texas Advanced Computing Center. 2016. Available online. http://www.openblas.net/.

Openmp, The OpenMP Api specification for parallel programming. Available online. https://www.openmp.org.

P. Gao, L. Yu, Y. Wu, and J. Li, Low latency rnn inference with cellular batching[C]. *In Proceedings of the Thirteenth EuroSys Conference (EuroSys '18)*. Association for Computing Machinery, New York, NY, USA, 31, 1–15. https://doi.org/10.1145/3190508.3190541.

X. Wang, L. Zhao and P. Li, High throughput cnn inference and training with in-cache computation[C]. *2020 IEEE 38th International Conference on Computer Design (ICCD)*, Hartford, CT, USA, 2020, 461-464, https://doi.org/10.1109/ICCD50377.2020.00084.

A. R. Choudhury, S. Goyal, Y. Sabharwal and A. Verma, Variable batch size across layers for efficient prediction on cnns[C]. *2020 IEEE 13th International Conference on Cloud Computing (CLOUD)*, Beijing, China, 2020, 435-444, https://doi.org/10.1109/CLOUD49709.2020.00065.