Intel® AI Edge Systems Verified Reference Blueprint –Scalable Performance Edge AI on Intel® Xeon Scalable 2S for Computer Vision, and GEN AI

Reference Architecture

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Revision History

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1 Introduction

Intel® AI Edge systems are a range of optimized commercial AI systems that are delivered and sold through OEM/ODM in the Intel® ecosystem. They are commercial platforms that are verified-configured, tuned and benchmarked using Intel®'s reference AI software application on Intel® hardware to deliver optimal performance for Edge Workloads.

Intel® AI Edge Systems offer a balance between computing and AI acceleration to deliver optimal TCO, scalability and security. AI systems enable our partners to jumpstart development through a hardened system foundation verified by Intel® and to increase the trust in their system performance. AI Edge systems enable the ability to add AI functionality through continuous integration into business applications for better business outcomes and streamlined implementation efforts.

To support the development of these Edge AI systems, Intel® is offering reference design and verified reference configuration blueprints with Edge AI system configurations that are tuned and benchmarked for different Edge AI System types that support Edge AI use cases. Verified reference blueprints (VRB) include Hardware BOM, Foundation Software configuration (OS, Firmware, Drivers) tested and verified with supported Software stack (software framework, libraries, orchestration management).

This document describes a verified reference blueprint using the dual socket 5th Gen Intel® Xeon® Scalable processor family.

When end users choose an Intel® AI Edge Systems Verified Reference Blueprint, they should be able to deploy the AI workload more securely and efficiently than ever before. End users spend less time, effort, and expense evaluating hardware and software options. Intel® AI Edge System Verified Reference Blueprint helps end users simplify design choices by bundling hardware and software pieces together while making the high performance more predictable.

Intel® AI Edge Systems Verified Reference Blueprint –Scalable Performance Edge AI on Intel® Xeon Scalable 2S for Computer Vision, and GEN AI is based on dual socket single-node architecture, that provides an environment to execute multiple AI workloads that are common to be deployed at the edge, such as the "Intel® Automated Self-Checkout Reference Package",and "Generative AI".

All Intel ® AI Edge Systems Verified Reference Blueprint Configurations feature a workload-optimized stack tuned to take full advantage of an Intel® Architecture (IA) foundation. To meet the requirements, OEM/ODM systems must meet a performance threshold that represents a premium customer experience.

There are two configurations for Intel ® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on** Intel® Xeon Scalable 2S for Computer Vision and GEN AI covering a base and plus configuration:

- Intel ® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on** Intel® Xeon Scalable 2S for Computer Vision, and GEN AI Plus configuration for the Node is defined with at least a 64-core 5th Generation Intel® Xeon® Scalable processor and high-performance network, with storage and integrated platform acceleration products from Intel® for maximum virtual machine density Intel ® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on** Intel® Xeon Scalable 2S for Computer Vision

and GEN AI Base configuration is defined with a 32-core or higher 5th Generation Intel® Xeon® Scalable processor and network, with storage and add-in platform acceleration products from Intel® targeting for optimized value and performance-based solutions.

Bill of Materials (BOM) requirement details for the configurations are provided in Chapter 2 of this document.

Intel ® AI Edge Systems Verified Reference Blueprint is defined in collaboration with our ecosystem partners to demonstrate the value of the solution for AI Inference use cases. The solution leverages the hardened hardware, firmware, and software to allow customers to integrate on top of this known good foundation.

Intel ® AI Edge Systems Verified Reference Blueprint provides numerous benefits to ensure end users have excellent performance for their Edge AI Inference applications. Some of the key benefits of the Reference Blueprint based on the 5th Generation Intel® Xeon® Scalable Processor Family processor include:

- High core counts and per-core performance
- Compact, power-efficient system-on-chip platform
- Streamlined path to cloud-native operations
- Accelerated AI inference using Intel® AMX and Intel® DL Boost
- Accelerated encryption and compression
- Platform-level security enhancements

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2 Design Compliance Requirements

This chapter focuses on the design requirements for Intel ® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® Xeon Scalable 2S** for Computer Vision, and GEN AI.

2.1 Platform Requirements

The checklists in this chapter are a guide for assessing the platform's conformance to Intel ® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on** Intel® Xeon Scalable 2S for Computer Vision, and GEN AI. The hardware requirements for the Plus Configuration and Base Configuration are detailed below.

Table 1. Platform Plus Configuration

Ingredient	Requirement	Required/ Recommended	Quantity
Processor	Intel® Xeon® Platinum 8592+ Processor at 1.9GHz, 64C/128T, 350W or higher number SKU	Required	2
Memory	16x 32 GB DDR5, 5600 MHz (512 GB total)	Required	16 (8 per NUMA)
Storage (Boot Drive)	480 GB or equivalent boot drive	Required	1
Storage (Capacity)	1 TB or equivalent drive (recommended Non-Uniform Memory Access (NUMA) aligned)	Recommended	2 (1 per NUMA)
Network	Intel® Ethernet Network Adapter E810-2CQDA2	Required	1
LAN on Motherboard (LOM)	10 Gbps or 25 Gbps port for Pre-boot Execution Environment (PXE) and Operation, Administration and Management (OAM)	Required	2 (1 per NUMA)
LAN on Motherboard (LOM)	1/10 Gbps port for Management Network Interface Controller (NIC)	Required	1

Table 2. Platform Base Configuration

Ingredient	Requirement	Required/ Recommended	Quantity
Processor	Intel® Xeon® Gold 6538N processor at 2.1 GHz, 32C/64T, 205W or higher number SKU	Required	2
Memory	32 GB DDR5, 5200 MHz (512 GB total)	Required	16 (8 per NUMA)
Storage (Boot Drive)	480 GB or equivalent boot drive	Required	1

Ingredient	Requirement	Required/ Recommended	Quantity
Storage (Capacity)	1 TB or equivalent drive (recommended NUMA aligned)	Recommended	2 (1 per NUMA)
Network	Intel® Ethernet Network Adapter E810-CQDA2	Recommended	1
LAN on Motherboard (LOM)	10 Gbps or 25 Gbps port for PXE/OAM	Required	2
	1/10 Gbps port for Management Network Interface Controller (NIC)	Required	1

2.2 BIOS Settings

To meet the performance requirements for an Intel ® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on** Intel® Xeon Scalable 2S for Computer Vision, and GEN AI, Intel® recommends using the BIOS settings for enabling processor P-state and C-state with Intel® Turbo Boost Technology ("turbo mode") enabled. Hyperthreading is recommended to provide higher thread density. For this solution Intel® recommends using the NFVI profile BIOS settings for on-demand Performance with power consideration.

The NFVI profile for BIOS settings is documented in ***chapter 3 of*** *BIOS Settings for Intel® Wireline, Cable, Wireless and Converged Access Platform (#747130).*

Table 3. Recommended BIOS Settings

Setting	Value
Hardware Prefetcher	Enabled
Intel® (VMX) Virtualization Technology	Enabled
Hyper-Threading	Enabled
Intel® Speed Shift Technology (P-States)	Enabled
Turbo Mode	Enabled
C-States	Enabled
Enhanced C-States	Enabled

Additionally, for this specific solution please make the corresponding addition BIOS changes on top of NFVI BIOS Profile to yield optimize performance for the solution configurations.

Table 4. Additional BIOS Settings on top of NFVI BIOS Profile

Setting	Value
Sub NUMA Clustering	SNC2
AVX P1	Level 2
AVX ICCP Pre-grant License	Enabled
AVC ICCP Pre-Grant Level	512 Heavy

Setting	Value
Memory Page Policy	Adaptive

Note: BIOS settings differ from vendor to vendor. Please contact your Intel® Representation for NFVI BIOS Profile Doc# 747130 or in case you have difficulty configuring for the exact setting in your system BIOS.

2.3 Solution Architecture

Figure 1 shows the architecture diagram of the Intel ® AI Edge Systems Verified Reference Blueprint. The software stack consists of three categories of AI software:

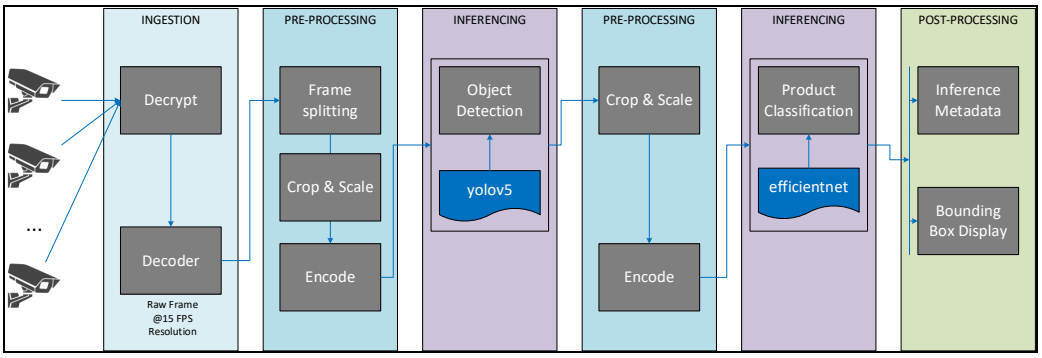
1. Vision AI
2. Generative AI
3. Network Security AI

All three applications are containerized using docker.

For the Vision AI use case, we are using the Intel® Automated Self-Checkout application which measures the stream density. The video data is ingested and pre-processed before each inferencing step. The inference is performed using two models - YOLOv5 and EfficientNet, where the YOLOv5 model does the object detection and the EfficientNet model performs the Object Classification. For additional information refer to Appendix A.1 .

Figure 2 shows the architecture diagram for the Intel® Automated Self-Checkout application, which in this case is deployed containerized via Docker. The Vision AI use case measures stream density in terms of the number of supported cameras at the target FPS, accounting for all stages within the processing pipeline. The video data is ingested and pre-processed before each inference stage. The inference is performed using two models: YOLOv5 and EfficientNet. The YOLOv5 model performs object detection while the EfficientNet model performs object classification. For additional information refer to the Appendix.

Figure 1. Test Methodology for the Intel® Automated Self-Checkout Pipeline



For the Generative AI use case, we are using Large Language Models (LLMs) using Intel® Extension of PyTorch (IPEX) framework for performing LLM inference on Intel® Xeon® Scalable Processor based CPUs and Intel® Data Center Flex GPUs. For additional information refer to Appendix 2.

For Network Security AI, we are using Malconv and finetuned BERT-base-cased for malicious portable executable (PE) file detection and email phishing detection respectively. For additional information refer to Appendix **Error! Reference source not found.**3 .

Figure 2. Architecture of the Intel ® AI Edge Systems Verified Reference Blueprint

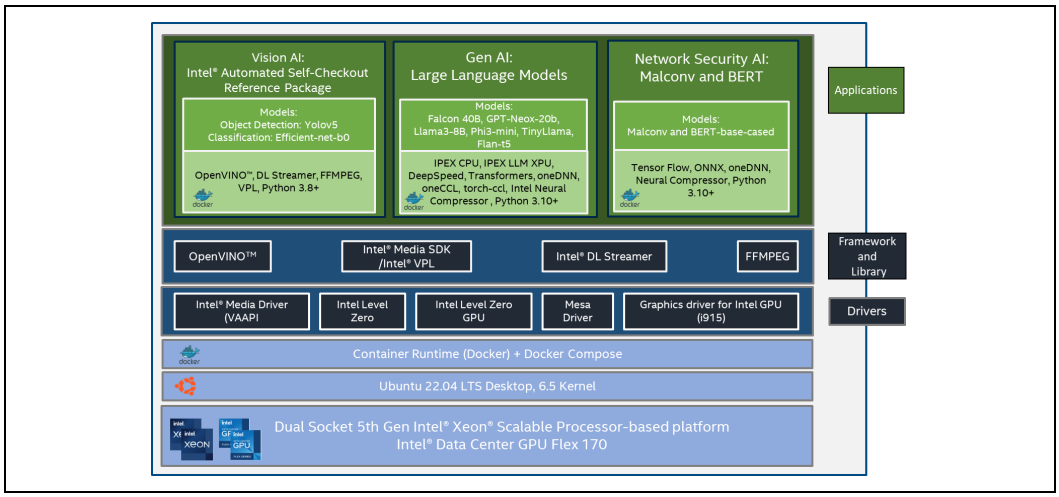


Figure 3 shows the architecture diagram for the Intel® Automated Self-Checkout application, which in this case is deployed containerized via Docker. The Vision AI use case measures stream density in terms of the number of supported cameras at the target FPS, accounting for all stages within the processing pipeline. The video data is ingested and pre-processed before each inference stage. The inference is performed using two models: YOLOv5 and EfficientNet. The YOLOv5 model performs object detection while the EfficientNet model performs object classification. For additional information refer to the Appendix.

Figure 3. Test Methodology for Retail Self-checkout Pipeline

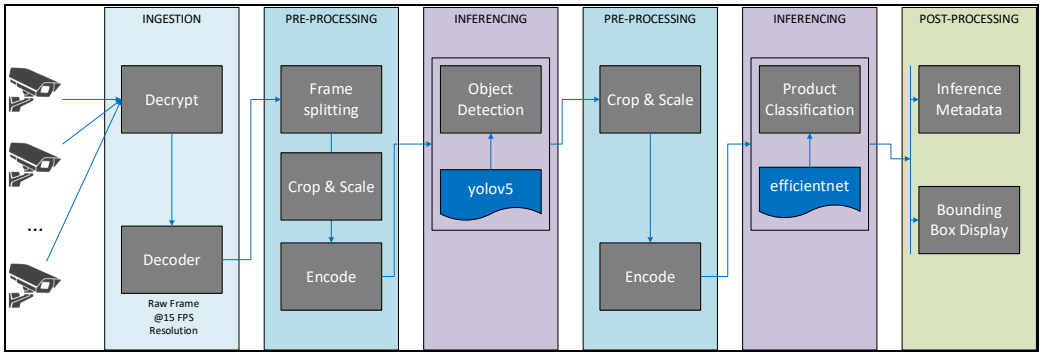


Table 5 is a guide for assessing the conformance to the software requirements of the Intel ® AI Edge Systems Verified Reference Blueprint. Ensure that the platform meets the requirements listed in the table below.

Table 5. SW Configuration

Ingredient	SW Version Details
OS	Ubuntu 22.04.4 LTS
Kernel	6.5 (in-tree generic)
OpenVINO	2024.0.1
Docker Engine	27.1.0
Docker Compose	2.29
Intel® Level Zero for GPU	1.3.29735.27
Intel® Graphics Driver for GPU (i915)	24.3.23
Media Driver VAAPI	2024.1.5
Intel® OneVPL	2023.4.0.0-799
Mesa	23.2.0.20230712.1-2073
OpenCV	4.8.0
DLStreamer	2024.0.1
FFmpeg	2023.3.0

2.4 Platform Technology Requirements

This section lists the requirements for Intel's advanced platform technologies.

The Intel ® AI Edge Systems Verified Reference Blueprint requires Intel® Virtualization Technology (VT) to be enabled to reap the benefits of hardware virtualization. Either Intel® Boot Guard or Intel® Trusted Execution Technology establishes the firmware verification, allowing for platform static root of trust.

Table 6. Platform Technology Requirements

Platform Technologies		Enable/Disable	Required/Recommended
Intel® VT	Intel® CPU Virtual Machine Extension (VMX) Support	Enable	Required
	Intel® I/O Virtualization	Enable	Required
Intel® AMX	Intel® Advanced Matrix Extenstions	Enable	Required
Intel® Boot Guard	Intel® Boot Guard	Enable	Required
Intel® TXT	Intel® Trusted Execution Technology	Enable	Recommended

2.5 Platform Security

For Intel® AI Edge Systems , it is recommended that Intel® Boot Guard Technology be enabled so that the platform firmware is verified suitable during the boot phase.

In addition to protecting against known attacks, all Intel® Accelerated Solutions recommend installing the Trusted Platform Module (TPM). The TPM enables administrators to secure platforms for a trusted (measured) boot with known trustworthy (measured) firmware and OS. This allows local and remote verification by third parties to advertise known safe conditions for these platforms through the implementation of Intel® Trusted Execution Technology (Intel® TXT).

2.6 Side Channel Mitigation

Intel® recommends checking your system's exposure to the "Spectre" and "Meltdown" exploits. This reference implementation has been verified with Spectre and Meltdown exposure using the latest Spectre and Meltdown Mitigation Detection Tool, which confirms the effectiveness of firmware and operating system updates against known attacks.

The spectre-meltdown-checker tool is available for download at https://github.com/speed47/spectre-meltdown-checker.

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3 Platform Tuning for Worker Node

3.1 Additional Linux Packages Installation

3.1.1 Install Docker

Follow the instructions at https://docs.docker.com/engine/install/Ubuntu*/ to install Docker Engine on Ubuntu*.

3.2 Kubernetes Installation (Optional)

3.2.1 Install Docker and cri-dockerd

Follow the instructions at https://docs.docker.com/engine/install/ubuntu/ to install Docker Engine on Ubuntu, and follow the instructions at https://www.mirantis.com/blog/how-to-install-cri-dockerd-and-migrate-nodes-from-dockershim/ to install cri-dockerd. Download the cri-dockerd binary package for version 0.3.4.

3.2.2 Install Kubernetes

Follow the instructions at https://kubernetes.io/docs/setup/production-environment/tools/kubeadm/install-kubeadm/ to install Kubernetes including the kubelet, kubeadm, and kubectl packages. To continue to initialize the Kubernetes cluster, follow the steps below:

Note that setup does not use swap memory so it must be disabled

```
# swapoff -a
# systemctl enable --now kubelet
# systemctl start kubelet

# cat <<EOF > /etc/sysctl.d/k8s.conf
net.bridge.bridge-nf-call-ip6tables = 1
net.bridge.bridge-nf-call-iptables = 1
EOF

# sysctl --system
```

In the below command, update the Kubernetes version being used and the host-ip to that of the system being used

```
# kubeadm init --kubernetes-version=v1.28.0 --pod-network-
cidr=10.244.0.0/16 --apiserver-advertise-address=<host-ip> --token-ttl 0
--ignore-preflight-errors=SystemVerification --cri-
socket=unix:///var/run/cri-dockerd.sock
```

3.2.3 Install Calico

Follow the instructions at https://docs.tigera.io/calico/latest/getting-started/kubernetes/quickstart to install Calico. In the second step of the "Install Calico" section, the cidr address of the file needs to be modified, so run the following steps instead of step 2 listed in the instructions:

Update the URL if necessary

```
# wget
https://raw.githubusercontent.com/projectcalico/calico/v3.26.1/manifests/
custom-resources.yaml
```

Update the cidr address in the "custom-resources.yaml" file to 10.244.0.0/16

```
# kubectl create -f custom-resources.yaml
```

Once completed, wait for the Calico pods to be running before starting to use the cluster.

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4 Performance Verification

This chapter aims to verify the performance metrics for the Intel ® AI Edge Systems Verified Reference Blueprint to ensure that there is no anomaly seen. Refer to the information in this chapter to ensure that the performance baseline for the platform is as expected.

The performance data was collected on August 30, 2024, with the following hardware and software configurations.

Table 7. Hardware and OS Configurations for Intel® AI Edge Systems Verified Reference Blueprint – Scalable Performance Edge AI on Intel® Xeon Scalable 2S Base and Plus

Hardware Config	Base	Plus
CPU	2x Intel® Xeon® Gold 6538N Processor	2x Intel® Xeon® Platinum EMR 8592+ Processor
Sockets	2	2
Cores per Socket	32	64
LLC Cache	60MB Cache	320MB Cache
TDP per CPU	205W	350W
Simultaneous Multithreading (SMT)	Intel® Hyper-Threading Technology Enabled	Intel® Hyper-Threading Technology Enabled
CPUs	128	256
CPU Frequency	2.1 GHz base clock speed 4.1 GHz max turbo frequency	1.9 GHz base clock speed, 2.9 GHz all-core turbo frequency, 3.9 GHz max turbo frequency,
NUMA Nodes	2	2
Hyperthreading	Enable	Enable
Turbo	Enable	Enable
C-State	Enable	Enable
Total Memory	16x32GB 512GB, DDR5-5200 MT/s, 1DPC, 8 channels	16x32GB 512GB, DDR5-5600 MT/s, 1DPC, 8 channels
Hard Drive/ Disk	1x 447.1G INTEL SSDSC2KB48	2x 447.1G INTEL SSDSC2KB48
Network Interface Card/AIC	1x Dual port Intel® Ethernet Network Adapter E810-2CQDA2 2x Ethernet Connection X722 for 10GBASE-T	1x Dual port Intel® Ethernet Network Adapter E810-2CQDA2 2x Ethernet Connection X722 for 1
Network speed	1 GbE	1 GbE
Microcode	0x21000240	0x21000240
OS/Kernel	Ubuntu 22.04.4 (kernel 6.5.0-18-generic)	Ubuntu 22.04.4 (kernel 6.5.0-44-generic)

4.1 Memory Latency Checker (MLC)

The Memory Latency Checker which can be downloaded from https://www.intel.com/content/www/us/en/developer/articles/tool/intelr-memory-latency-checker.html. Download the latest version, unzip the tarball package, go into the Linux* folder, and execute `./mlc`. Table 8 and Table 9 below should be used as a reference for verifying the validity of the system setup.

Table 8. Memory Latency Checker

Key Performance Metric	Local Socket (Base)	Local Socket (Plus)
Idle Latency (ns)	100	90
Memory Bandwidths between nodes within the system (using read-only traffic type) (MB/s)	128991	624033

Table 9. Peak Injection Memory Bandwidth (1 MB/sec) Using All Threads

Peak Injection Memory Bandwidth (1 MB/sec) using all threads	Base Solution	Plus Solution
All Reads	518515	624252
3:1 Reads-Writes	432482	549163
2:1 Reads-Writes	420184	542341
1:1 Reads-Writes	395431	533820
STREAM-Triad	401704	545087
Loaded Latencies using Read-only traffic type with Delay=0 (ns)	203	327
L2-L2 HIT latency (ns)	55	61
L2-L2 HITM latency (ns)	56	62

Note: If the latency performance and memory bandwidth performance are outside the range, please verify the validity of the Platform components, BIOS settings, kernel power performance profile used, and other software components.

4.2 Vision AI

The Intel® Automated Self-Checkout Reference Package provides critical components required to build and deploy a self-checkout use case using Intel® hardware, software, and other open-source components. The Intel® Automated Self-Checkout serves as a proxy workload for Vision AI applications and leverages the YOLOv5 model for performing detection along with the efficientnet-b0 model for performing classification.

The video stream is cropped and resized to enable the inference engine to run the associated models. The object detection and product classification features identify the SKUs during checkout. The bar code detection, text detection, and recognition feature further verify and increase the accuracy of the detected SKUs. The inference details are then aggregated and

pushed to the enterprise service bus or MQTT to process the combined results further. This proxy workload supports either running directly on the CPU or fully offloading to the GPU, including encoding/decoding, along with inferencing.

Figure 4. Vision AI Video Analytics Pipeline

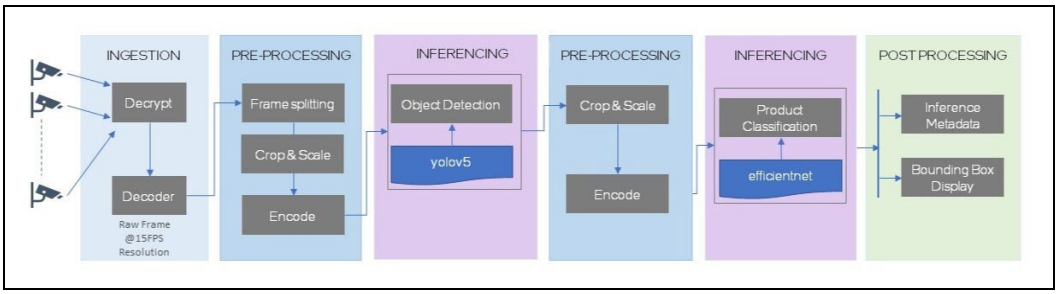


Table 10. Intel® Automated Self-Checkout Workload Configuration

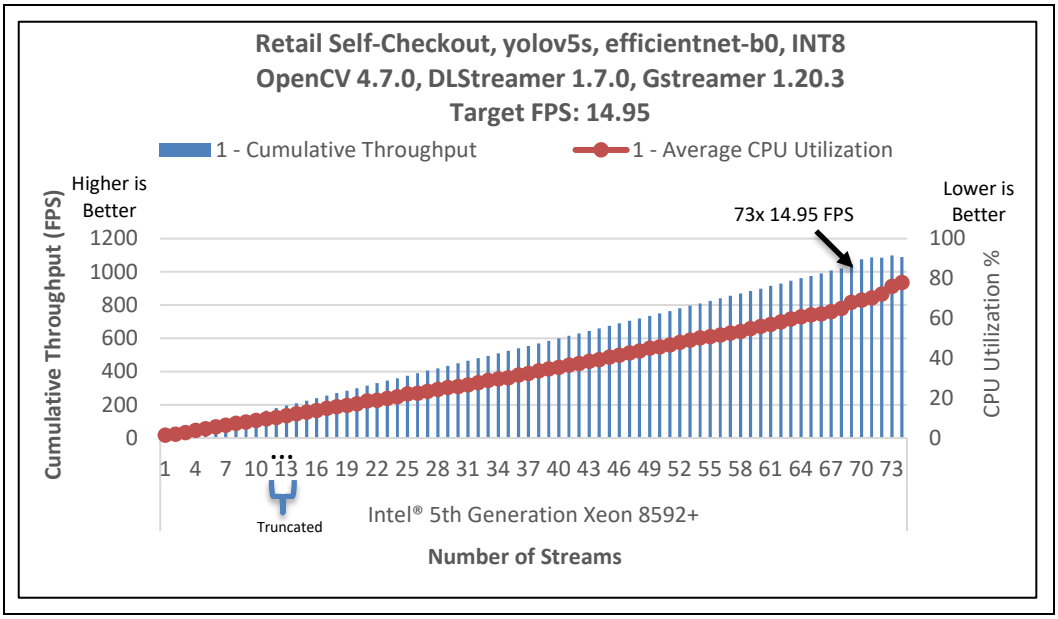
Ingredient	Software Version Details
OpenVINO™	2024.0.1
DLStreamer	2024.0.1
FFmpeg	2023.3.0
VPL	2023.4.0.0-799
Python	3.8+
OS	Ubuntu Desktop LTS, Kernel 6.5 (gcc 11.4.0)

4.2.1 Intel® Automated Self-Checkout on Dual Socket Intel® Xeon® Scalable Processor

The Intel ® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on** Intel® Xeon Scalable 2S Plus platform with Dual Socket Intel® Xeon® Platinum 8592+ should be able to service up to **73** IP camera streams at 14.95 FPS per stream, for an aggregate of up to 1098 FPS.

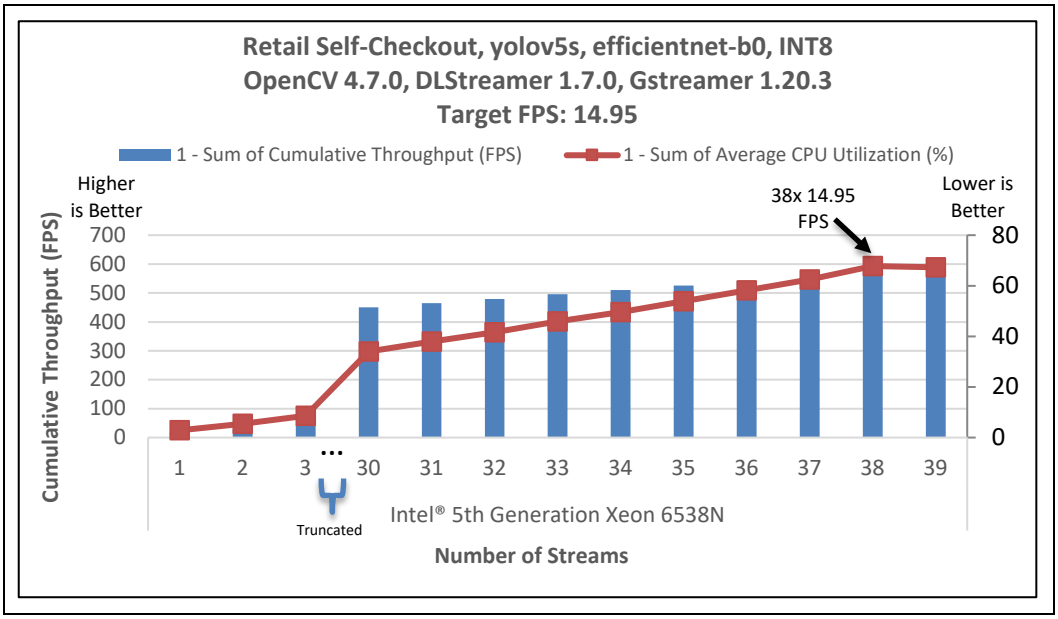
The Intel ® AI Edge Systems Verified Reference Blueprint– **Scalable Performance Edge AI** Intel® Xeon Scalable 2S Base platform with Dual Socket Intel® Xeon® Xeon® Gold 6538N should be able to service up to **38** IP camera streams at 14.95 FPS per stream, for an aggregate of up to 570 FPS.

Figure 5. Intel® Automated Self-Checkout Workload Performance (Plus CPU Configuration)



The graph above presents the maximum number of supported IP camera streams at a target of 14.95 FPS. The Vision AI workload is running exclusively on Intel® Xeon® Platinum 8592+Scalable Processor. In addition, the chart depicts the amount of remaining CPU utilization headroom available for running other workloads.

Figure 6. Intel® Automated Self-Checkout Workload Performance (-Base CPU Configuration)



The graph above presents the maximum number of supported IP camera streams at a target of 14.95 FPS. The Vision AI workload is running exclusively on Intel® Xeon® Gold 6538N Scalable

Processors. In addition, the chart depicts the amount of remaining CPU utilization headroom available for running other workloads.

4.3 GEN AI

In the current technological landscape, Generative AI (GenAI) workloads and models have gained widespread attention and popularity. Large Language Models (LLMs) have emerged as the dominant models driving these GenAI applications. The generation task is memory bound due to iterative decode and KVCache which needs special management to reduce memory overheads.

Intel® Extension for PyTorch* provide a lot of specific optimizations for these LLMs with platform features optimizations for performance boost on Intel® hardware. The optimizations take advantage of Intel® Advanced Vector Extensions 512 (Intel® AVX-512) Vector Neural Network Instructions (VNNI) and Intel® Advanced Matrix Extensions (Intel® AMX) on Intel® CPUs as well as Intel® Xe Matrix Extensions (XMX) AI engines on Intel® discrete GPUs. Moreover, Intel® Extension for PyTorch* provides easy GPU acceleration for Intel® discrete GPUs through the PyTorch* xpu device.

To better trade-off the performance and accuracy, different low-precision solutions like weight-only-quantization is also enabled. Additionally, tensor parallel and pipeline parallelism mechanism is also adopted for distributed inference to get lower latency for LLMs.

4.3.1 GEN AI on Dual Socket 5th Gen Intel® Xeon® Scalable Processor

The Large Language Model (LLM) proxy workload highlights the Generative AI processing capabilities of the Intel® AI Edge Systems Verified Reference Blueprint –Scalable Performance Edge AI on Intel® Xeon Scalable 2S platform, with the 8B to 40B parameter model is supported directly on 5th Gen Intel® Xeon® Scalable processors. Specifically, we have tested Llama3-8B, GPT-Neox20B and Falcon40B model with bfloat16, INT8 and INT4 precision.

The weight only quantization method was used for model quantization for converting model from bfloat16 to INT8 and INT4. For faster inference on dual socket CPUs with multiple NUMA regions, we have used auto tensor-parallelism (TP) using DeepSpeed optimization with Sub-NUMA Clustering (SNC) setting.

Table 11. GEN AI Workload Configuration

Ingredient	Software Version Details
Framework /Toolkit	CPU: PyTorch v2.3.100+cpu Deepspeed v0.14.0 Transformers v4.38.1 IPEX-LLM
Topology or ML Algorithm	tiiuae/falcon-40b EleutherAI/gpt-neox-20b meta-llama/Llama-3-8b-hf microsoft/Phi-3-mini-4k-instruct

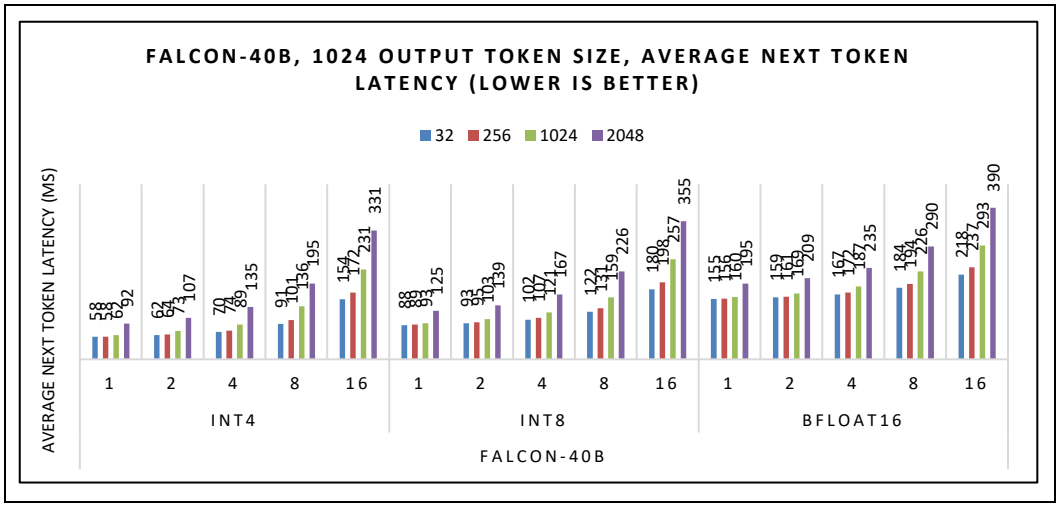
Ingredient	Software Version Details
	TinyLlama/TinyLlama-1.1B-Chat-v1.0
Libraries	oneDNN v3.4.1 oneCCL v2021.11 torch-ccl v2.3.0+cpu Intel® Neural Compressor v2.4.1
Model Precision	BF16, INT8, INT4
Quantization methods	weight-only-quantization
Warmup steps	1
Number of Iterations	4
Batch Size	1, 2, 4, 8, 16, 32
Beam Width	1 (greedy search)
Input Token Size	32, 256, 1024, 2048
Output Token Size	1024
Compiler	GCC version 12.3.0
Python	3.10.12
OS	Ubuntu Desktop LTS, Kernel 6.5

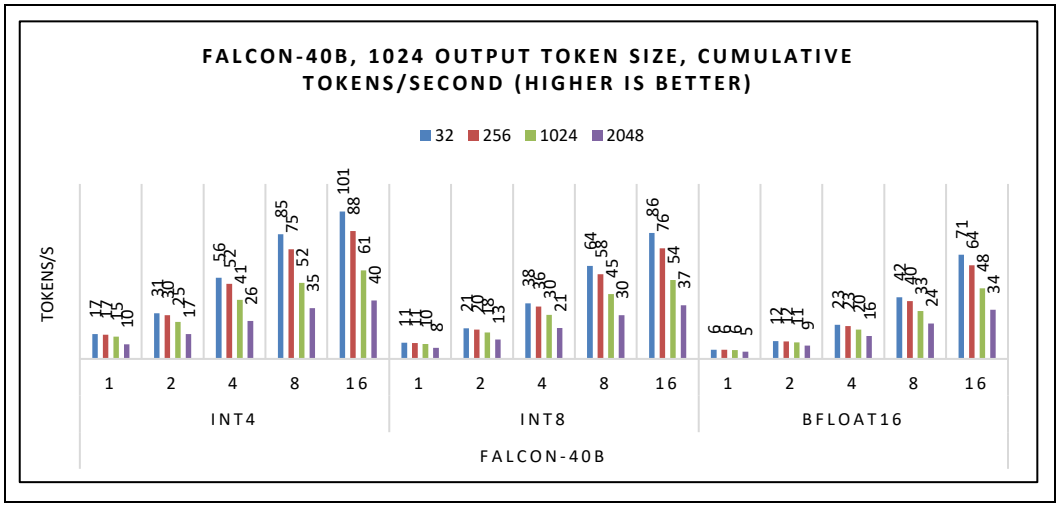
Intel® AI Edge Systems Verified Reference Blueprint –Scalable Performance Edge AI on Intel® Xeon Scalable 2S -Base platform and Large-Plus platform ensure that the results of the system follow the expected results as shown below to baseline the performance of the platform. The results shown include performance values for the next token latency, the achievable number of tokens per second, and the inference latency.

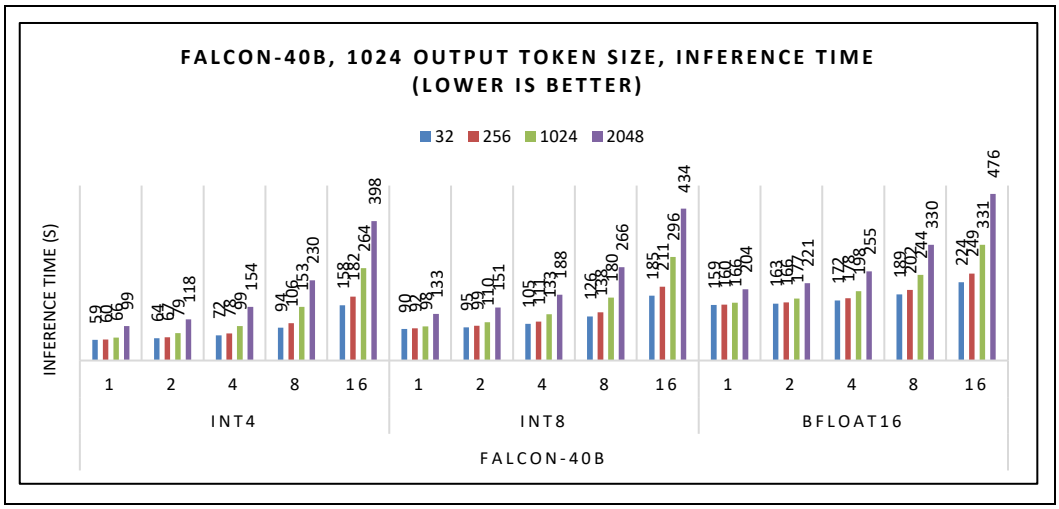
Table 12. Generative AI Workload Performance on Large-Plus

Gen AI Models	Precision	Input Tokens	Output Tokens	Batch Size	Average Next Token latency (ms)	Inference time
Falcon 40B	INT4	1024	1024	1	66	<60s
GPT-NEOX-20B	INT8	1024	1024	1	55	< 60s
	INT4				36	
Llama3-8B	INT4 INT8 BF16	1024	1024	1	14 20 32	< 60s

Figure 7. Falcon-40B Model Performance on Large-Plus CPU Configuration

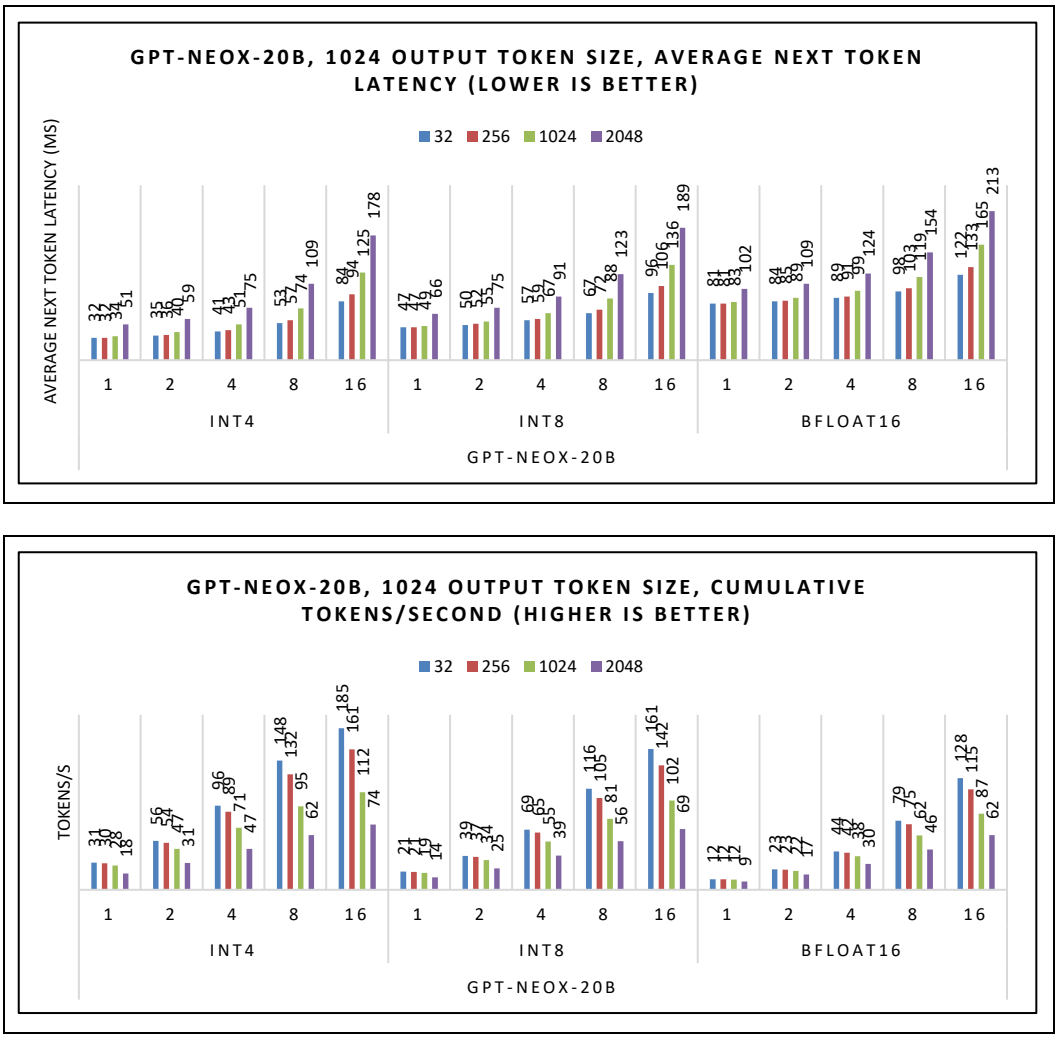


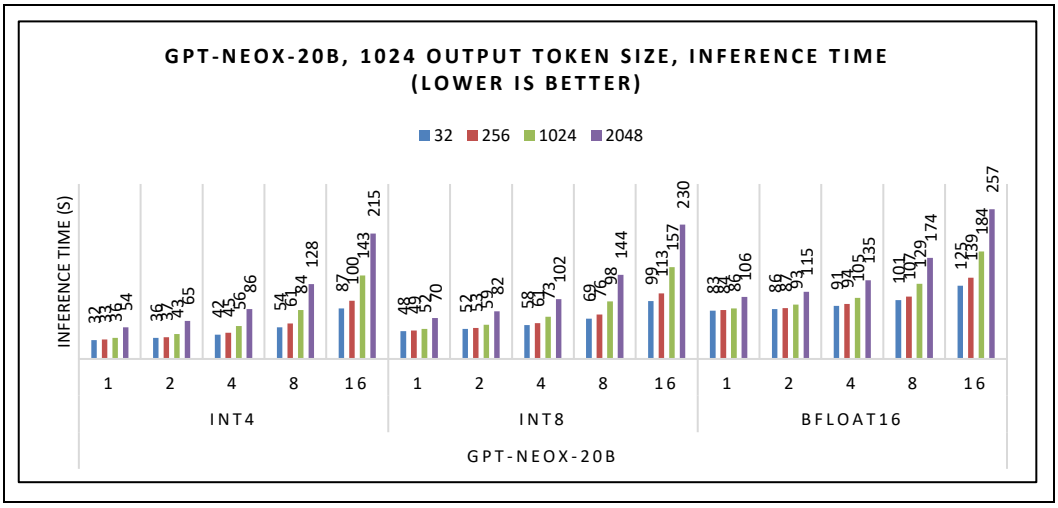




For the Falcon-40b model, a dual socket Intel® Xeon® Platinum 8592+ Processor can achieve a next token latency down to 58 ms for a single batch size using an input token size of 256 with INT4 precision with an inference time of 60 sec.

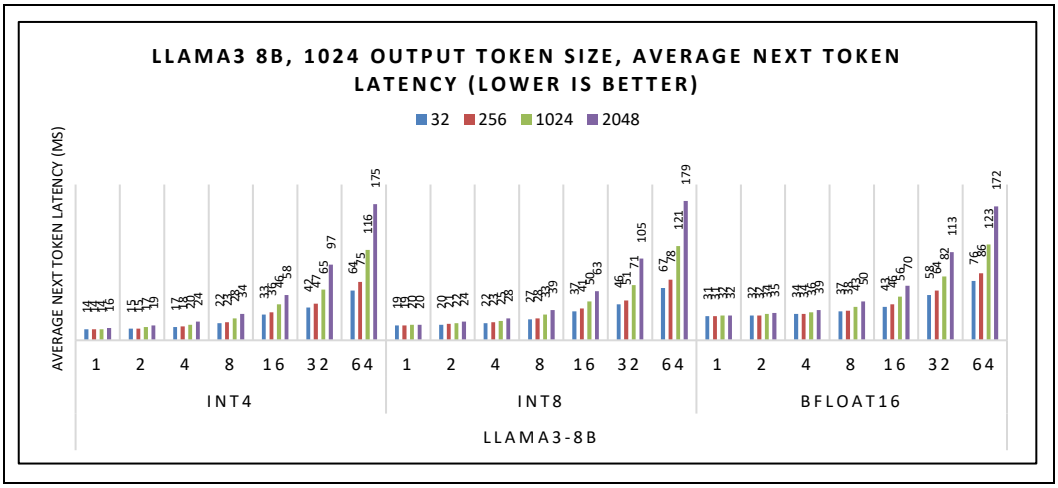
Figure 8. GPT-NEOX-20B Model Performance on Large-Plus CPU Configuration

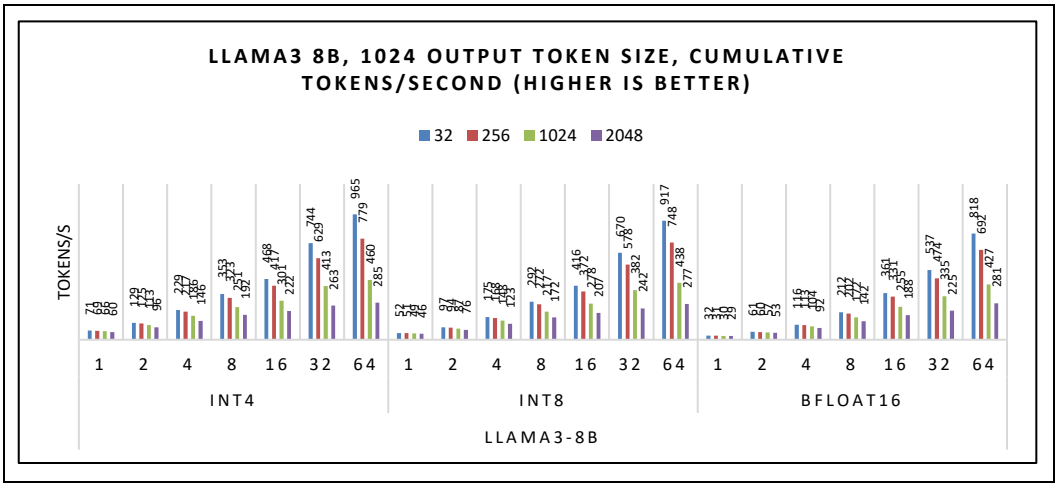


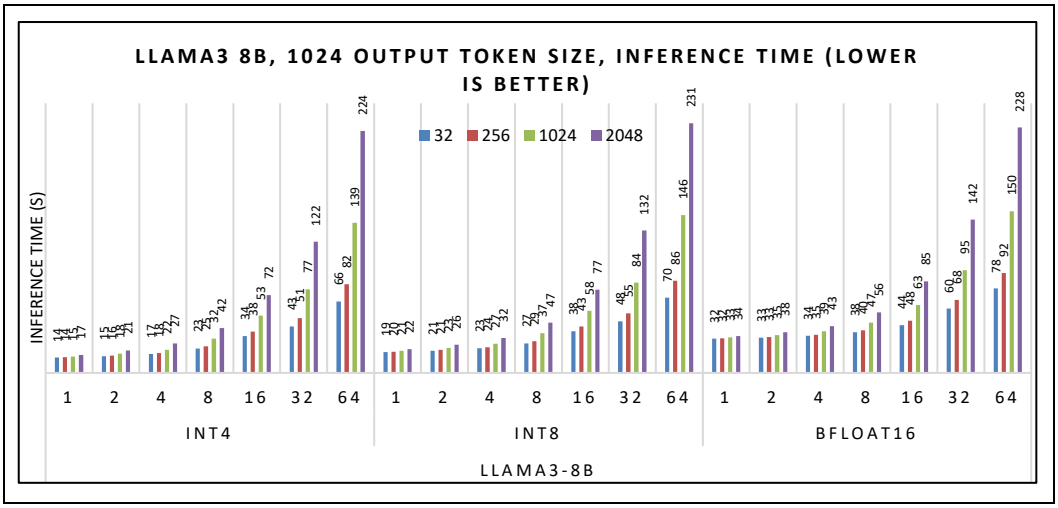


For the GPT-Neox-20 model, a dual socket Intel® Xeon® Platinum 8592+ Processor can achieve a next token latency down to 32 ms for a single batch size using an input token size of 256 with INT4 precision with an inference time of 33 sec.

Figure 9. Llama3-8B Model Performance on Large-Plus CPU Configuration





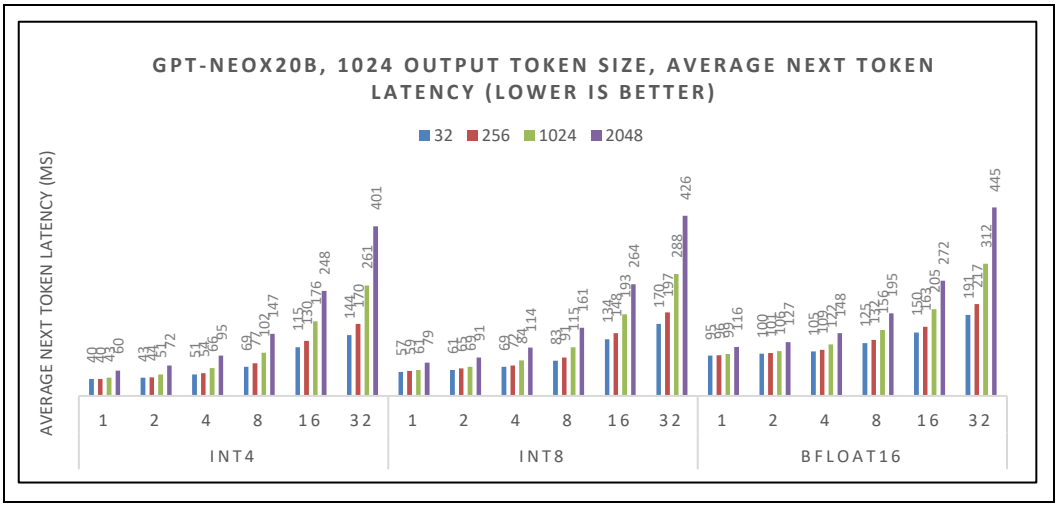


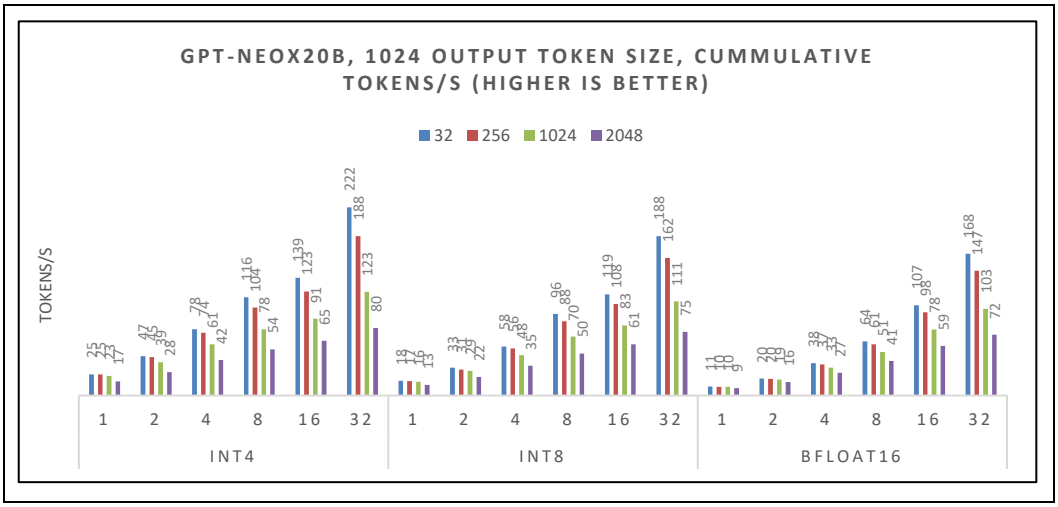
For the Llama3-8b model, a dual socket Intel® Xeon® Platinum 8592+ Processor can achieve a next token latency down to 14 ms for a single batch size using an input token size of 1024 with INT4 precision with an inference time of 15 sec.

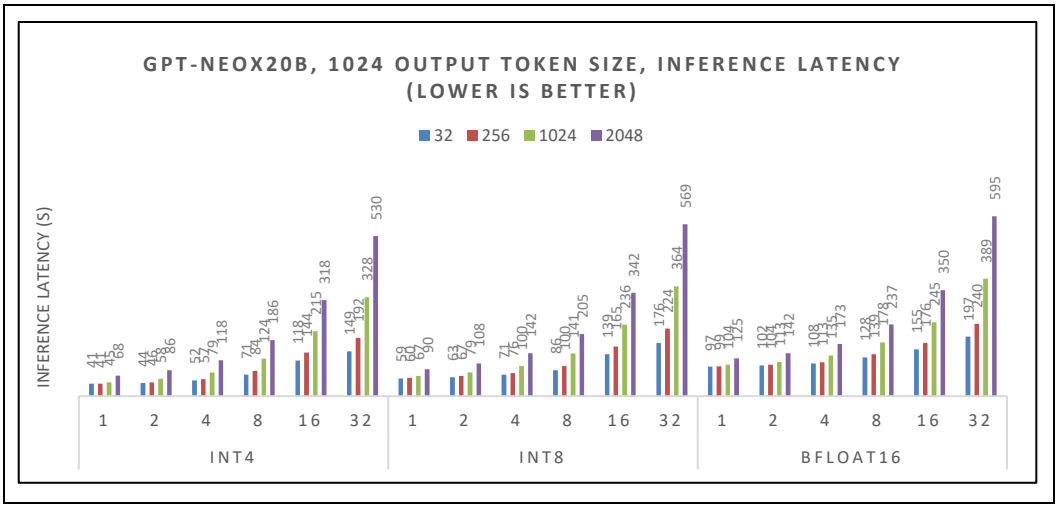
Table 13. GEN AI Workload Performance on Large-Base

Models	Precision	Input Tokens	Output Tokens	Batch Size	Average next token latency (ms)	Inference time
GPT-NEOX-20B	INT4	1024	1024	1	43	< 60s
Llama-3-8B	BF16 INT8 INT4	1024	1024	1	38 24 18	< 60s
Phi3-mini-4k-instruct	BF16 INT8 INT4	1024	1024	1	22 16 13	< 60s

Figure 10. GPT-NEOX-20B Model Performance on Large-Base CPU Configuration

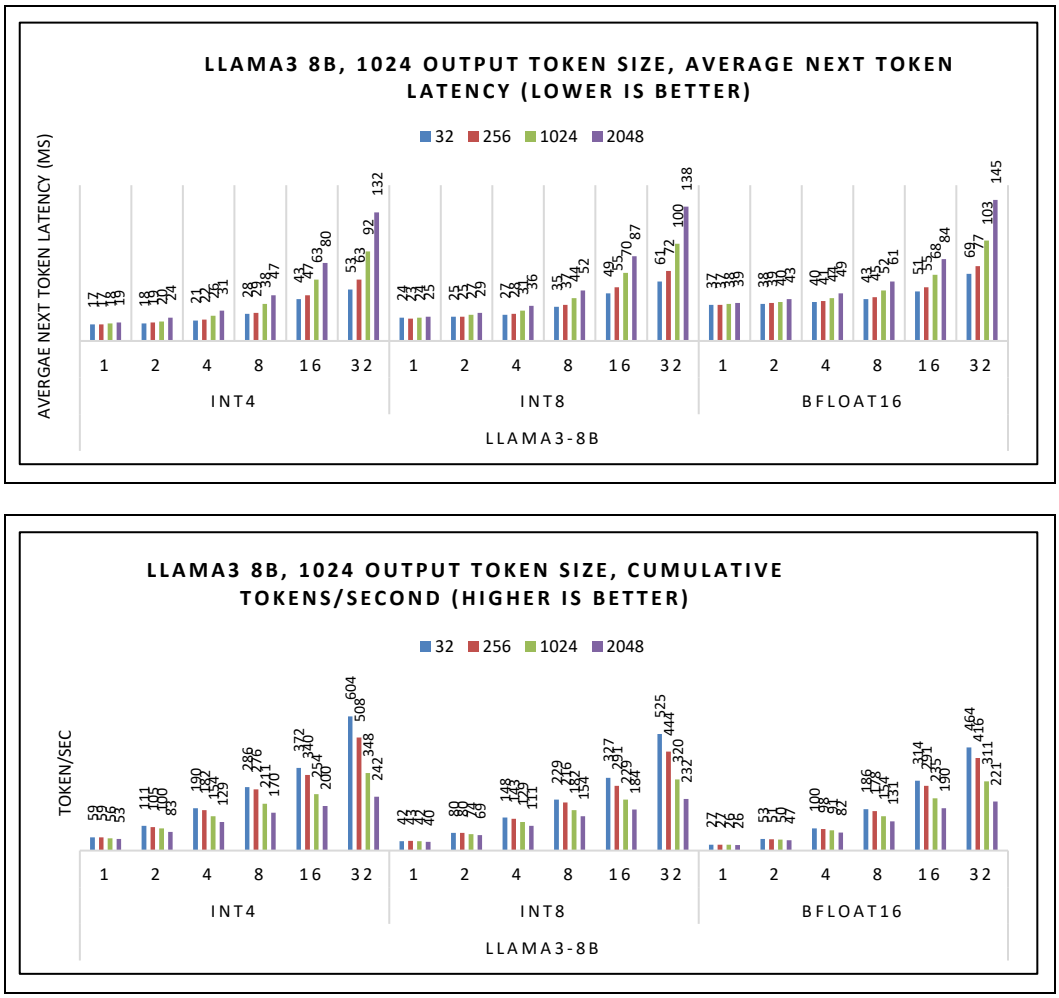


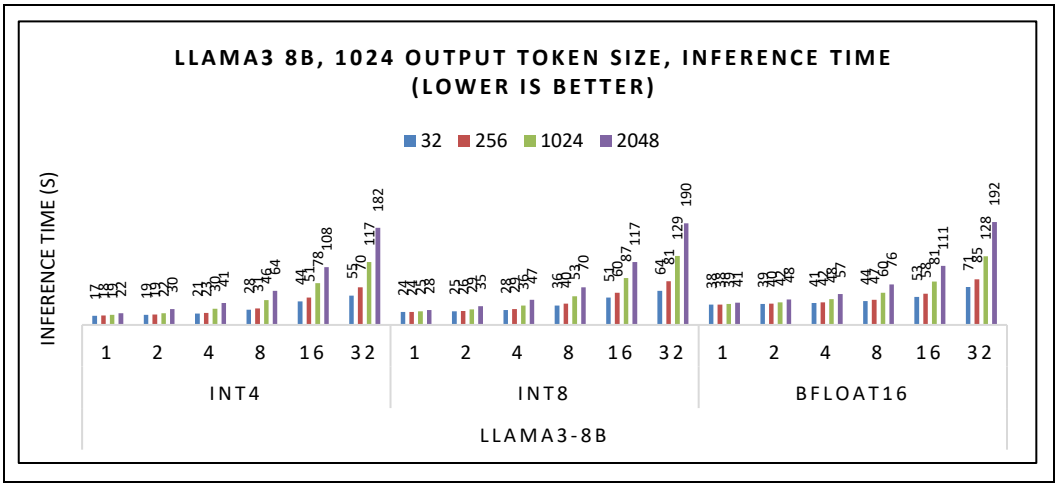




For the GPT-Neox-20 model, a dual socket Intel® Xeon® Gold 6538N Processor can achieve a next token latency down to 40 ms for a single batch size using an input token size of 256 with INT4 precision with an inference time of 41 sec

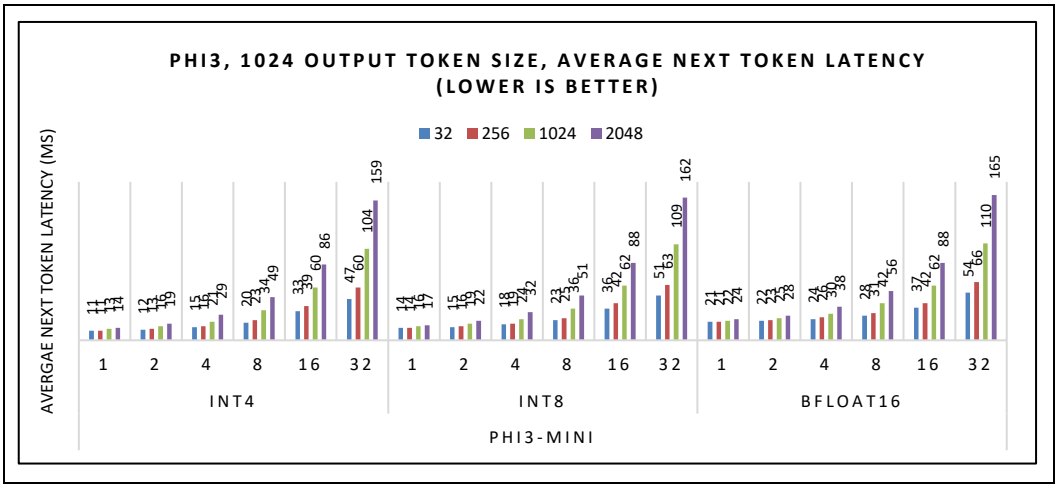
Figure 11. Llama3-8B Model Performance on Large-Base CPU Configuration

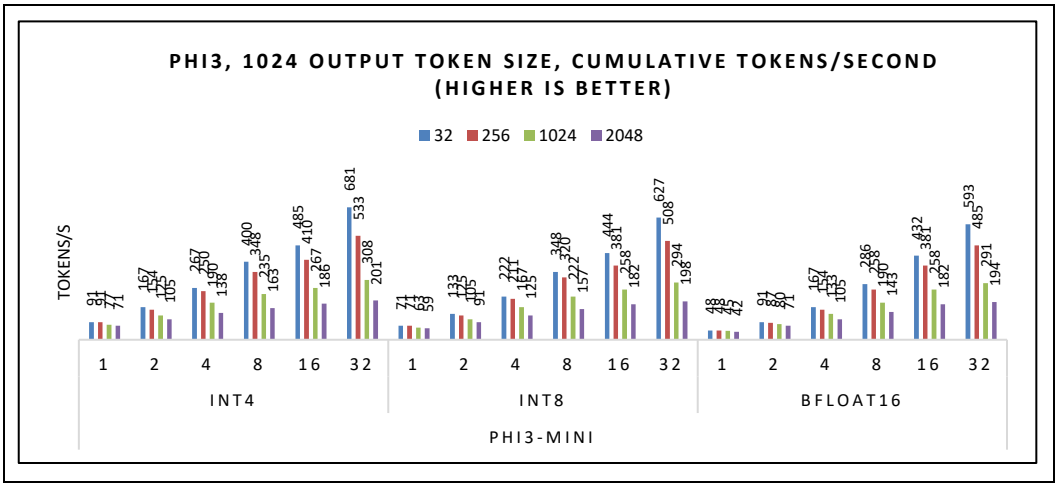


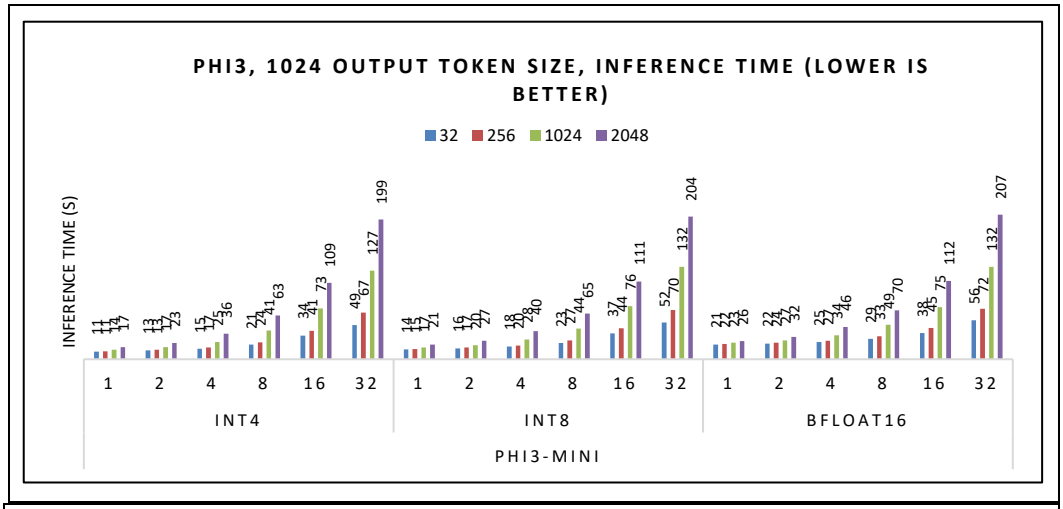


For the Llama3-8b model, a dual socket Intel® Xeon® Gold 6538N Processor can achieve a next token latency down to 17 ms for a single batch size using an input token size of 256 with INT4 precision with an inference time of 18 sec.

Figure 12. Phi3-min-4K-instruct Model Performance on Large-Base CPU Configuration







For the Phi3-mini model, a dual socket Intel® Xeon® Gold 6538N Processor can achieve a next token latency down to 13 ms for a single batch size using an input token size of 1024 with INT4 precision with an inference time of 14 sec

4.4 Network Security AI

For the Network Security AI performance verification, we will use Malconv and finetuned BERT-base-cased for malicious portable executable (PE) file detection and email phishing detection respectively.

4.4.1 MalConv for Malicious portable executable (PE) detection

AI inference is used in network/security to help prevent advanced cyber-attacks. To improve the latency associated with this application, the Intel® Xeon® Scalable Processor contains technologies to accelerate AI inference such as AVX-512, Advanced Matric Extensions

(AMX), and Vector Neural Network Instructions. The MalConv AI workload utilizes the TensorFlow deep-learning framework, Intel® oneAPI Deep Neural Network Library (oneDNN), AMX, and Intel® Neural Compressor to improve the performance of the AI inference model.

The starting model for the MalConv AI workload is an open-source deep-learning model called MalConv which is given as a pre-trained Keras H5 format file. This model is used to detect malware by reading the raw execution bytes of files. An Intel® optimized version of this H5 model is used for this workload, and the testing dataset is about a 32GB subset of the dataset from https://github.com/sophos/SOREL-20M. The performance of the model can be improved by various procedures including conversion to a floating-point frozen model and using the Intel® Neural Compressor for post-training quantization to acquire BF16, INT8, and ONNX INT8 precision models.

Intel ® AI Edge Systems Verified Reference Blueprint– Large-Base platform and Large-Plus platform ensure that the results of the system follow the expected results as shown below in order to baseline the performance of the platform. Table 16 shows the software used for the testing while Figures 19 and 20 show a graph of the mean inference time for each model. For the 6538N configuration, with 2 cores per instance, the INT8 model with AVX512_CORE_AMX enabled was able to reach a performance of less than 10 ms. For the 8592+ configuration, with 4 cores per instance, the INT8 model with AVX512_CORE_AMX enabled was able to reach a performance of less than 10 ms.

Note: Refer to https://hub.docker.com/r/intel/malconv-model-base for the Intel® Optimized MalConv Model.

Table 14. MalConv AI Workload Configuration

Ingredient	Software Version Details
TensorFlow	2.13.0
Intel® Extension for Tensorflow	2.13.0.1
oneDNN	2024.2.0
Python	3.11.7
Intel® Neural Compressor	2.6
ONNX	1.16.1

Figure 13. MalConv AI Entry Platform Performance Graph (6538N)

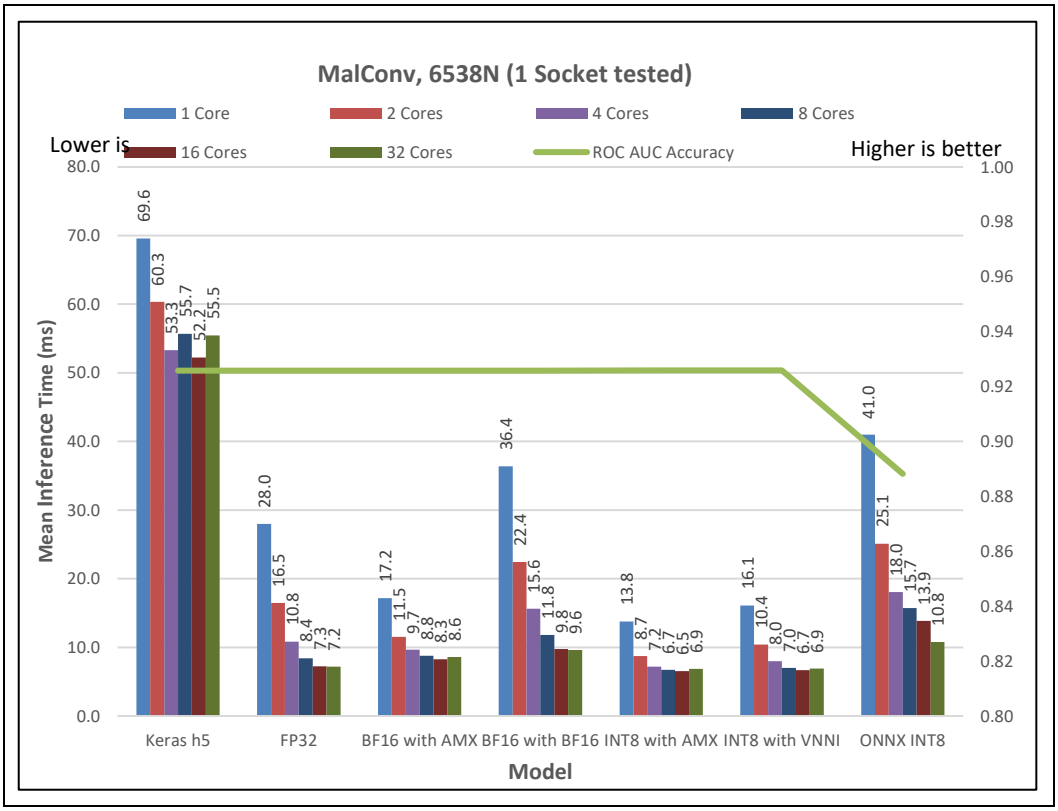
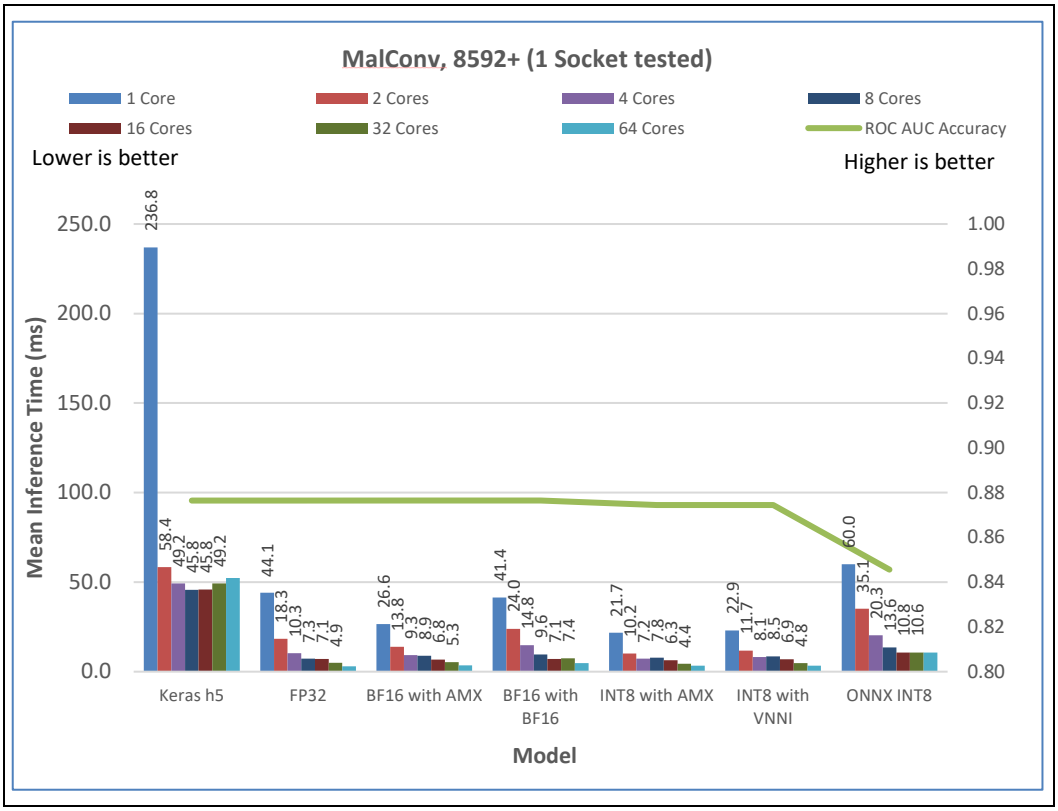


Figure 14. MalConv AI Entry Platform Performance Graph (8592+)



4.4.2 BERT for email phishing detection

BERT is a pre-trained language representation model developed by Google AI Language researchers in 2018, which consists of transformer blocks with a variable number of encoder layers and a self-attention head. The model used in the testing is a fine-tuned version of the Hugging Face BERT base cased model.

To detect phishing emails, the input email is first tokenized into chunks of words using the Hugging Face tokenizer, with a special CLS token was added at the beginning. The tokens are then padded to the maximum BERT input size, which by default is 512. The total input tokens are converted to integer IDs and fed to the BERT model. A dense layer is added for email classification, which takes the last hidden state for the CLS token as input.

Ensure that the results of the tests follow the expected results as shown in the following graph to baseline the performance of the platform. Table 17 shows the software used for the testing, while Figures 21 and 22 shows a graph of the results for the INT8 and FP32 BERT models. For both the 6538N and the 8592+ configurations, with 8 cores per instance, the mean latency of the INT8 model reaches below 20ms.

Note: Refer to https://huggingface.co/bert-base-cased for the original Hugging Face BERT base model.

Note: The phishing email test dataset can be found at https://github.com/IBM/nlc-email-phishing/tree/master/data

Table 15. BERT AI Workload Configuration

Ingredient	Software Version Details
Torch	2.1.2
Intel® Extension for PyTorch	2.1.100
Intel® oneDNN	2024.2.0
Python	3.11.7
Intel® Neural Compressor	2.6

Figure 15. BERT AI Entry Platform Performance Graph (6538N)

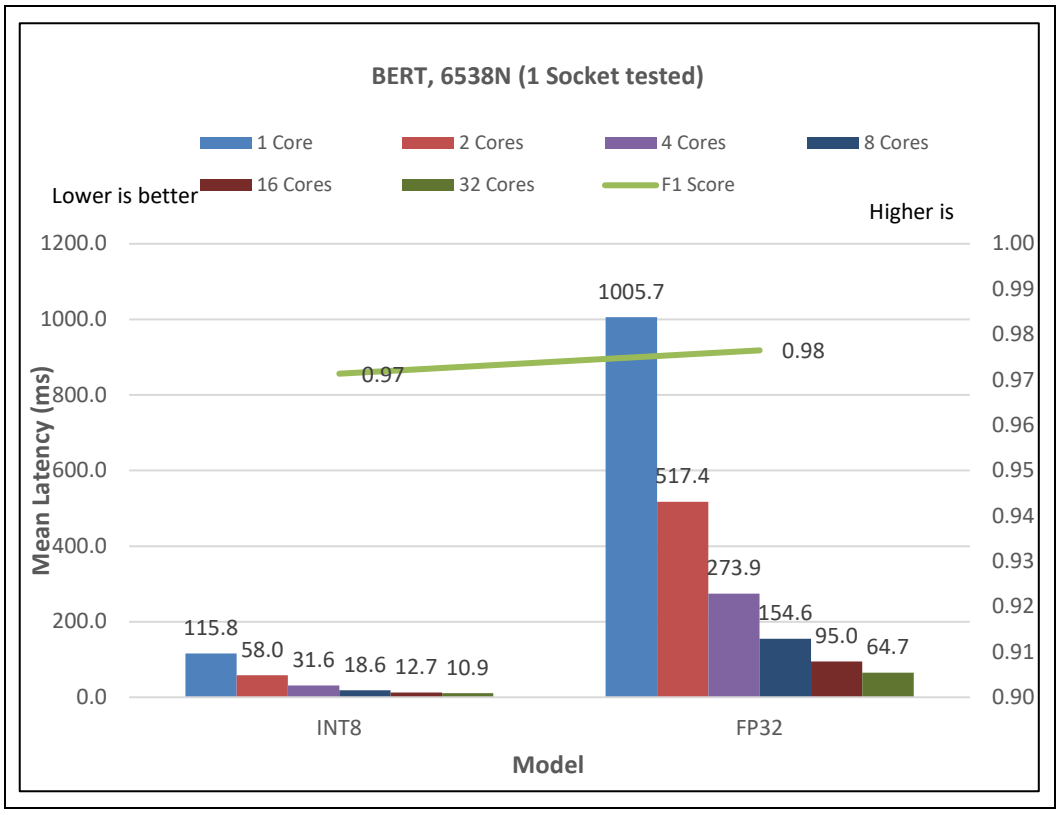
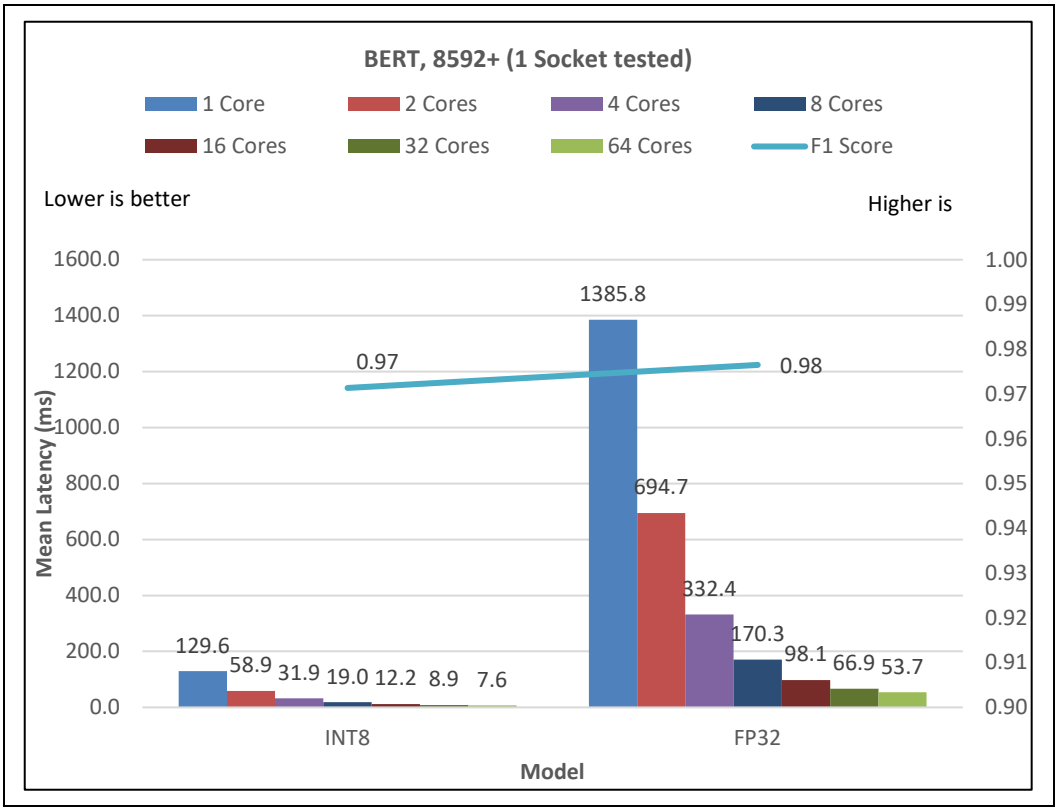


Figure 16. BERT AI Entry Platform Performance Graph (8592+)



5 Summary

The Intel® AI Edge Systems Verified Reference Blueprint –Scalable Performance Edge AI on Intel® Xeon Scalable 2S for Computer Vision, and GEN AI defined on dual socket 5th Gen Intel® Xeon® Scalable processors addresses the capabilities for AI inference offering the following value proposition:

Table 16. Vision AI Summary

Configuration	No. of IP Camera Streams
Base (CPU only)	38
Plus (CPU only)	78

Table 17. GEN AI Summary

Config	Model	Tokens/s
Plus CPU configuration (CPU only)	Llama3 8B model with INT8 precision Batch size of 32	670 tokens/s
Plus CPU configuration (CPU only)	GPT-NEOX-20B model with INT8 precision Batch size of 2	Up to 39 tokens/s
Plus CPU configuration (CPU only)	GPT-NEOX-20B model with INT8 precision Batch size of 2	Up to 39 tokens/s
Plus CPU configuration (CPU only)	Falcon40B model with INT4 precision Batch size of 1	Up to 17 tokens/s

The threshold figure reported by frameworks like Intel®ESDQ could be less than the figure above for ease of use.

This blueprint, combined with architectural improvements, feature enhancements, and integrated Accelerators, provides a significant performance and scalability advantage in support of today's AI workload

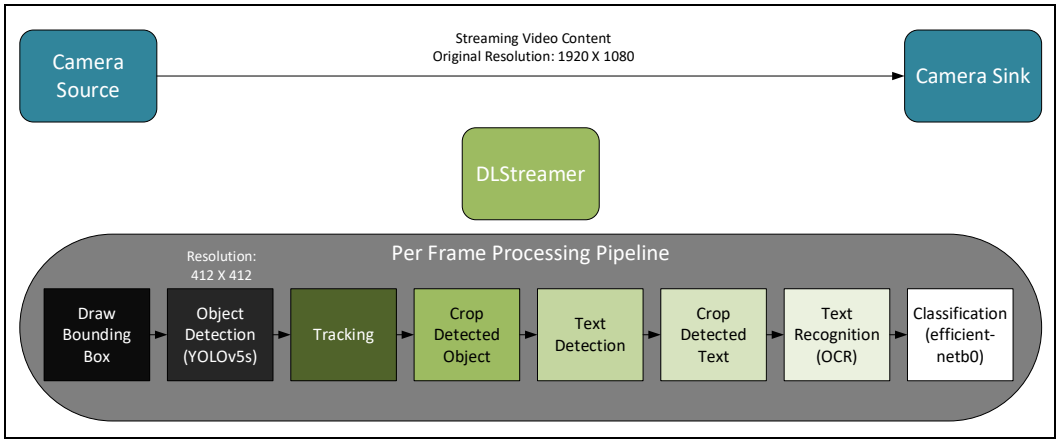
§

Appendix A Appendix

The following section provides detailed instructions for benchmarking a platform with each of the proxy workloads for Vision AI, Generative AI, along with Network Security AI. The benchmarking process leverages the tools and scripts provided as part of the Intel ® AI Edge Systems Verified Reference Blueprint will be available later, please reach out to your Intel® Field Representative for access.

A.1 Automated Self-Checkout Test Methodology

Figure 17. Test Methodology for the Automated Self-Checkout Proxy Workload



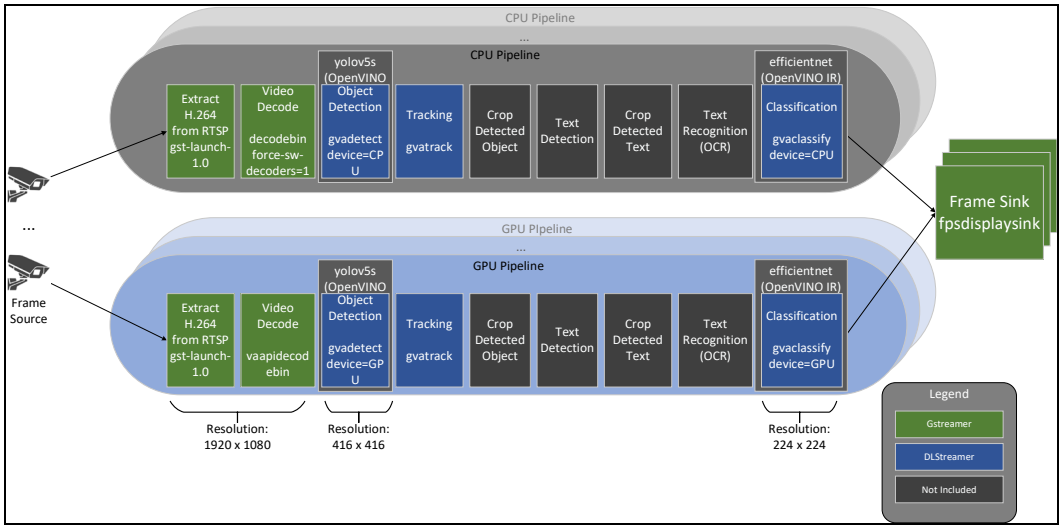
The Intel® Automated Self-Checkout Reference Package provides critical components required to build and deploy a self-checkout use case using Intel® hardware, software, and other open-source software. Vision workloads are large and complex and need to go through many stages. For instance, in the pipeline shown within the figure below, the video data is ingested, pre-processed before each inferencing stage, inferenced using two models - YOLOv5 and EfficientNet, and post-processed to generate metadata along with drawing the bounding boxes for each frame. The camera source plays back pre-recorded video content, which is then processed by the media analytics pipeline. The video stream input is decoded within the CPU pipeline using software-based decodebin API calls, while for the GPU pipeline the decoding is offloaded using vaapidecodebin API calls. The video content is freely available from https://www.pexels.com .

The Intel® Automated Self-Checkout Reference makes use of Intel® Deep Learning Streamer (Intel® DL Streamer), which leverages the open-source media framework GStreamer to provide optimized media operations along with the Deep Learning Inference Engine from the OpenVINO™ Toolkit to provide optimized inference. DLStreamer accelerates the media analytics pipeline for the Vision AI use case and allows for offloading to the underlying Intel® ARC™ and Intel® Data Center Flex GPUs.

The media analytics pipeline for Vision AI utilizes DLStreamer to performs object classification on the Region(s) of Interest (ROI) detected by gvadetect using the gvaclassify element and Intermediate Representation (IR) formatted object classification model. The models used for detection are in OpenVINO Intermediate Representation format, which is optimized for Intel® CPUs and GPUs. One advantage for the OpenVINO IR format is that the models can be used as-is without the need for retraining to leverage Intel® CPUs and GPUs. The Vision AI pipeline also uses object tracking for reducing the frequency of object detection and classification, thereby increasing the throughput, using gvatrack. The pipeline publishes the detection and classification results within a JSON file, which is then parsed, and the final results are reported in a log file.

Note: The GStreamer multi-media framework is used to stream video content by the frame source and the frame sink endpoints. The current release does not make use of the underlying media engines, offloading to the media engines is planned for future releases of the Intel® Automated Self-Checkout Reference.

Figure 18. Detailed Test Methodology for Retail Self-Checkout Pipeline



The test methodology implements the following to measure the maximum number of streams that the system can sustain:

- Detection Model: Yolov5s
- Classification Model: efficientnet-b0
- OpenVino 2024.0.1
- DLStreamer 2024.0.1
- FFmpeg 2023.3.0
- VPL 2023.4.0.0-799

The test measures the number of streams that the server can sustain at the target FPS. For each test iteration, the number of camera streams is monotonically increased until the currently measured FPS value falls below the target FPS value.

Upon test completion, the results are captured for the average FPS, the cumulative FPS, along with the peak number of streams achieved at the target FPS.

Optionally, platform metrics can be collected including CPU utilization, CPU power, CPU frequency, CPU temperature, along with wall power.

To run the automated self-checkout test, follow the steps below:

1. Pre-Requisites:

- Install Docker
- Set HTTP_PROXY and HTTPS_PROXY proxies in environment if necessary
- Python version 3.8 is recommended

2. Change to the automated self-checkout test directory and initialize the environment:

```
# cd enterprise_ai/common/retail-self-checkout/

# ./init_rsc.sh
```

Optionally, update the collect_server_power.sh script with the BMC information of the server to collect the wall power metrics during the automated self-checkout benchmark.

Note: The collect_server_power.sh script is provided for convenience to collect wall power measurements and is designed to be run within a lab environment and not within a production environment.

```
# $EDITOR collect_server_power.sh



#!/usr/bin/env bash



…

ip_address=<server-ip-address>

un=<bmc-username>

pw=<bmc-password>

…
```

Note: Start the benchmark on the 5th Gen Intel® Xeon® Scalable Processor using a batch size of By default, the benchmark will use a target FPS of 14.95 along with an initial duration of 40 seconds to allow the system to reach steady state.

```
# ./benchmark_rsc.sh 1 cpu
```

3. The results will be stored within a CSV file located under rsc_results.

```
# cat ~/rsc_results/stream-density-cpu-yolov5s-effnetb0-density-
increment_1_init-duration_40_target-fps_14_95_batch_1.csv
```

4. Optionally, if turbostat is installed on the server then CPU related metrics can be converted into a CSV file as follows:

```
python3 turbostat_log_parser_infer_streams.py \

```

```
--log-file ~/rsc_results/turbostat_gpu_batch_1.log \

--num-streams <max_stream_num> \

--csv-file-name ~/rsc_results/turbostat_gpu_batch_1.csv
```

5. Optionally, if the BMC credentials have been provided then server power related metrics can be converted into a CSV file as follows:

```
python3 server_power_log_parser.py --log-file
~/rsc_results/server_power_cpu_batch_1.log --csv-file-name
~/rsc_results/server_power_cpu_batch_1.csv
```

6. Start the benchmark against Intel® Data Center GPU Flex Series using a batch size of 1.

Note: By default, the benchmark will use a target FPS of 14.95 along with an initial duration of 40 seconds to allow the system to reach a steady state.

```
# ./benchmark_rsc.sh 1 gpu
```

7. The results will be stored within a CSV file located under rsc_results.

```
# cat ~/rsc_results/stream-density-gpu-yolov5s-effnetb0-density-
increment_1_init-duration_40_target-fps_14_95_batch_1.csv
```

8. Optionally, if turbostat is installed on the server then CPU related metrics can be converted into a CSV file as follows:

```
python3 turbostat_log_parser_infer_streams.py \

--log-file ~/rsc_results/turbostat_gpu_batch_1.log \

--num-streams <max_stream_num> \

--csv-file-name ~/rsc_results/turbostat_gpu_batch_1.csv
```

9. Optionally, if the BMC credentials have been provided then server power related metrics can be converted into a CSV file as follows:

```
python3 server_power_log_parser.py --log-file
~/rsc_results/server_power_cpu_batch_1.log --csv-file-name
~/rsc_results/server_power_cpu_batch_1.csv
```

A.2 Generative AI Test Methodology

A.2.1 IPEX-LLM Testing Methodology on CPU

The Generative AI benchmark on Intel® dual socket CPU was performed using Intel® Extension of PyTorch (IPEX) for LLM. To reduce the inference latency and improve throughput, tensor parallel is also enabled in our solution. We use DeepSpeed to auto shard the model and then use Distributed Inference with DeepSpeed with AutoTP feature.

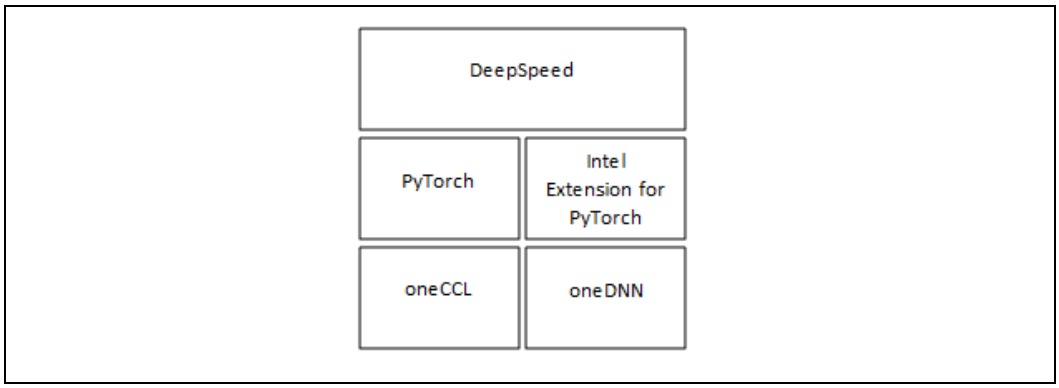
DeepSpeed builds on top of PyTorch, which has been highly optimized for CPU inference and training. Intel® Extension for PyTorch adds state-of-the-art optimizations for popular LLM

architectures, including highly efficient matrix multiplication kernels to speed up linear layers and customized operators to reduce the memory footprint.

The runtime software components for DeepSpeed Inference on CPU are shown in Figure 23:

- Intel® oneAPI Deep Neural Network Library (oneDNN) uses Intel® AVX-512 VNNI and Intel® AMX optimizations.
- Intel® oneAPI Collective Communications Library (oneCCL) is a library that implements the communication patterns in deep learning.
- Intel® Neural Compressor was used to convert the LLMs from FP32 datatype to bfloat16 or int8 datatype.

Figure 19. Software components for DeepSpeed Inference on CPU



Follow the steps to setup the IPEX-CPU test and benchmark on Dual socket Intel® Xeon® Scalable Processor. The user is expected to have privileged rights.

1. Install the baseline dependencies:

```
# sudo apt update

# sudo apt install -y make git numactl

# sudo apt install -y python3

# sudo pip install –upgrade pip
```

2. Clone the IPEX project:

```
# git clone https://github.com/intel/intel-extension-for-pytorch.git

# cd intel-extension-for-pytorch

# git checkout v2.3.100+cpu

# git submodule sync

# git submodule update --init --recursive
```

3. Build the IPEX docker image:

```
# DOCKER_BUILDKIT=1 docker build --build-arg HTTPS_PROXY=${HTTPS_PROXY} --
-build-arg HTTP_PROXY=${HTTP_PROXY} -f
```

```
examples/cpu/inference/python/llm/Dockerfile --build-arg COMPILE=ON -t
ipex-cpu:2.3.100 .
```

Note: The ipex-cpu container build takes approx. 30 mins

4. Verify the IPEX container is built

```
# docker images | grep ipex

REPOSITORY   TAG       IMAGE ID       CREATED       SIZE

ipex-cpu     2.3.100   d5ce81fe66f8   3 hours ago   4.61GB
```

5. Download the LLM models from HuggingFace:

```
# huggingface-cli download <model_card> --local-dir ~/<local_model_path>
--token <your_huggingface_token>
```

6. Start the ipex-cpu docker container

```
# export DOCKER_IMAGE=ipex-cpu:2.3.100

# export CONTAINER_NAME=ipex-cpu

# export MODEL_PATH=<CHANGE TO PATH TO THE MODEL DIRECTORY>



# docker run --rm -it --privileged --memory="256G" --shm-size="128G" --
name=$CONTAINER_NAME -v $MODEL_PATH:/llm/models $DOCKER_IMAGE bash
```

Note: It's recommended to use shard_model before running distributed inference to save time during model inference.

7. Shard model for Distributed inference inside the ipex-cpu docker container

```
# cd ./llm/utils

# create_shard_model.py -m /llm/models/<MODEL_ID> --save-path
/llm/models/<SHARD-MODEL-DIRECTORY>
```

8. Copy the benchmark_cpu_ds.sh and extract_kpis.py script to the container:

```
# docker cp ~/applications.platform.intel-select-for-
network/enterprise_ai/common/ipex-llm-cpu/benchmark_cpu_ds.sh ipex-
cpu://home/ubuntu/llm/



# docker cp ~/applications.platform.intel-select-for-
network/enterprise_ai/common/ipex-llm-cpu/extract_kpis.py ipex-
cpu://home/ubuntu/llm/
```

9. Change the user:group of the scripts inside the container:

```
# sudo chown ubuntu:ubuntu benchmark_cpu_ds.sh

# sudo chown ubuntu:ubuntu extract_kpis.py
```

10. Edit the shard model path and model name in the benchmark_cpu_ds.sh script as shown

```
model_shard="/llm/models/llama3-8B/shard_model_hf"

model_name="llama3-8B"
```

11. Download the prompt json files for model tests

```
For Llama3 models download the below prompt file

# wget -O prompt.json https://intel-extension-for-
pytorch.s3.amazonaws.com/miscellaneous/llm/prompt-3.json



For other models, use the below prompt file

# wget https://intel-extension-for-
pytorch.s3.amazonaws.com/miscellaneous/llm/prompt.json
```

12. Run the benchmark script for distributed inference. This script will create a "result-model_name_mmddyyhhss" folder in the same directory and will contain text files for each test iteration

```
# ./benchmark_cpu_ds.sh
```

13. Extract KPIs using the python script. This script generate a CSV file named llm_benchmark_results.csv with all the KPIs

```
# python extract_kpis.py --results-dir results-model_name_mmddyyhhss
```

14. Copy the llm_benchmark_results.csv file from docker to host

```
# docker cp ipex-cpu:/home/ubuntu/llm/llm_benchmark_results.csv
./root/workspace
```

A.3 Network Security AI Test Methodology

A.3.1 MalConv AI Test Methodology

Follow the instructions below to run the MalConv AI testing:

1. You will need to provide your own testing dataset to use. Create the following directories:

```
# mkdir -p malconv/datasets/KNOWN
# mkdir -p malconv/datasets/MALICIOUS
```

2. Place the benign files into the "malconv/`datasets/KNOWN`" directory, and place the malicious files in the "malconv/`datasets/MALICIOUS`" directory
3. Use the "build_dockerfile.sh" script to build the Dockerfile image for the MalConv testing. If proxy variables for Internet access are needed, please set them in the Dockerfile before running the script.
4. Run the "`run_malconv_test.sh`" script to run the MalConv benchmarking test. The generated "malconv_results`.log`" file will contain five runs of the mean inference time results and ROC AUC accuracy of each model tested with different numbers of cores per instance.

A.3.2 Bert AI Test Methodology

Follow the instructions below to run the BERT testing:

1. Use the "build_dockerfile.sh" script to build the Dockerfile image for the MalConv testing. If proxy variables for Internet access are needed, please set them in the Dockerfile before running the script.
2. Run the "`run_bert_test.sh`" script to run the benchmarking test. The generated "`bert_results.log`" file will contain five runs of the testing showing multiple statistics for different numbers of cores per instance. The mean latency value is highlighted in the results shown in Section 4.4.2.

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