Intel® AI Edge Systems Verified Reference Blueprint – Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU for Computer Vision and GEN AI

Reference Architecture

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Revision History

Document Number	Revision Number	Description	Revision Date
834791	1.2	Re-named Document to align with Reference Edge Systems Roadmap	March 2025
834791	1.0	Initial release	March 2025

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1 Introduction

Intel® AI Edge Systems are a range of optimized commercial AI systems delivered and sold through OEM/ODM in the Intel® ecosystem. They are commercial platforms 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. Intel® AI Edge 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 AI Edge systems, Intel® is offering reference design and verified reference blueprints with AI Edge system configurations that are tuned and benchmarked for different AI Edge System types that support Edge use cases. Verified Reference Blueprints (VRB) include hardware BOM, foundational 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 architecture for the 14th Gen Intel® Core processor family.

When end customers choose an Intel® AI Edge System Verified Reference Blueprint, it enables them to deploy the AI workloads more securely and efficiently than ever before. End users spend less time, effort, and expense evaluating hardware and software options. Intel® AI Edge Systems 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® 14th Generation Core with Intel® GPU for Computer Vision and GEN AI is based on a 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 "Gen AI" .

All Intel® AI Edge Systems Verified Reference Blueprints 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® 14th Generation Core with Intel® GPU 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® 14th Generation Core with Intel® GPU** for Computer Vision and GEN AI Plus configuration for the Node is defined with at least a 32-core 14th Generation Intel® Core processor and high-performance network, with storage and integrated platform acceleration products from Intel® for maximum containerized workload density.

- Intel® AI Edge Systems Verified Reference Blueprint— **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** for Computer Vision and GEN AI Plus configuration for the Node are defined with a 24-core 14th Generation Intel® Core processor, with storage and add-in platform acceleration products from Intel® targeting 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 enterprise vertical users, service providers, and our ecosystem partners to demonstrate the solution's value for AI Inference use cases. The solution leverages 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 AI Inference applications. Some of the key benefits of the Reference Blueprint on the 14th Generation Intel® Core Processor Family and Intel ARC-A Series discrete GPU include:

- High core count and per-core performance
- Compact, power-efficient system-on-chip platform
- Streamlined path to cloud-native operations
- Accelerated AI inference with integrated processor capabilities
- Discrete GPU support to accelerate for AI inference workload
- The Xe kernel of Intel® GPUs integrates Extended Vector Engine (XVE) and Extended Matrix Engine (XMX), which accelerate AI workflow and provide powerful and real-time computing power support for AI inference at the edge 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® 14th Generation Core with Intel® GPU** 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® 14th Generation Core with Intel® GPU** for Computer Vision, and GEN AI. The hardware requirements for the Base Configuration and Plus Configuration are detailed below.

Table 1. Platform - Base Configuration

Ingredient	Requirement	Required/ Recommended	Quantity
Processor	Intel® 14th Generation CoreTM i7-14700 Processor 8 P-Cores, 12 E-Cores, 65 W or higher number SKU	Required	1
Memory	128 GB DDR5 4800 MT/s	Required	1
Network	Intel® Ethernet Network Adapter i226-V/LM/IT (2.5 Gbps)	Required	1
Storage (Boot/Capacity Drive)	1 TB or equivalent boot drive	Required	1
dGPU	Intel® Arc™ A380 or A750	Required	1
IP cameras	4K video streaming with support for at least 15 FPS and RTSP	Required	4
LAN on Motherboard (LOM)	1 Gbps I219-LM for Operation, Administration and Management (OAM)	Required	1

Table 2. Platform - Plus Configuration

Ingredient	Requirement	Required/ Recommended	Quantity
Processor	Intel® 14th Generation CoreTM i9-14900E Processor 8 P-Cores, 16 E-Cores, 65 W or higher number SKU	Required	1
Memory	128 GB DDR5 4800 MT/s	Required	1
Network	Intel® Ethernet Network Adapter i226-V/LM/IT (2.5 Gbps)	Required	1
Storage (Boot/Capacity Drive)	1 TB or equivalent boot drive	Required	1

Ingredient	Requirement	Required/ Recommended	Quantity
dGPU	Intel® Arc™ A750	Required	1
IP cameras	4K video streaming with support for at least 15 FPS and RTSP	Required	8
LAN on Motherboard (LOM)	1 Gbps I219-LM for Operation, Administration and Management (OAM)	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® 14th Generation Core with Intel® GPU** 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.

Refer to the following table for the set of recommended BIOS settings.

Table 3. Recommended BIOS Settings

Setting	Value
Hardware Prefetcher	Enabled
Intel® (VMX) Virtualization Technology	Enabled
Hyper-Threading	Enabled
Intel® Speed Shift Technology	Enabled
Turbo Mode	Enabled
C-States	Enabled
Enhanced C-States	Enabled
C-State Auto Demotion	C1
C-State Un-Demotion	C1
MonitorMWait	Enabled
Enforce DDR Memory Frequency POR	POR
Maximum Memory Frequency	Auto
Primary Display	Auto
Internal Graphics	Auto
Graphics Clock Frequency	Max CdClock freq based on Reference Clk
VT-d	Enabled
Re-Size BAR Support	Enabled

Setting	Value
SR-IOV Support	Enabled

BIOS settings differ from vendor to vendor. Please contact your Intel® Representative if you do not see the exact setting in your BIOS.

2.3 Solution Architecture

Figure 1**Error! Reference source not found.** shows the architecture diagram of Intel® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** for Computer Vision, and GEN AI. The software stack consists of three categories of AI software:

1. Vision AI
2. Gen 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 stream density. The video data is ingested and pre-processed before each inferencing step. The inference is performed using two models: YOLOv5 and EfficientNet. The YOLOv5 model detects objects, and the EfficientNet model classifies Objects.

For the Gen AI use case, we are using large language models (LLMs) and Intel® Extension of PyTorch (IPEX) framework to perform LLM inference on Intel® CPU and Intel® GPU.

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.

Figure 1. Architecture of the Intel® AI Edge Systems Verified Reference Blueprint

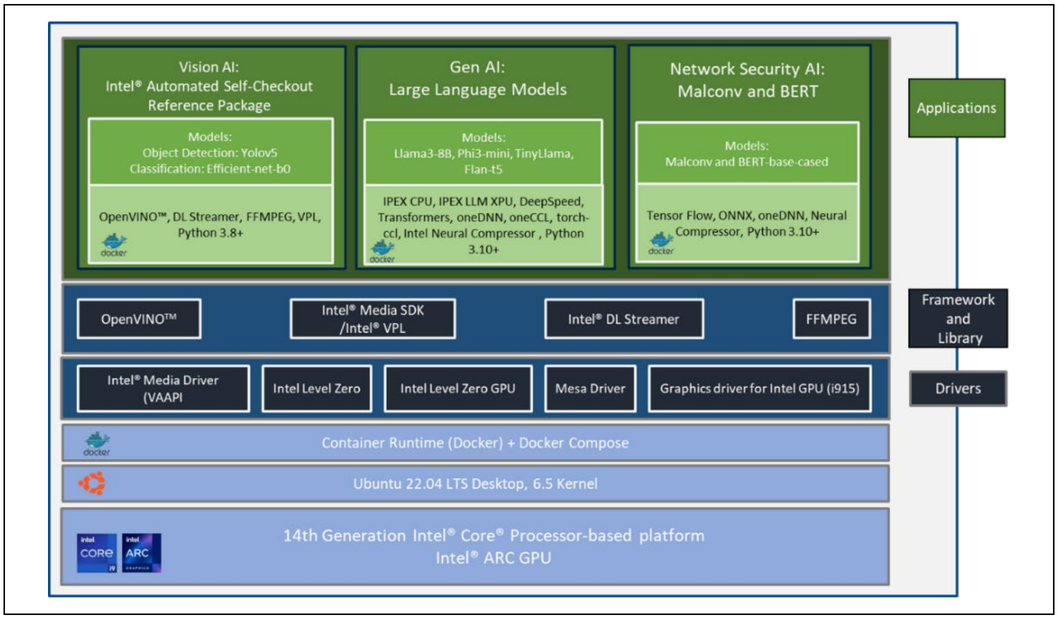

Figure 2 shows the architecture diagram for the Intel® Automated Self-Checkout application, which in this case is deployed containerized via Docker. The Vision AI use case measures stream density in terms of the number of supported cameras at the target FPS, accounting for all stages within the processing 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 2. Test Methodology for Retail Self-checkout Pipeline

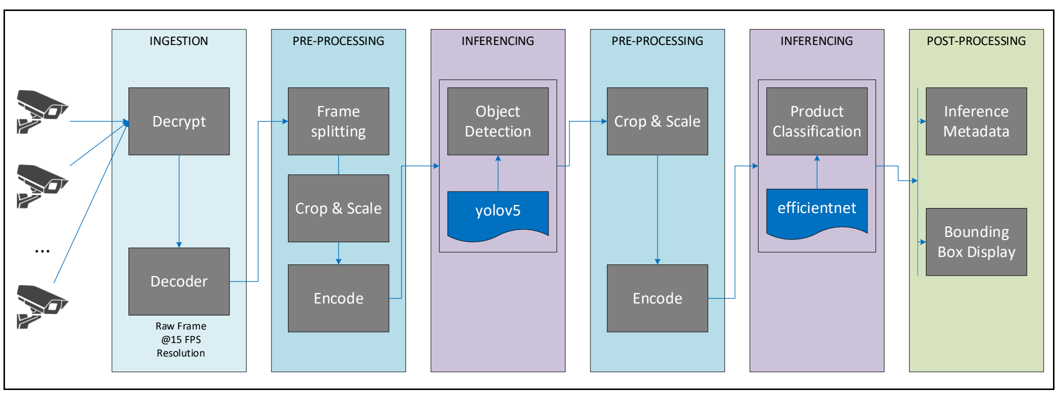

Table 4 is a guide for assessing the conformance to the software requirements of the Intel® AI Edge Systems Verified Reference Blueprint to ensure that the platform meets the requirements listed in the table below.

Table 4. 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 Reference Blueprint recommends that the 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 5. Platform Technology Requirements

<table>
<tr><th colspan="2">Platform Technologies</th><th>Enable/Disable</th><th>Required/Recommended</th></tr>
<tr><td rowspan="2">Intel® VT</td><td>Intel® CPU Virtual Machine Extension (VMX) Support</td><td>Enable</td><td>Required</td></tr>
<tr><td>Intel® I/O Virtualization</td><td>Enable</td><td>Required</td></tr>
<tr><td>Intel® Boot Guard</td><td>Intel® Boot Guard</td><td>Enable</td><td>Required</td></tr>
<tr><td>Intel® TXT</td><td>Intel® Trusted Execution Technology</td><td>Enable</td><td>Recommended</td></tr>
</table>

2.5 Platform Security

For Intel® AI System for the Edge, it is recommended that Intel® Boot Guard Technology to 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 module 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

3.1 Boot Parameter Setup

For the workload testing, note that it is not necessary to enable hugepage support nor is necessary to enable isolcpu support. If SR-IOV will be utilized, then in the "/etc/default/grub" file update the line "GRUB_CMDLINE_LINUX" to include the following parameters:

"intel_iommu=on iommu=pt"

After modifying the grub file, run "update-grub" and "reboot" to apply the changes and verify the change with "cat /proc/cmdline":

```
cat /proc/cmdline
BOOT_IMAGE=/vmlinuz-6.5.0-45-generic root=UUID=2f851afa-7405-4e84-8c11-
5f541adfd173 ro intel_iommu=on iommu=pt quiet splash vt.handoff=7
```

3.2 Install Intel® ARC™ GPU Drivers

Refer to the following for instructions on installing the Intel® Client GPU driver: https://dgpu-docs.intel.com/driver/client/overview.html#installing-client-gpus-on-ubuntu-desktop-22-04-lts. Refer to **Error! Reference source not found.** for a list of the installed software versions.

3.3 Kubernetes Installation

3.3.1 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.

3.3.2 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
```

3.3.3 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 Entry solution was tested on August 31, 2024, with the following hardware and software configurations:

- 1 NUMA nodes
- 1x Intel® 14th Generation Core® i9-14900E processor
- Total Memory: 128 GB, 4 slots/32 GB/3600 MT/s DDR5
- Hyperthreading: Enabled
- Turbo: Enabled
- C-State: Enabled
- Storage: 1x 1TB Advantech SQFlash (SQF-S25V4-1TDSDC)
- Network devices: 1x Intel® Ethernet I226-LM, 1x Intel® Ethernet I219-LM
- Network speed: 1 GbE
- BIOS: American Megatrends International, LLC. 5.27
- Microcode: 0x123
- OS/Software: Ubuntu 22.04.4 (kernel 6.5.0-45-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 6 and Table 7 below should be used as a reference for verifying the validity of the system setup.

Table 6. Memory Latency Checker

Key Performance Metric	Local Socket (Entry)
Idle Latency (ns)	123.8
Memory Bandwidths between nodes within the system (using read-only traffic type) (MB/s)	53577.1

Table 7. Peak Injection Memory Bandwidth (1 MB/sec) Using All Threads

Peak Injection Memory Bandwidth (1 MB/sec) using all threads	Entry Solution
All Reads	52574.6

Peak Injection Memory Bandwidth (1 MB/sec) using all threads	Entry Solution
3:1 Reads-Writes	50359.3
2:1 Reads-Writes	50319.6
1:1 Reads-Writes	50145.0
STREAM-Triad	50231.9
Loaded Latencies using Read-only traffic type with Delay=0 (ns)	464.78
L2-L2 HIT latency (ns)	47.0
L2-L2 HITM latency (ns)	47.3

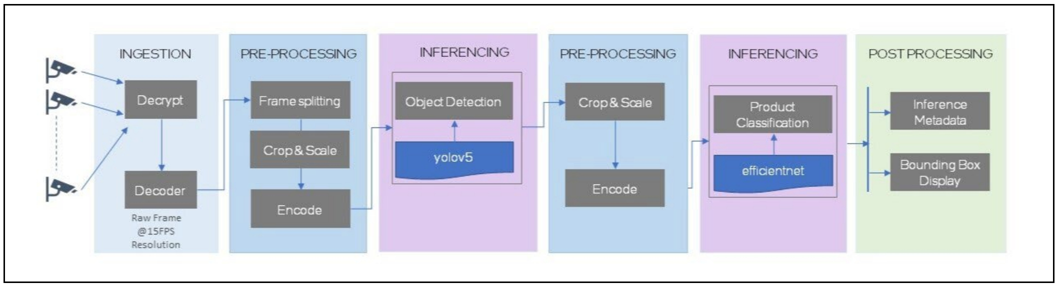
If the latency performance and memory bandwidth performance are outside the range, please verify the validity of the Platform components, BIOS settings, kernel power performance profile used, and other software components.

4.2 Vision AI

The Automated Self-Checkout Reference Implementation provides critical components to build and deploy a self-checkout use case using Intel® hardware, software, and other open-source software such as OpenVINOTM. For instance, in this case all the models in the pipeline are converted into OpenVINO format. In addition, this proxy workload makes use of both GStreamer for media processing and DLStreamer for inferencing, which includes detection and classification. This reference implementation provides a pre-configured automated self-checkout pipeline optimized for Intel® hardware. For more details see Appendix.

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 3. Vision AI Video Analytics Pipeline



Refer to Table 8 for the software version details.

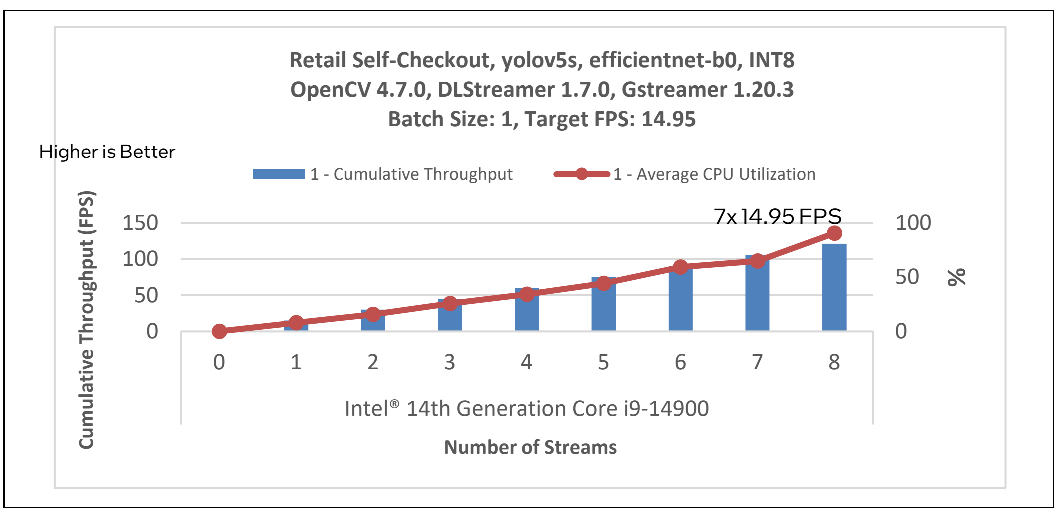
Table 8. Vision AI Workload Configuration

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 Vison AI on Core

The results for the Vision AI Workload running on CPU only are shown below.

Figure 4. Vision AI Workload Entry Configuration Performance



configuration platform with Intel® 14th Generation Core i9-14900E should be able to service up to 7 IP camera streams at 14.95 FPS per stream, for an aggregate of up to 105.75 FPS (CPU only).

4.2.2 Vision AI on GPU

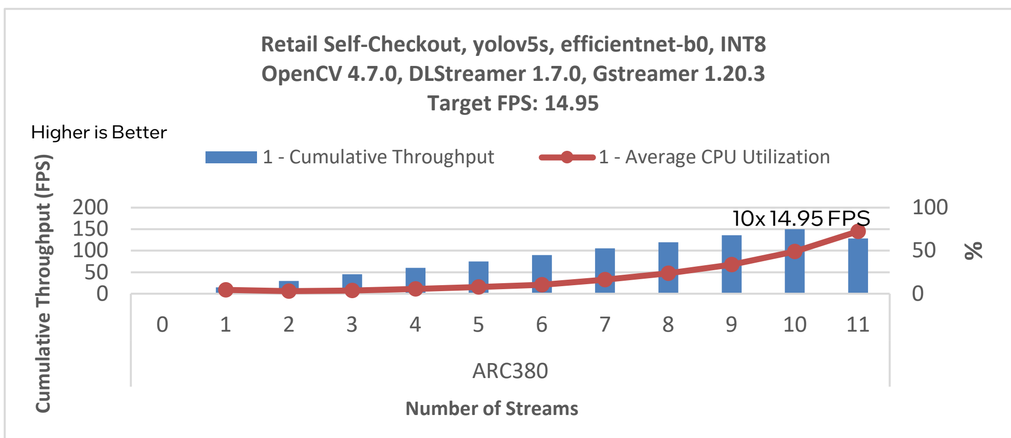
The results for the Vision AI workload running on GPU only are shown below.

Intel® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** for Computer Vision and GEN AI – Base platform with Intel® ARC A380 should be able to service up to 10 IP camera streams at 14.95 FPS per stream, for an aggregate of up to 150.31 FPS.

Intel® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** for Computer Vision and GEN AI – Plus platform with Intel® ARC A750 should be able to service up to 12 IP camera streams at 14.95 FPS per stream, for an aggregate of up to 180.06 FPS.

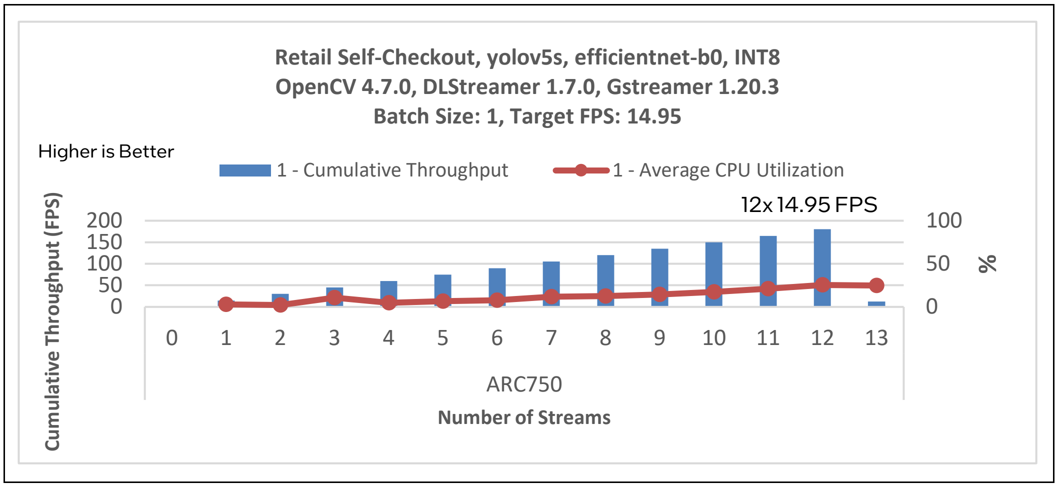
Refer to Table 8 for the software version details.

Figure 5. Vision AI Workload Entry Configuration Performance



The graph above presents a maximum number of 10 supported IP camera streams at a target of 14.95 FPS running on a single Intel® ARC™ A380 GPU only. In addition, the chart depicts the amount of remaining CPU utilization headroom available for running other workloads on Intel® Core Processors.

Figure 6. Vision AI Workload Mainstream Configuration Performance



The graph above presents the maximum number of 12 supported IP camera streams at a target of 14.95 FPS running on a single Intel® ARC™ A750 GPU only. In addition, the chart depicts the amount of remaining CPU utilization headroom available for running other workloads on the Intel® Core Processors.

4.3 Gen AI on Core

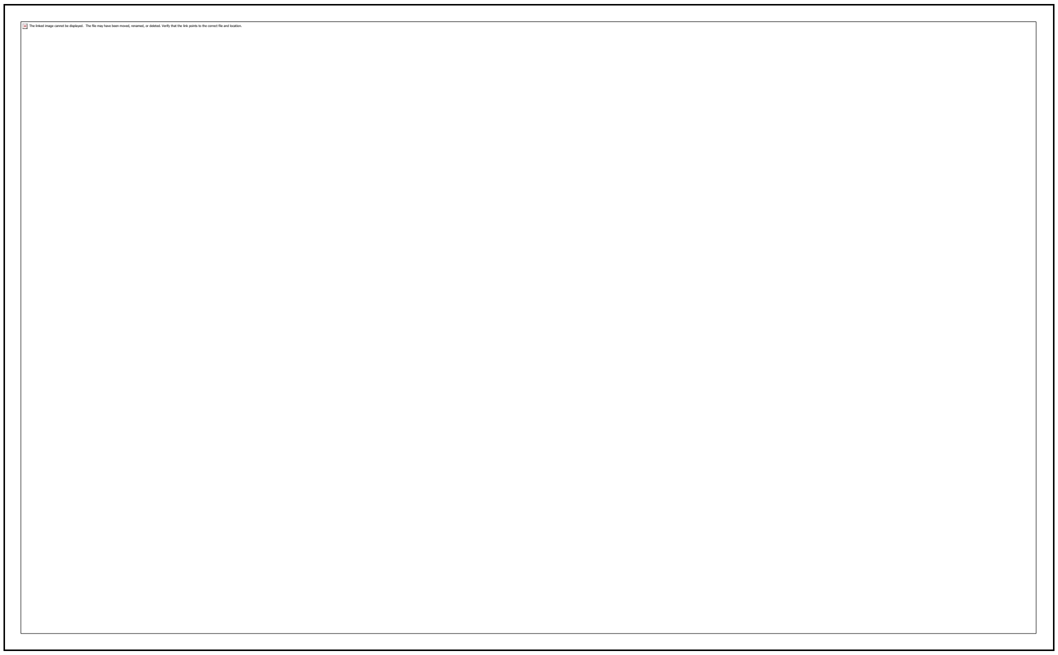
The Large Language Model (LLM) proxy workload highlights the Gen AI processing capabilities of the Intel® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** for Computer Vision and GEN AI configuration - Base platform, specifically with the Phi-3 4K Instruct model supported directly on Intel® 14th Generation Core processors.

Intel® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** Base Platform, ensure that the results of the system follow the expected results as shown below in order 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, along with the time per query.

Table 9. Gen AI Workload Configuration

Ingredient	Software Version Details
Docker Engine	27.1.0
Docker Compose	2.29
OpenVino Toolkit	20224.1.0
OS	Ubuntu* 22.04 LTS Kernel 6.5

Figure 7. Gen AI Entry Configuration Performance Graph (Phi-3 4K Instruct with Intel® 14th Generation Core i9-14900)



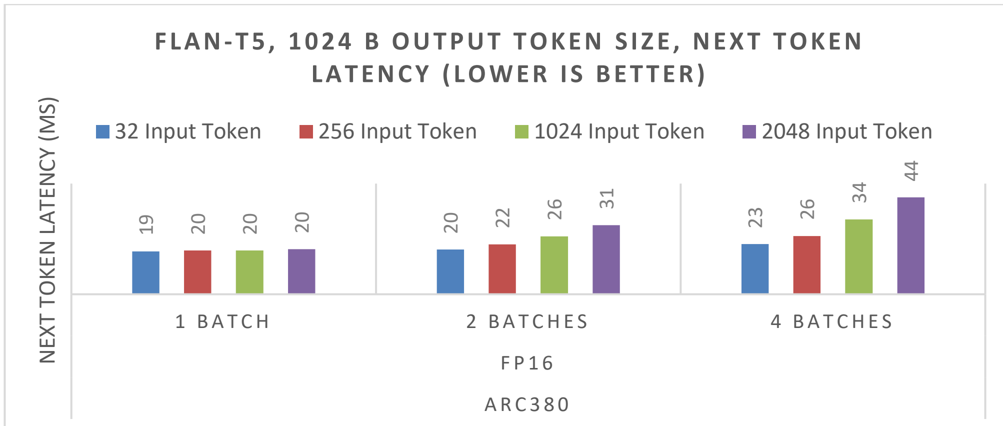
Based on the results in the figure above, at a KV cache size of 16 GB on Intel® 14th Generation i9-14900, the setup can reach up to 81.01 tokens per second with no pre-empted requests.

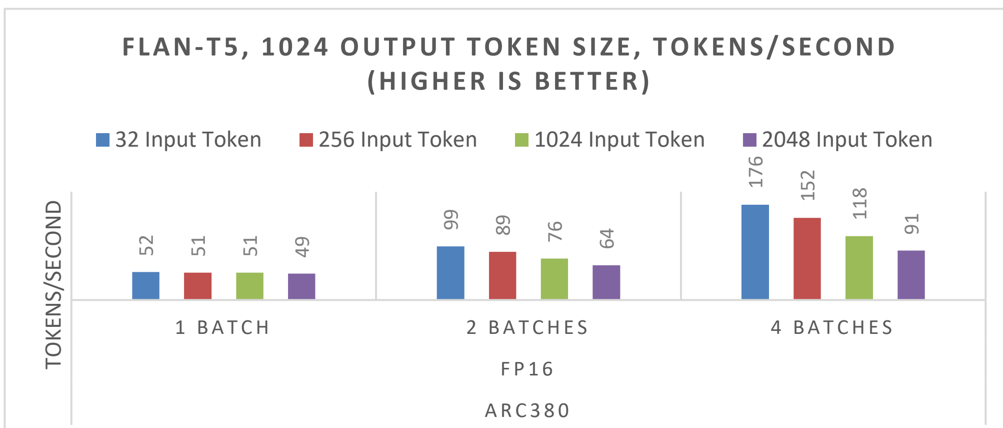
4.4 Gen AI on GPU

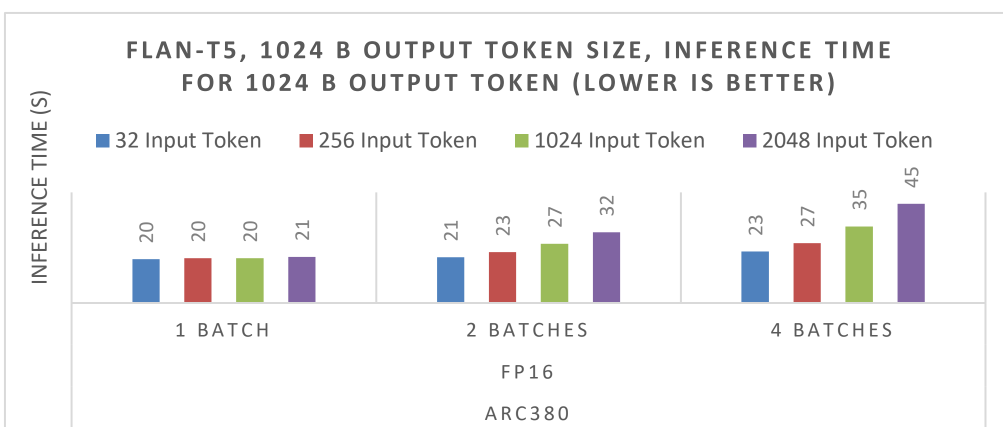
The large language model (LLM) proxy workload highlights the Gen AI processing capabilities of the Intel® AI Edge Systems Verified Reference Blueprint— **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** Base and Plus platform. It includes multiple models, including the Flan-t5, TinyLLama 1B, Phi-3 4K Instruct, and Llama3 8B models with Intel® ARC A380 and Intel® ARC A750 GPUs.

Intel® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** Base platform and 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, along with the time per query.

Figure 8. Gen AI Entry Configuration Performance Graph (flan-t5 with Intel® ARC380)



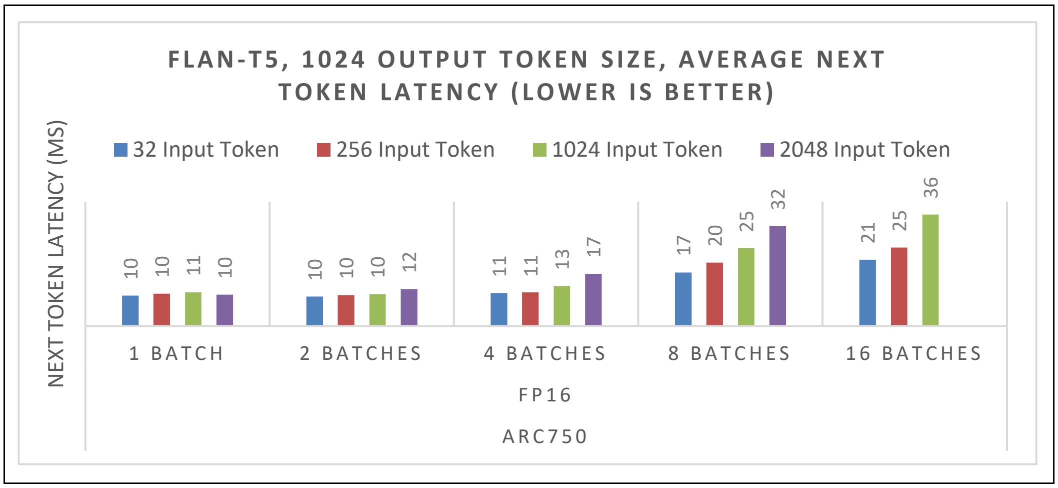




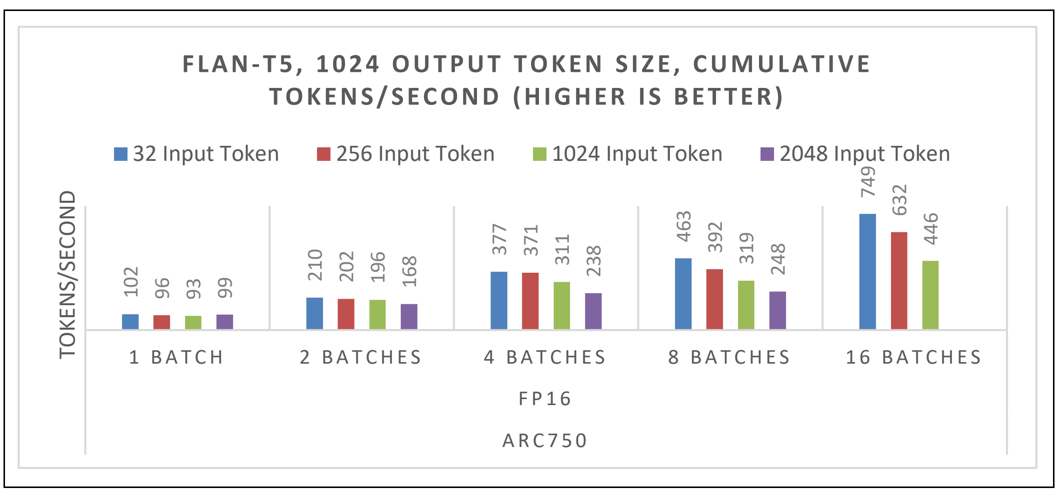
For the flan-t5 model, a single Intel® ARC™ A380 GPU can achieve a next token latency down to 19 ms for a single batch size using an input token size of 32 with FP16 precision.

For the flan-t5 model, a single Intel® ARC™ A380 GPU can achieve up to 176 tokens per second with a batch size of 4 using an input token size of 32 with FP16 precision. Similarly, a single Intel® ARCTM A380 GPU can achieve an inference time down to 20 sec for a single batch size using an input token size of 32 with FP16 precision.

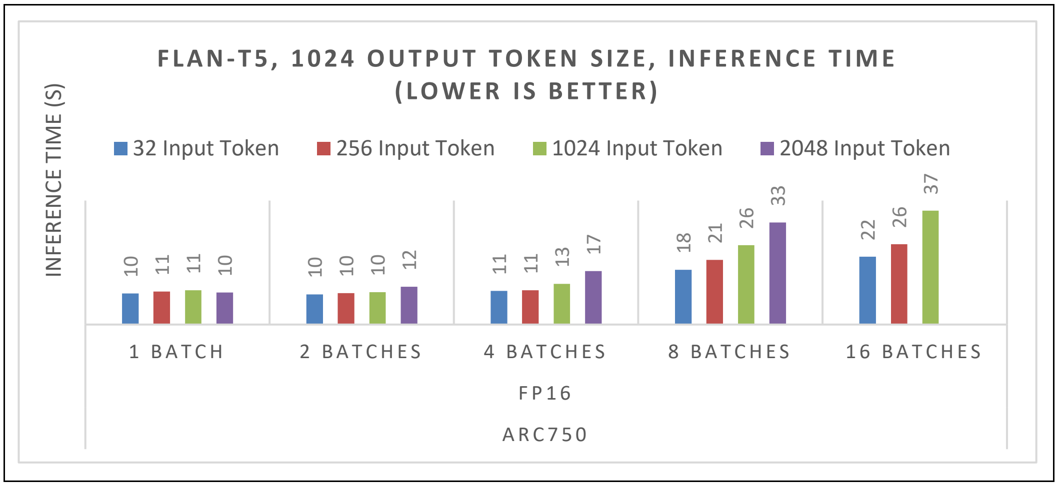
Figure 9. Gen AI Entry Configuration Performance Graph (flan-t5 with Intel® ARC750)



For the flan-t5 model, a single Intel® ARC™ A750 GPU is able to achieve a next token latency down to 10 ms for a batch size of 2 using an input token size of 1024 with FP16 precision.

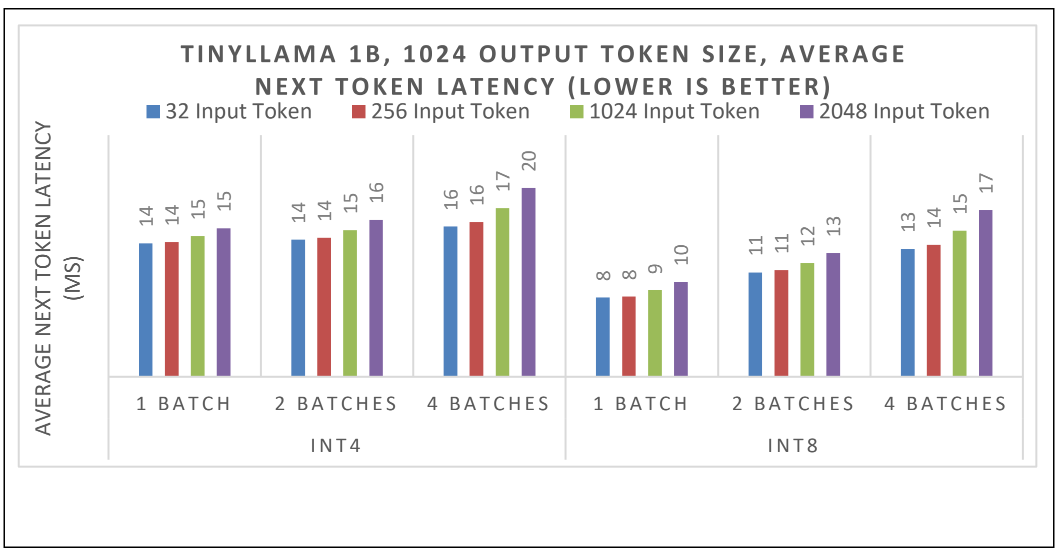


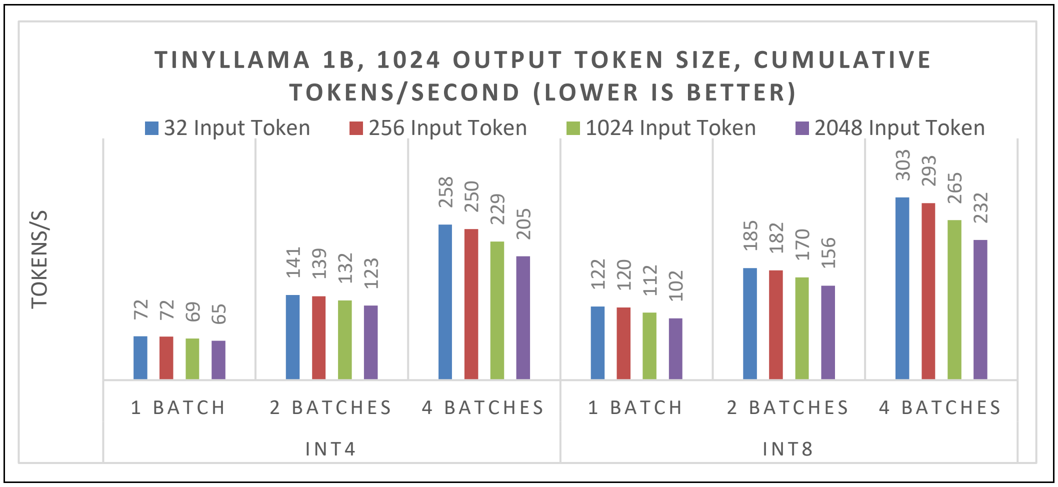
For the flan-t5 model, a single Intel® ARCTM A750 GPU is able to achieve up to 749 tokens per second with a batch size of 16 using an input token size of 32 with FP16 precision.

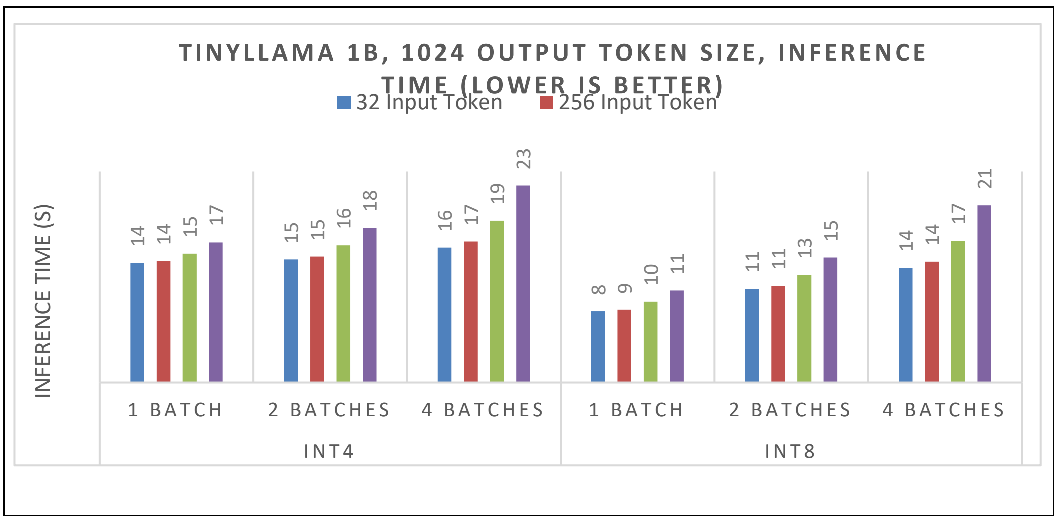


For the flan-t5 model, a single Intel® ARCTM A750 GPU is able to achieve an inference time down to 10 sec for a batch size of 2 using an input token size of 1024 with FP16 precision.

Figure 10. Gen AI Entry Configuration Performance Graph (TinyLlama with Intel® ARC380)

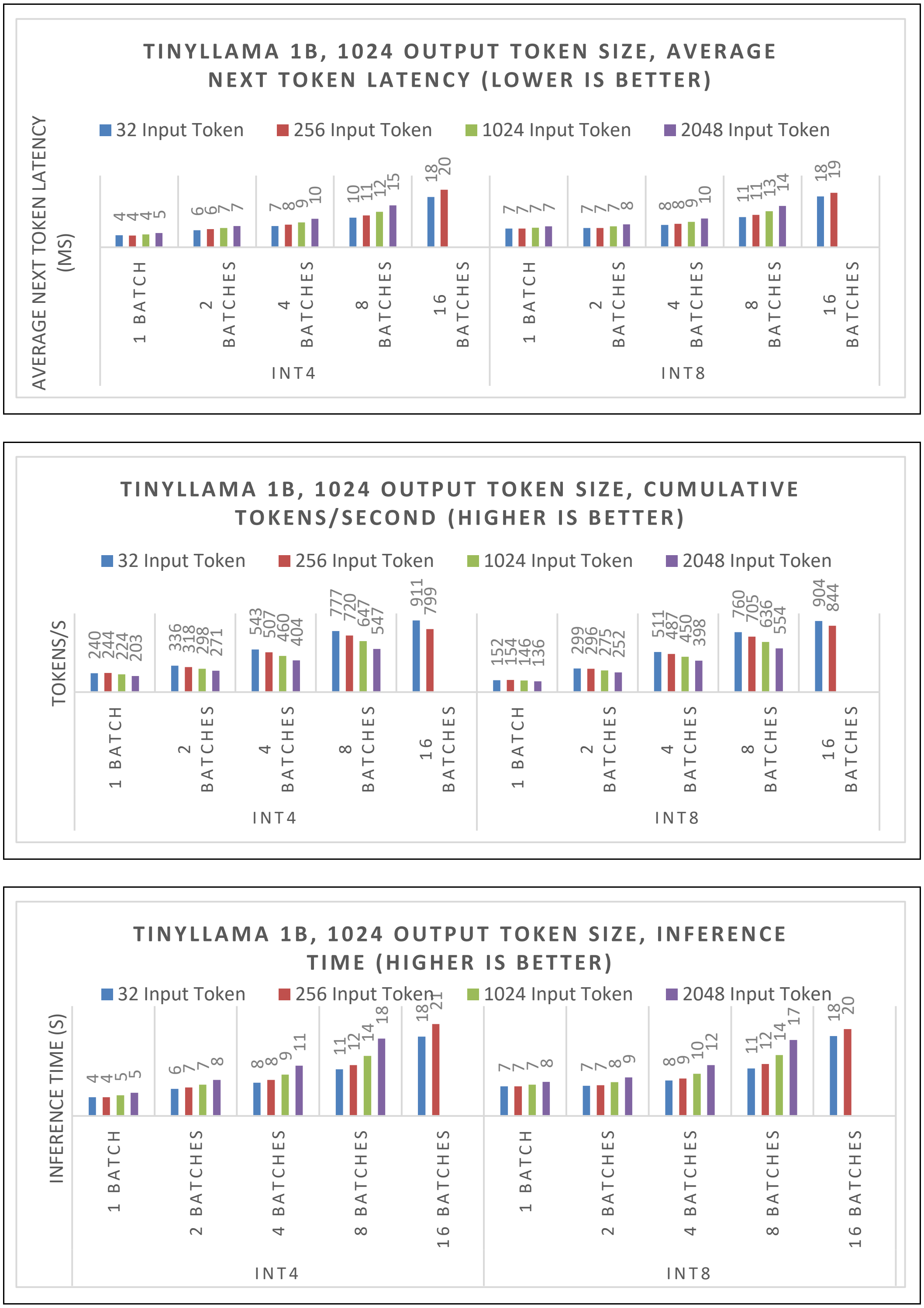






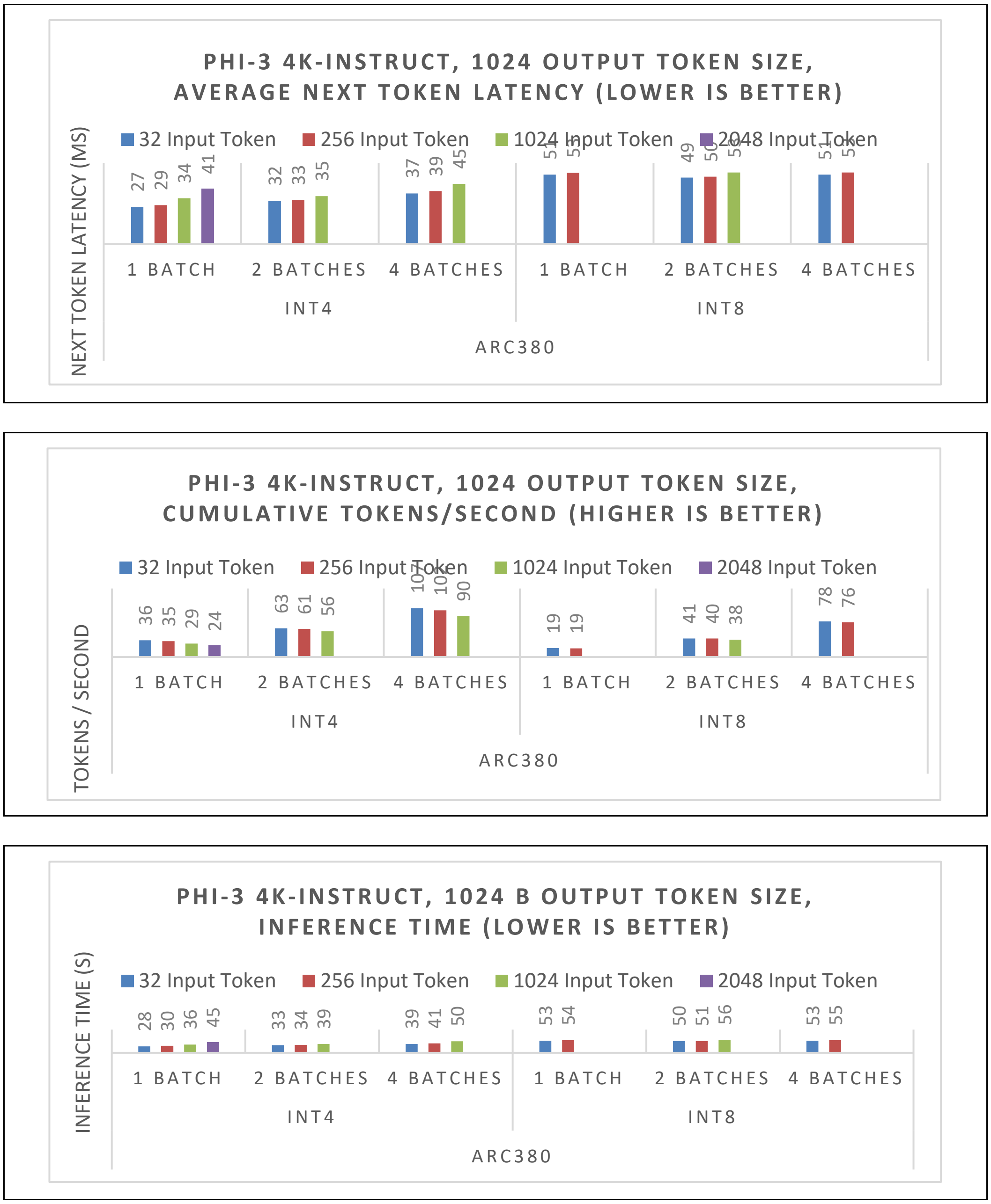
For the tinyLlama model, a single Intel® ARCTM A380 GPU is able to achieve a next token latency down to 8 ms for a single batch size using an input token size of 256 with INT8 precision. For the tinyLlama model, a single Intel® ARCTM A380 GPU is able to achieve up to 303 tokens per second with a batch size of 4 using an input token size of 32 with INT8 precision. For the tinyLlama model, a single Intel® ARCTM A380 GPU is able to achieve an inference time down to 8 sec for a single batch size using an input token size of 32 with INT8 precision.

Figure 11. Gen AI Entry Configuration Performance Graph (TinyLlama with Intel® ARC A750)



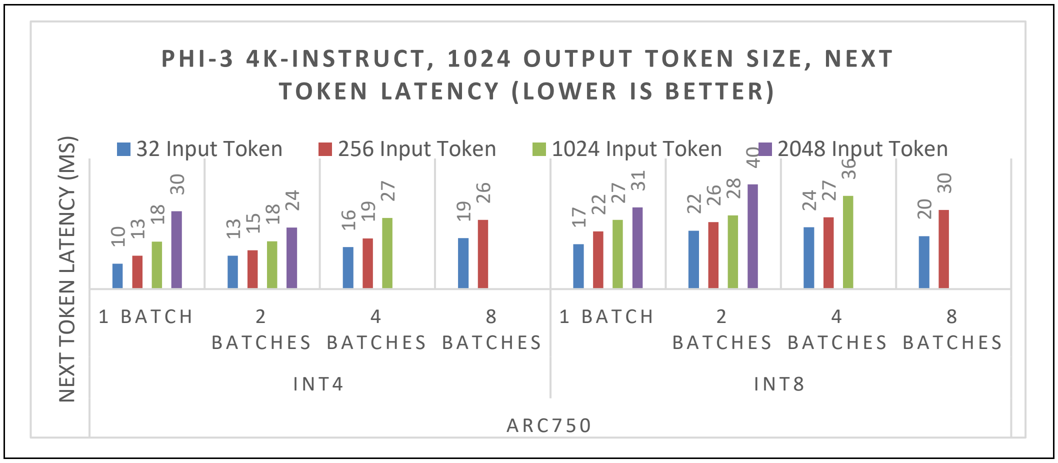
For the tinyLlama model, a single Intel® ARC™ GPU is able to achieve a next token latency down to 4 ms for a single batch size using an input token size of 1024 with INT4 precision. For the tinyLlama model, a single Intel® ARCTM A750 GPU is able to achieve up to 911 tokens per second with a batch size of 16 using an input token size of 32 with INT4 precision. For the tinyLlama model, a single Intel® ARCTM A750 GPU is able to achieve an inference time down to 4 sec for a single batch size using an input token size of 256 with INT4 precision.

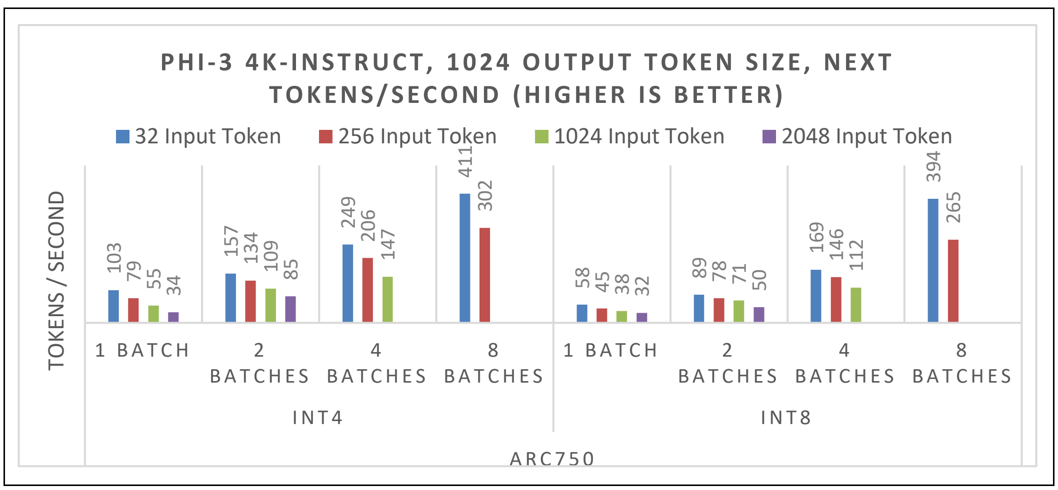
Figure 12. Gen AI Entry Configuration Performance Graph (Phi-3 4K-Instruct with Intel® ARC380)

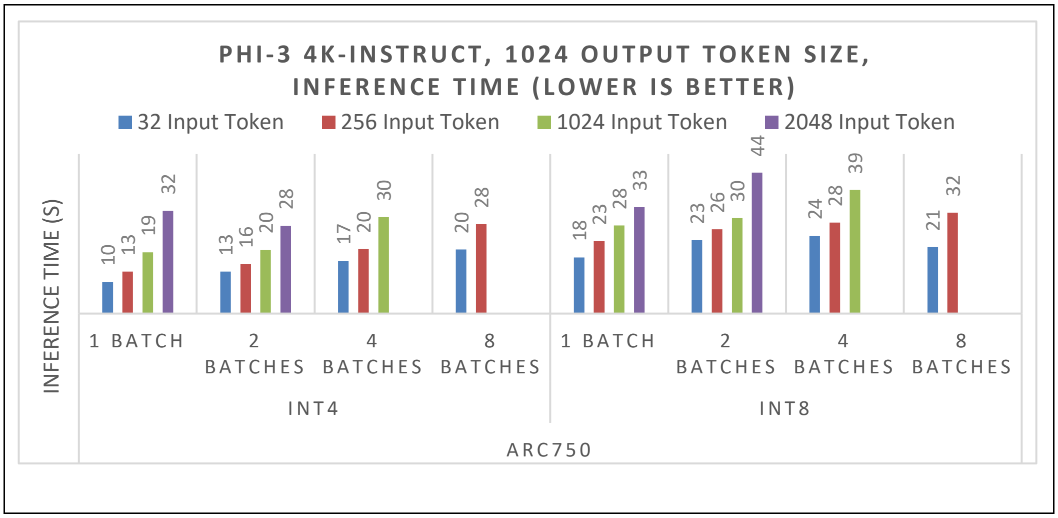


For the Phi-3 4K-Instruct model, a single Intel® ARCTM A380 GPU is able to achieve a next token latency down to 27 ms for a single batch size using an input token size of 32 with INT4 precision. For the Phi-3 4K-Instruct model, a single Intel® ARCTM A380 GPU is able to achieve up to 107 tokens per second with a batch size of 4 using an input token size of 32 with INT4 precision. For the Phi3 4K-Instruct model, a single Intel® ARCTM A380 GPU is able to achieve an inference time down to 28 sec for a single batch size using an input token size of 32 with INT4 precision.

Figure 13. Gen AI Entry Configuration Performance Graph (Phi-3 4K-Instruct with Intel® ARC A750)







For the Phi-3 4K-Instruct model, a single Intel® ARCTM A750 GPU is able to achieve a next token latency down to 10 ms for a single batch size using an input token size of 32 with INT4 precision. For the Phi-3 4K-Instruct model, a single Intel® ARCTM A750 GPU is able to achieve up to 411 tokens per second with a batch size of 8 using an input token size of 32 with INT4 precision. For the Phi-3 4K-Instruct model, a single Intel® ARCTM A750 GPU is able to achieve an inference time down to 10 sec for a single batch size using an input token size of 32 with INT4 precision.

4.5 Malconv and BERT

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.

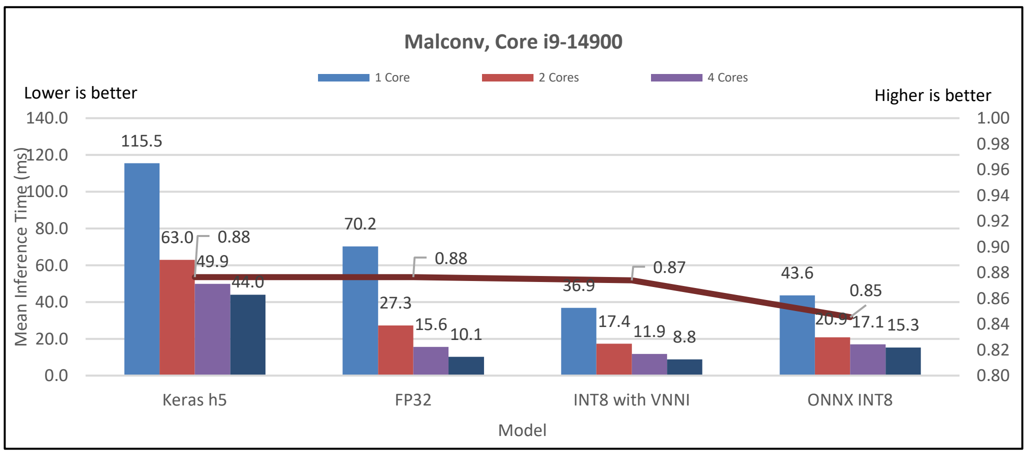
Ensure that the test results follow the expected results, as shown in the following tables, to establish a baseline for the platform's performance. Table 10 shows the software used for the testing while Error! Reference source not found. shows a graph of the mean inference time for each model. With 8 cores per instance, the INT8 model with AVX512_CORE_VNNI enabled was able to reach a performance of less than 10 ms.

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

Table 10. 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 14. Malconv AI Entry Platform Performance Graph



For Intel® 14th Generation Core i9-14900 the MalConv model with INT8 precision with VNNI instruction support achieves an inference time down to 8.8 ms with an accuracy up to 0.87.

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 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 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 test results follow the expected results, as shown in the following graph, to establish a baseline for the platform's performance. Table 11 shows the software used for the testing, while **Error! Reference source not found.** shows a graph of the results for the FP32 BERT model. With 8 cores per instance, the mean latency of the model reaches below 150ms.

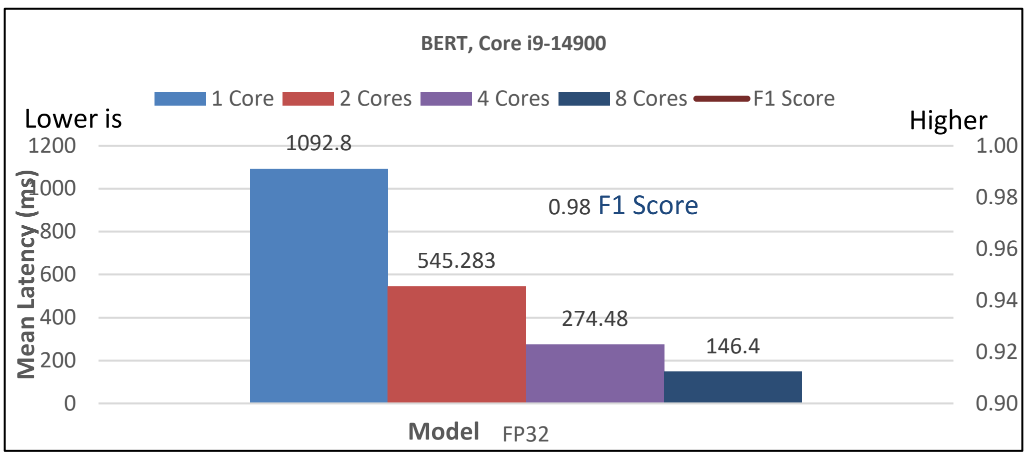
Note: Refer to https://huggingface.co/bert-base-cased for the original Hugging Face BERT base model.

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

Table 11. BERT AI Workload Configuration

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

Figure 15. BERT AI Entry Platform Performance Graph



For Intel® 14th Generation Core i9-14900 the Bert model with FP32 precision is able to achieve a mean latency down to 146.4 ms with 8 cores.

§

5 Summary

The Intel® AI Edge Systems Verified Reference Blueprint – **Scalable Performance Edge AI on Intel® 14th Generation Core with Intel® GPU** for Computer Vision and GEN AI defined on 14th Gen Intel® Core processors with Intel® Arc GPUs addresses the capabilities for AI inference by offering the following value proposition detailed within the tables below.

Table 12. Vision AI Summary

Configuration	Number of IP Camera Streams
1x Intel® Core i9-14900	7
1x Intel® ARC™ A380	10
1x Intel® ARC™ A750	12

Table 13. GEN AI Summary

Configuration	Model	Batch Size	Tokens / Second
Intel® 14th Generation Core (CPU only)	Phi-3 mini 4K Instruct model with FP32 precision and KV cache size of 16 GB		81.08
1x Intel® ARC™ A380	flan-t5	4	176 (FP16)
1x Intel® ARC™ A750	flan-t5	16	749 (FP16)
1x Intel® ARC™ A380	tinyLlama	4	303 (INT4) 250 (INT8)
1x Intel® ARC™ A750	tinyLlama	8	777 (INT4) 705 (INT8)
1x Intel® ARC™ 380A380	Phi-3 4K Instruct	4	107 (INT4) 76 (INT8)
1x Intel® ARC™ 750A750	Phi-3 4K Instruct	8	411 (INT4) 265 (INT8)
3x Intel® Data Center Flex GPU 140	Phi-3 4K Instruct	1	18 (INT4)
1x Intel® Data Center Flex GPU 170	Phi-3 4K Instruct	8	361 (INT4) 342 (INT8)
2x Intel® Data Center Flex GPU 170	Phi-3 4K Instruct	16	448 (INT4) 367 (INT8)
3x Intel® Data Center Flex GPU 140	Llama3 8B	2	40 (INT4)
1x Intel® Data Center Flex GPU 170	Llama3 8B	8	215 (INT4) 188 (INT8)
2x Intel® Data Center Flex GPU 170	Llama3 8B	8	257 (INT4) 236 (INT8)

Table 14. Performance Summary for the Malconv Network Security AI Workload

Configuration	Model	Cores per Instance
1x Intel® Core i9-14900	FP32	8
1x Intel® Core i9-14900	INT8 with VNNI	4

Table 15. Performance Summary for the Bert Network Security AI Workload

Configuration	Mean Latency (ms)
1x Intel® Core i9-14900	150.4 (FP32)

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.

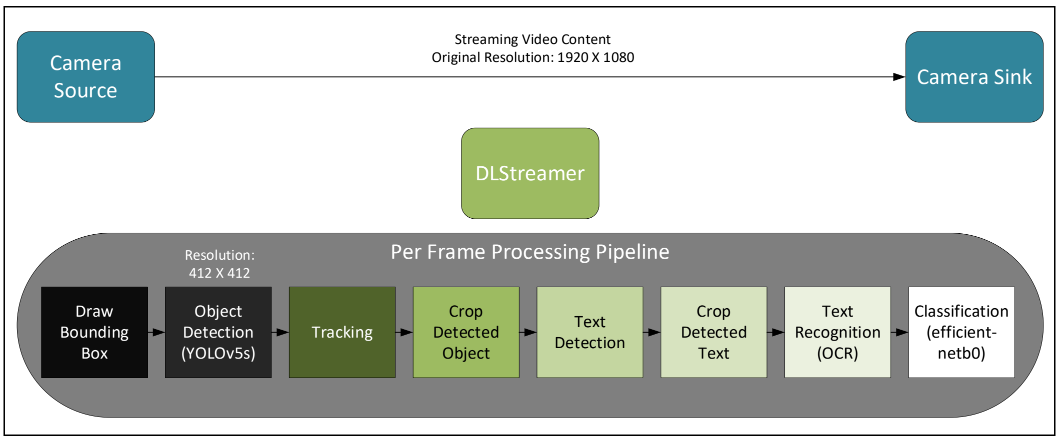
§

Appendix A Appendix

The following section provides detailed instructions for benchmarking a platform with each of the proxy workloads for Vision AI, Gen AI, along 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 16. Test Methodology for the Automated Self-Checkout Proxy Workload



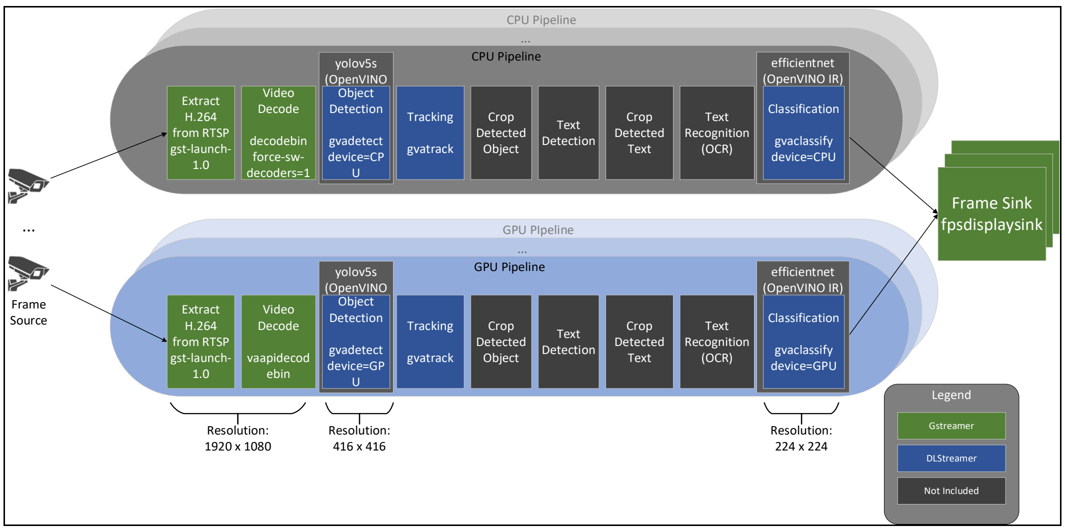
The Intel® Automated Self-Checkout Reference Package provides critical components required to build and deploy a self-checkout use case using Intel® hardware, software, and other open-source software. Vision workloads are large and complex and need to go through many stages. For instance, in the pipeline 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 17. 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: efficient net-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. The number of streams is then monotonically decremented until the target FPS is met.
- 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.

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

1. Pre-Requisites:

- Install Docker
- Set the HTTP and HTTPS proxy environment variables as 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>
…
```

3. Start the benchmark against Intel® 14th Generation Core 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 steady state.

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

4. 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
```

5. 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
```

6. 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
```

7. Start the benchmark against Intel® ARCTM GPUs 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
```

8. 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
```

9. 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
```

10. 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
```

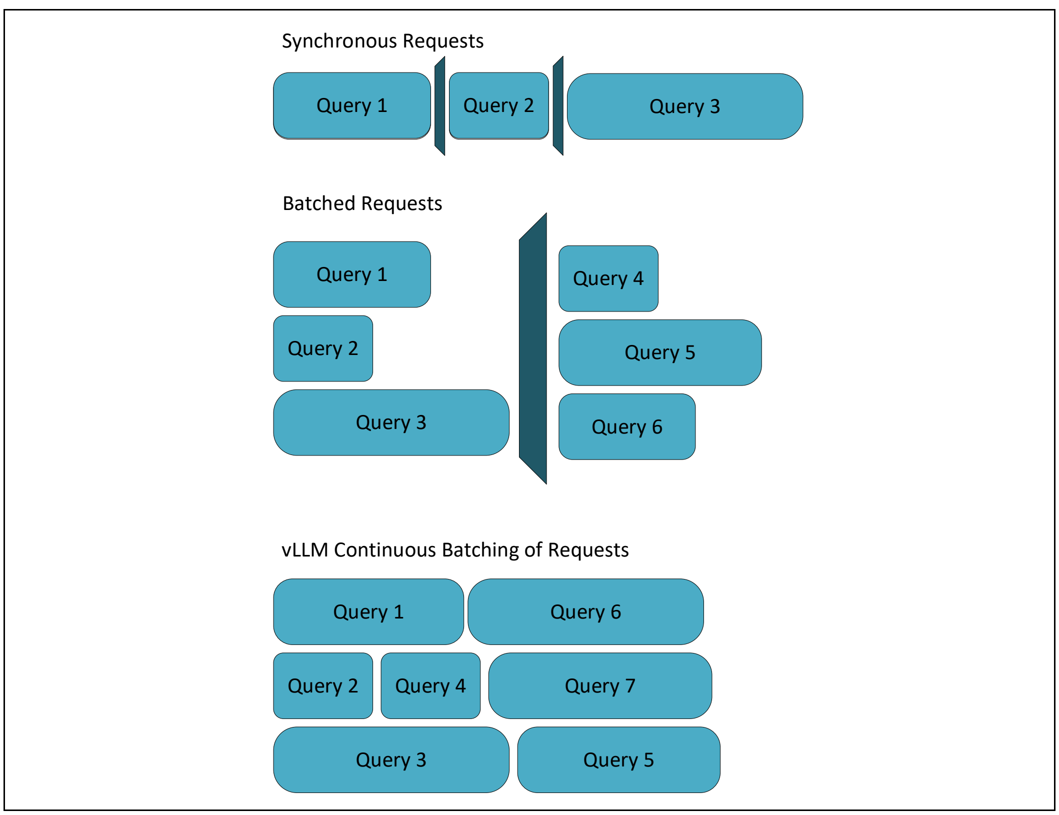
Note: The directory structure and file names may vary depending on whether the Network Security AI test is run as part of the Intel® ESDQ for Intel® AI System qualification tool or independently.

A.2 Gen AI Test Methodology

A.2.1 vLLM Testing Methodology on Core

The Gen AI benchmark on the 14th Generation Intel® Core leverages vLLM, which, as shown in the figure below, performs continuous batching of requests to the LLM.

Figure 18. vLLM Continuous Batching



To setup the vLLM testcase and benchmark on Intel® 14th Generation Core:

1. Clone the vLLM project and install the baseline dependencies:

```
# git clone https://github.com/vllm-project/vllm.git
# cd vllm
# pip install -e .
# apt-get update
# apt-get install python3
# pip install -upgrade pip
# pip install -r requirements-build.txt -extra-index-url
https://download.pytorch.org/whl/cpu
```

2. Install vLLM with the OpenVino backend:

```
# PIP_EXTRA_INDEX_URL="https://download.pytorch.org/whl/cpu"
VLLM_TARGET_DEVICE=openvino python -m pip install -v .
```

3. Download the Phi-3 4K Instruct model from HuggingFace:

```
# huggingface-cli download microsoft/Phi-3-mini-4k-instruct --local-dir
~/Phi-3-mini-4k-instruct
```

4. Download the dataset:

```
#
wget https://huggingface.co/datasets/anon8231489123/ShareGPT_Vicuna_unfiltered/resolve/main/ShareGPT_V3_unfiltered_cleaned_split.json
```

5. Set the vLLM environment variables. For example, to use a KV cache size of 1GB:

```
# export VLLM_OPENVINO_KVCACHE_SPACE=1
# export VLLM_OPENVINO_CPU_KV_CACHE_PRECISION=u8
# export VLLM_OPENVINO_ENABLE_QUANTIZED_WEIGHTS=ON
# export TOKENIZERS_PARALLELISM=false
```

6. Start the vLLM benchmark:

```
# python3 ./benchmark_throughput.py --model ~/Phi-3-mini-4k-instruct --
dataset ./ShareGPT_V3_unfiltered_cleaned_split.json --enable-chunked-
prefill --max-num-batched-tokens 256
```

Note: The directory structure and file names may vary depending on whether the Network Security AI test is run as part of the Intel® ESDQ for Intel® AI System qualification tool or independently.

A.2.2 IPEX-LLM Testing Methodology on GPU

The Gen AI benchmark on Intel® ARC GPUs leverages the IPEX-LLM framework and is deployed in a containerized manner.

To run the Generative AI benchmark on Intel® ARC™ GPUs:

1. Download the IPEX-LLM container image:

```
# export DOCKER_IMAGE=intelanalytics/ipex-llm-serving-xpu:2.1.0-SNAPSHOT
# docker pull intelanalytics/ipex-llm-serving-xpu:2.1.0-SNAPSHOT
```

2. Launch the IPEX-LLM container. For example, to benchmark with the Meta Llama3-8B model:

```
# export CONTAINER_NAME=ipex-llm-serving-xpu
# export MODEL_PATH=~/llama3-8b
# docker run -itd \
```

```
        --net=host \
        --device=/dev/dri/card0 \
        --device=/dev/dri/renderD128 \
        --memory="64G" \
        --name=$CONTAINER_NAME \
        --shm-size="16g" \
        -v $MODEL_PATH:/llm/models \
        $DOCKER_IMAGE bash
```

3. Copy the run-arc-sweep.sh script to the container:

```
# docker cp ~/applications.platform.intel-select-for-network/enterprise_ai/common/ipex-llm-gpu/run-arc-sweep.sh ipex-llm-serving-xpu:/benchmark/all-in-one/
```

4. Login to the container and update the run-arc-sweep.sh script to use the appropriate model. For example, to benchmark with the Meta Llama3-8B model:

```
# docker exec -it ipex-llm-serving-xpu /bin/bash
# cd /benchmark/all-in-one/
# $EDITOR run-arc-sweep.sh

…
current_model_name="llama3-8b"
…
```

5. Login to the container and start the benchmark:

```
# bash run-arc-sweep.sh
```

6. Review the benchmark results:

```
# cat optimize_model_gpu-results*.csv
```

Note: The directory structure and file names may vary depending on whether the Network Security AI test is run as part of the Intel® ESDQ for Intel® AI System qualification tool or independently.

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.

Note: The directory structure and file names may vary depending on whether the Network Security AI test is run as part of the Intel® ESDQ for Intel® AI System qualification tool or independently.

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 4.6.

Note: The directory structure and file names may vary depending on whether the Network Security AI test is run as part of the Intel® ESDQ for Intel® AI System qualification tool or independently.

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