NNStreamer: Efficient and Agile Development of On-Device AI Systems

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Abstract—We propose NNStreamer, a software system that handles neural networks as filters of stream pipelines, applying the stream processing paradigm to deep neural network applications. A new trend with the wide-spread of deep neural network applications is on-device AI. It is to process neural networks on mobile devices or edge/IoT devices instead of cloud servers. Emerging privacy issues, data transmission costs, and operational costs signify the need for on-device AI, especially if we deploy a massive number of devices. NNStreamer efficiently handles neural networks with complex data stream pipelines on devices, significantly improving the overall performance with minimal efforts. Besides, NNStreamer simplifies implementations and allows reusing off-the-shelf media filters directly, which reduces developmental costs significantly. We are already deploying NNStreamer for a wide range of products and platforms, including the Galaxy series and various consumer electronic devices. The experimental results suggest a reduction in developmental costs and enhanced performance of pipeline architectures and NNStreamer. It is an open-source project incubated by Linux Foundation AI, available to the public and applicable to various hardware and software platforms.

Index Terms—neural network, on-device AI, stream processing, pipe and filter architecture, open source software

I. INTRODUCTION

We have witnessed the proliferation of deep neural networks in the last decade. With the ever-growing computing power, embedded devices start to run neural networks, often assisted by hardware accelerators [2], [7], [18], [20], [21], [27], [32], [38]. Such accelerators are already common in the mobile industry [2], [32]. Running AI mechanisms directly on embedded devices is called on-device AI [26]. On-device AI can be highly attractive with the following advantages of in-place data processing.

- Avoid data privacy and protection issues by not sharing data with cloud servers.
- Reduce data transmissions, which can be crucial for processing video streams in real-time.
- Save operating costs of servers, especially crucial with millions of devices deployed.

Limited computing power, high data bandwidth, and short response time are significant challenges of on-device AI: e.g., AR Emoji [31], Animoji [1], robotic vacuums, and live video processing. With more sophisticated AI applications, multiple input streams and neural networks may exist simultaneously as in the complex camera systems of high-end smartphones of today. Numerous neural networks may share inputs, and outputs of a neural network may be inputs of others or the network itself. Composing a system with multiple networks allows training and reusing smaller networks, which may reduce costs, increase performance, enhance robustness, or help construct modular neural networks [33], [34], [36]. Managing data flows and networks may become highly complicated with interconnections of networks and other nodes along with fluctuating latency, complex topology, and synchronizations. Such interconnections are data streams between nodes; thus, we may describe each node as a filter and a system as a pipeline, “pipe and filter architectures” [29].

The primary design choice is to employ and adapt a multimedia stream processing framework for constructing neural network pipelines, not constructing a new stream framework. The following significant problems and requirements, which are part of the observed ones of our on-device AI projects, have already been addressed by conventional multimedia frameworks for years:

P1. Fetching and pre-processing input streams may be extremely complicated; i.e., video inputs may have varying formats, sizes, color balances, frame rates, and sources determined at run-time. Besides, with multiple data streams, processors, and algorithms, data rates and latency may fluctuate and synchronizing data streams may become extremely difficult.

P2. Components should be highly portable. We have to reuse components and their pipelines for a wide range of products.

P3. It should be easy to construct and modify pipelines even if there are filters executed in parallel requiring synchronization. The execution should be efficient for embedded devices.

P4. We want to reuse a wide range of off-the-shelf multimedia filters.
We are applying NNStreamer APIs of Tizen, an OS for a wide range of consumer electronics. We provide numerous GStreamer plugins, data types, and tools, to analyze media stream pipelines for different operating systems, programming languages and utilities to construct, execute, and sample applications. It supports Tizen Studio natively (C and C#) and NNStreamer Foundation AI, released for Tizen, Android, Ubuntu, OpenEmber, iOS, and MacOS. It is highly portable and modular, and virtually everything can be updated in a plug and play fashion. To address P1 to P7, we choose GStreamer [16] as the basis framework. Gstreamer is a battle-proven multimedia framework for various products and services and has hundreds of off-the-shelf filters. It is highly portable and modular, and virtually everything can be updated in a plug and play fashion. To address P1 to P7, we choose GStreamer as our framework of choice. Gstreamer plugins, data types, and tools, as described in Section II, provide numerous GStreamer plugins, data types, and tools, along with hundreds of off-the-shelf filters, which NNStreamer inherits. Gstreamer is highly modular; every filter and path control is a plugin attachable in run-time. Various systems, whose reliability and performance are crucial, use Gstreamer. For example, the BBC uses Gstreamer for its broadcasting systems [3]. Samsung (Tizen) and LG (WebOS) use it as the media engine of televisions. Centricular uses it for TVs, set-top boxes, medical devices, in-vehicle infotainment, and on-demand streaming solutions [11], [12], [17], [39]. [40].

FFmpeg [5], another popular multimedia framework, is not modular, and everything is built-in; thus, it is not suitable for our purposes. StageFright [13] is the multimedia framework of Android, depending on Android services. Unlike Gstreamer, it is not portable for general Linux systems and does not allow applications to construct arbitrary pipelines. AVFoundation [3] is the multimedia framework of iOS and MacOS. AVFoundation may provide input frames to Core ML [4], the machine learning framework of iOS and MacOS, to construct a neural network pipeline. However, app developers cannot apply neural networks as native filters of multimedia pipelines, and they need to implement interconnections between neural networks and multimedia pipelines. DirectShow [6] is the multimedia framework of Windows. DirectShow and AVFoundation are proprietary software for proprietary platforms; thus, we cannot alter them for the given purposes.

Google has proposed MediaPipe [25] to process neural networks as filters of pipelines. It supports Linux, Android, and MacOS, but it is not portable enough. Its dependency on Google’s in-house tool, Basel, and inflexible library requirements make it not portable for embedded systems; i.e., it is hard to share system libraries with other software. MediaPipe re-implements a pipeline framework and cannot reuse conventional media filters; thus, P1 to P4 are only partially met while P5 is not an issue. Initially, it has targeted server-side AI services, not embedded devices; thus, P1, P2, and P4 might have been not considered. Specifically, for in-house servers, they may restrict input formats (P1 and P4 are irrelevant) and consider homogeneous platforms and architectures (P2 is irrelevant). Another issue is that MediaPipe allows only a specific version of TensorFlow as NNFWs; e.g., TensorFlow 2.1 for MediaPipe 0.7.4. Such inflexibility makes integrating other NNFWs or hardware accelerators unnecessarily tricky. In Section IV, we show an example (E4) of how critical this can be. We expect that they probably have more features hidden in-house; they have partially opened MediaPipe since 2019. On the other hand, NNStreamer has been fully opened since 2018.

Nvidia DeepStream [22], [23] provides Gstreamer plugins to process neural networks with NVidia’s proprietary hardware; thus, P2 and P7 cannot be achieved while P1, P3, and P4 are achieved. DeepStream addresses P5 indirectly and partially by embedding tensors in metadata of streams (no recurrence support). In other words, DeepStream requires conventional media (audio/video/text) for inputs and does not consider tensors as first-class citizens of stream data. Therefore, if the topology is complicated or inputs are arbitrary binaries, writing a pipeline can be difficult.

II. RELATED WORK

Gstreamer [16] is the multimedia framework of Tizen and many Linux distributions. Gstreamer provides APIs in various programming languages and utilities to construct, execute, and analyze media stream pipelines for different operating systems along with hundreds of off-the-shelf filters, which NNStreamer inherits. Gstreamer is highly modular; every filter and path control is a plugin attachable in run-time. Various systems, whose reliability and performance are crucial, use Gstreamer. For example, the BBC uses Gstreamer for its broadcasting systems [3]. Samsung (Tizen) and LG (WebOS) use it as the media engine of televisions. Centricular uses it for TVs, set-top boxes, medical devices, in-vehicle infotainment, and on-demand streaming solutions [11], [12], [17], [39]. [40].


**NNStreamer** provide interconnections between pipelines of different frameworks or remote nodes by proposing a standard tensor stream protocol via Flatbuf [14] and Protobuf [15]. **NNStreamer** can collaborate with MediaPipe pipelines by embedding MediaPipe pipelines into **NNStreamer** pipelines.

### III. Design and Implementations

Each neural network model is an atomic filter of a pipeline (pipe and filter architecture [29]). We delegate executions of neural network models to their corresponding NNFWs, such as TensorFlow. Delegation allows **NNStreamer** to execute each model efficiently with P6 and P7 satisfied and to focus on how to describe and integrate interconnections and filters. For example, to accelerate a TensorFlow model with GPU in a pipeline, users simply need to make sure that a compatible TensorFlow-GPU exists. Similarly, installing libraries properly and writing a pipeline consisting of Vivante models allows accelerating the pipeline with a Vivante NPU [57]. This approach keeps the performance of and compatibility with off-the-shelf execution environments.

We recognize tensors as first-class citizens of stream data, unlike DeepStream [28], not limiting streams to conventional media, and add stream path controls for tensors. We define two GStreamer data types: `other`/`tensor` and `other`/`tensors`. An `other`/`tensor` has an element type, dimensions, and a frame rate (e.g., `uint8, 640:480:3, 20 Hz`). An `other`/`tensors` combines up to 16 (default limit of memory chunks in a frame) different tensors with a synchronized frame rate. We store each tensor in an individual memory chunk so that mux and de-mux do not incur memory copies.

We do not express rank numbers in tensor stream types; thus stream types of compatible data formats (e.g., `640:480` [rank 2] and `640:480:1:1` [rank 4]) are considered to be equivalent by stream type checkers of GStreamer, which “negotiates” stream types between elements of pipelines in run-time. However, there are a few NNFWs (e.g., TensorFlowRT), which require to identify the rank numbers of input and output data as well as their dimensions and types. Users may explicitly express rank numbers (e.g., “input=640:480” denotes rank 2 and “input=640:480:1:1” denotes rank 4) in such cases to satisfy such NNFWs.

Figure 1 shows an exemplary pipeline demonstrating **NNStreamer** components omitting a few trivial filters, such as queues. Lightly shaded boxes with bold borders are **NNStreamer** components. Clear boxes are off-the-shelf components. Shaded boxes with thin borders show properties of tensors. In the figure, names are abbreviated; i.e., “T” denotes Tensor, the prefix of **NNStreamer** filers.

The two neural networks in the figure, NN models, 1 and 2, use TensorFlow-lite and NCSDK2 sub-plugins (plugins of a plugin) of **Tensor-Filter** plugins, respectively. **NNStreamer** 1.6.0 of October 2020 provides sub-plugins for ARMNN, Caffe2, NFNV(ONE)-Runtime, OpenVINO, PyTorch, Qualcomm SNPE, Samsung SNAP, TensorFlow, TensorFlow-Lite, TensorFlowRT, EdgeTPU, NSDK2 (Movidius-X), Vivante, MediaPipe, and custom functions in C, C++, and Python. Users may use such sub-plugins or write their own with the provided code templates and generators.

**Tensor-Filter** and its sub-plugin structure allow developers to use neural network models of the above frameworks with a unified interface even without pipelines as well. In order to allow developers using the unified interface without pipelines, we provide “Single API sets” for Tizen (C/.NET) and Android (Java) products.

Inputs and outputs of **Tensor-Filter** are tensor streams. **Tensor-Converter** converts media streams to tensor streams. Sub-plugins of **Tensor-Converters** may accept unconventional (neither audio, video, nor text) data streams, e.g., Flatbuf [14] or Protobuf [15] streams. **Tensor-Decoder** may convert tensor streams to media or other data streams with sub-plugins, e.g., create a video stream of transparent backgrounds with boxes of detected objects or a Flatbuf stream from tensors.

**Tensor-Mux** bundles multiple `other/tensor` streams to an `other/tensors` stream. **Tensor-Demux** un-bundles such a stream back to individual tensor streams. **Tensor-Merge** creates an `other/tensor` (no “s”) from multiple `other/tensor` streams, modifying dimensions. **Tensor-Split** splits an `other/tensor` stream into multiple `other/tensor` streams. From two 3x4 streams, **Tensor-Merge** creates a 6x4, 3x8, or 3x4x2 stream, and **Tensor-Mux** creates a {3x4, 3x4} stream. Users may choose synchronization policies for Mux and Merge: slowest (drop frames of faster sources), fastest (duplicate frames of slower sources), and base (keep the frame rate of the designated source). **Tensor-Aggregator** merges frames temporally (e.g., merging frames 2i and 2i + 1, halving the frame rate), which may help implement LSTM or Seq2seq [35]. All merging filters choose the latest timestamp. A **Tensor-Repo-Src/Sink** pair may share a named repository to construct a recurring data path without a GStreamer stream, which prohibits cycles. **Tensor-Src-IIO** creates tensor streams from Linux Industrial I/O [19] sensors, **Tensor-Transform** applies operators to tensors: typecast, add/sub/mult/div, normalization, transpose, and so on. Streams may be connected to and from application threads, networks, or files. There are components not shown in the figure, as well. **Tensor-ROS-Src/Sink** interact with ROS [30], a popular robotics framework. **Tensor-Src-TizenSensor** connects with Tizen Sensor Framework. **Amsrc** connects with Android MediaCodec (AMC).

Product engineers have added more technical requirements during commercialization.

- Transparent and easy-to-apply parallelism, which is met and shown with experiments (E1).
- Dynamic pipeline topology, which is achieved by the nature of GStreamer.
- Interact with other frameworks such as ROS [30], Android media framework, Tizen sensor framework, and Linux IIO [19], which are achieved by **NNStreamer** components.
- Dynamic flow control, which is mostly achieved by off-the-shelf filters if application threads may control flows directly: valve and input/output-selector. With **Tensor-If**, developers can control flows based on tensor values without the interventions of application threads.
• Rate override and QoS control, which is addressed by Tensor-Rate.

IV. Evaluations

We have released NNStreamer for multiple consumer electronics prototypes and products of different software and hardware platforms. Quality control teams have tested NNStreamer, and related products will soon be available for consumers. We show the following sets of experimental results:

E1. Multi-model pipelines with AMLogic A311D SoC: 4 Cortex-A73 and 2 Cortex-A53 cores, 4 GiB RAM, and a Vivante neural processing unit (NPU, a hardware accelerator for neural networks). E1 demonstrates how efficiently and easily NNStreamer utilizes different computing resources. E1 has the same configuration with some 2021 consumer electronics models.

E2. Activity Recognition Sensor (ARS) with Nexell S5P4418 SoC: 4 Cortex-A9 cores and 1 GiB RAM. E2 shows how easily and efficiently developers can implement and execute multi-modal and multi-model applications. ARS is deployed to hospitals and elderly care facilities.

E3. Multi-Task Cascaded Convolutional Networks (MTCNN)\[10, 42\]. E3 evaluates an extremely complicated pipeline in various hardware platforms.

E4. Performance comparison against MediaPipe in a desktop PC (Intel i7-7700 and 16 GiB RAM).

E1 in Figure 2 evaluates the performance with heterogeneous resources: CPU and NPU. Table 1 compares the conventional implementation (Control) and various configurations of NNStreamer pipelines (NNS) with 3000 input frames at 30 frames/s (fps). Before the introduction of NNStreamer, product engineers have implemented conventional code (Control), which processes every required operation serially for each input frame. Higher performance (throughput), lower overheads (CPU, memory), and ease of implementation have successfully helped them abandon the conventional and adopt NNStreamer.

Case c and d show performance improvement with the stream pipeline architecture. Case e shows the base performance with CPU cores by using TensorFlow-lite instead of Vivante-NPU and its run-time libraries. Case f shows that NNStreamer can efficiently execute multiple models sharing an NPU with virtually no overheads; it has improved the overall performance by 4.5%. The output rates of individual models in g and h are virtually not affected while both are simultaneously executed; they suffer only 0.8% and 4.0% of overheads. This result shows that NNStreamer efficiently utilizes heterogeneous computing resources. Case i shows that NNStreamer can utilize shared resources and heterogeneous resources simultaneously and efficiently. The improved throughput (or overhead of multi-model executions) is calculated by \( \frac{\text{fps}_{\text{I3}}}{\text{fps}_{\text{c}}} + \frac{\text{fps}_{\text{Y3}}}{\text{fps}_{\text{d}}} + \frac{\text{fps}_{\text{CPU-I3}}}{\text{fps}_{\text{e}}} \) where \( \#\text{HW} \) is 1 in f and 2 in g to i. The capability to execute multiple models in parallel with virtually no overheads and with higher performance combined with the ease and flexibility of writing pipeline applications has been the reason for replacing the conventional implementations with NNStreamer. The memory usage cannot be compared against a and b directly because a and b are too inefficient, caching everything in memory. Comparing h to \{f, g, h\} or \{f, g, h\} to \{c, d, e\} suggests that a larger pipeline with multiple models may be much more efficient than individual pipelines with a single model, especially if they are executed serially.

E2 evaluates the performance and developmental efficiency of ARS, whose pipeline is shown in Figure 3, which consists of multiple sensors and neural networks. Input stream feeding and synchronizations of such pipelines are not trivial and have a significant impact on performance and reliability. The introduction of NNStreamer to ARS has significantly reduced developmental effort. Before NNStreamer, a few developers have been implementing the pipeline partially for several weeks. Then, with NNStreamer, one developer has completed the pipeline within a few hours (only a dozen lines of codes) and optimized its performance by tweaking parameters within a couple of days.

The NNStreamer pipeline runs faster and more efficiently, as well. The memory usage is reduced by 48% (448 MiB to 234 MiB). The CPU workload with 30 fps live inputs is reduced by...
TABLE I
E1 results of 100-second executions. I3 is Inception-V3, and Y3 is YOLO-V3. C/I3 uses CPU; others use NPU. Negative values show resource sharing overheads.

| Number of models | Configuration                  | Throughput (frames/s) | CPU usage (%) | Memory usage (MiB) | Improved throughput |
|------------------|--------------------------------|------------------------|---------------|---------------------|---------------------|
| 1                | a. Control / I3               | 19.4                   | 161.8         | 84.5                | –                   |
|                  | b. Control / Y3              | 9.5                    | 145.2         | 87.4                | –                   |
|                  | c. NNStreamer / I3           | 28.0                   | 17.0          | 24.5                | 44.3% / a           |
|                  | d. NNStreamer / Y3           | 10.8                   | 40.7          | 27.4                | 13.7% / b           |
|                  | e. NNStreamer / C/I3        | 1.2                    | 115.0         | 47.9                | –                   |
| 2                | f. NNStreamer / I3 + Y3      | 11.0, 7.0              | 44.7          | 32.6                | 4.5% / c+d          |
|                  | g. NNStreamer / I3 + C/I3    | 27.8, 1.2              | 122.0         | 58.8                | –0.8% / c+e         |
|                  | h. NNStreamer / Y3 + C/I3    | 10.5, 1.1              | 146.6         | 63.3                | –4.0% / d+e         |
| 3                | i. NNS / I3 + Y3 + C/I3     | 11.0, 6.7, 1.1        | 151.7         | 68.4                | –2.3% / c+d+e       |

Fig. 2. Pipeline of E1 (case i in Table I). Others (cases c to h) are sub-pipelines of i.

Fig. 3. Pipeline of E2, which is a multi-modal and multi-model pipeline for ARS devices.

43% (90.43% to 51.35%), and both do not have frame drops. The batch processing rate for recorded inputs is improved by 65.5% with NNStreamer: 46.0 to 59.4 in (a), 2.5 to 3.2 in (b), and 9.3 to 25.5 in (c) of Figure 3. Note that because of aggregators, (b) and (c) process at slower rate.

E3 evaluates MTCNN performance. Figure 4 describes the complex topology of MTCNN. The output is a video display (“Video Sink”) showing both camera inputs and inference results simultaneously. We compare C/C++ implementations of NNStreamer and ROS [30] (Control) with Full-HD videos in various devices: A (mid-end embedded, Exynos 5422), B (high-end automotive embedded, Exynos 8890), and C (PC with Intel i7-7700). A ROS-fluent team (independent from the NNStreamer team) is assigned for Control so that developers would implement efficient codes for Control.

There are several sub-pipelines with neural networks and merging points, which require synchronization and stream throttling. For example, in P-Net Stage, processing a layer much faster (e.g., 30 fps) than other layers (e.g., 15 fps) is meaningless and deteriorates the overall performance. Exploiting parallelism with proper synchronization and throttling becomes trivial with NNStreamer as in E2: e.g., a dozen lines of C codes describe P-Net Stage.

Table II compares the performance of NNStreamer and Control. NNStreamer (NNS) has lower overall latency (measured with 1 fps inputs) and higher throughput (measured with 30 fps inputs). Row 2 compares the performance without the impact of pipeline data-parallelism [23] by processing a single input frame at a time, but with the effects of functional parallelism at P-Net (row 3) despite slower R-Net and O-Net (row 4 and 5). The NNStreamer case has 1959 lines of C codes (1004 of them are re-implementation of non-max suppression, bounding box regression, and image patch), which is slightly longer than Control (1644 lines of C++ codes). Note that the NNStreamer case supports exception handling and dynamic layers and video formats, which are not supported by Control, and provides a higher degree of parallelism.

E4 compares the performance of a MediaPipe sample pipeline and its equivalent NNStreamer pipeline. The neural network model for E4 is “ssdlite_object_detection.tflite”.

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Fig. 4. Pipeline of E3 (MTCNN). N denotes non-maximum suppression (NMS). B denotes bounding box regression (BBR). I denotes image patch generation.

**TABLE II**

| Performance | Mid-end | High-end | PC | Improved by
| A / Control | B / Control | C / Control | NNStreamer (%) |
|-------------|-----------|-----------|----|--------------|
| 1. Throughput (fps) | 1.01 | 1.73 | 4.02 | 82.21 |
| 2. Overall latency (ms) | 981.8 | 811.0 | 704.5 | 539.4 |
| 3. P-Net latency (ms) | 795.7 | 531.5 | 614.3 | 358.1 |
| 4. R-Net latency (ms) | 82.4 | 174.4 | 67.7 | 9.7 |
| 5. O-Net latency (ms) | 103.6 | 105.2 | 91.1 | 80.2 |

Fig. 5. Pipelines of E4. NNStreamer with 2 TensorFlow versions: a and b, MediaPipe: c, hybrid: d.

**TABLE III**

E4 results with 10 executions of 1818 full-HD frames. ± shows standard deviations.

| (a) NNStreamer-a | (b) NNStreamer-b | (c) MediaPipe | (d) Hybrid |
|------------------|-----------------|--------------|-----------|
| 1. CPU (%) | 52.8 ± 0.44 | 168.7 ± 0.13 | 168.2 ± 0.08 | 168.0 ± 0.11 |
| 2. Throughput (fps) | 46.9 ± 0.14 | 13.8 ± 0.03 | 13.3 ± 0.03 | 12.8 ± 0.01 |
| 3. Latency (ms) | 20.8 ± 1.21 | 72.7 ± 2.05 | 74.5 ± 2.20 | 76.3 ± 2.18 |
| 4. Mem access (billions) | 21.9 ± 0.11 | 21.8 ± 0.05 | 23.5 ± 0.04 | 25.3 ± 0.08 |
| 5. Mem size (MiB) | 199.5 ± 5.60 | 194.9 ± 0.32 | 185.1 ± 0.39 | 300.4 ± 3.36 |

a MediaPipe reference model. Figure 5 shows the 4 cases: a and b test NNStreamer pipelines of different TensorFlow-lite versions (a: 1.15.2 and b: 2.1), c tests a MediaPipe pipeline, and d tests an NNStreamer pipeline that has the pipeline c embedded as a filter. We have removed some queues from c and d because they deteriorate their performance. The cycle from “Detection_Tensors” feeds the flow status so that FlowLimiter may throttle input rates. NNStreamer does not need it because GStreamer already has a bi-directional metadata stream channels for QoS controls embedded in the unidirectional data stream, which is why a stream path cycle is prohibited.

Table III shows the benchmark results of E4. Comparing (b) and (c) indicates that NNStreamer has higher throughput (3.8%) and lower latency (2.4%). More significantly, if NNStreamer uses TensorFlow-lite 1.15.2 (a) instead of 2.1 (b), the throughput is more than tripled (x3.54), and the latency is almost quartered (1/3.67). This improvement demonstrates the significant disadvantage of the inflexibility; i.e., MediaPipe of May 2020 (commit b6e6860647) is strictly bound with TensorFlow 2.1 by its build system. In other words, the ability to choose different NNFW versions may enhance the performance dramatically. Therefore, the inflexibility, forfeiting P6, not only loses the compatibility with hardware accelerators and NNFWs
but also misses the chances to perform better.

Another inefficiency comes from the primary design choice of re-implementing the pipeline framework. This choice enforces to re-implement media filters and path controls; thus, abandoning opportunities for code reusing. For 1818 input frames, if we execute pre-processors only, pre-processors of (b) and (c) consume CPU time (overhead) of 29.5 s and 41.4 s and real time (latency) of 9.86 s and 12.34 s, respectively; thus, MediaPipe’s Open-CV re-implementations of media plugins perform 25% worse and have 40% of more overheads. Inefficient pre-processing of (c) may be responsible for the performance deterioration, only partially; pipeline architectures can hide latency from throughput. More critically, devices often have media processing hardware accelerators, which signifies the importance of off-the-shelf filters; i.e., mobile phones and TVs often have media decoders and format converters on chips and integrated with media frameworks.

In (d), pre-processors of both NNStreamer and MediaPipe exist; however, those of MediaPipe have less workload (already pre-processed by NNStreamer), which results in not-so-deteriorated performance even though both frameworks are simultaneously used. This implies that NNStreamer may import and execute arbitrary MediaPipe pipelines without a significant performance penalty.

Row 4, the number of memory access measured by perf [41], shows that MediaPipe accesses memory more by 8.0%. Massive memory accesses can significantly deteriorate the performance of embedded devices with NPUs, where NPUs enhance computing power, but memory bandwidth is limited; i.e., in E3, memory read bandwidths of a PC (c) and an embedded device (a) are measured to be 18.5 GiB/s and 2.6 GiB/s, respectively. Row 5, memory size measured by peak VmRSS, suggests that NNStreamer may consume a little more memory. Memory size is affected by queues we have added to promote higher parallelism; each of the two queues may consume up to 17.8 MiB in (a) and (b).

NNStreamer provides pipeline and functional parallelism transparently. It also allows higher utilization and sharing of different hardware resources virtually without efforts or overheads. In other words, merely describing the topology with NNStreamer enables a higher degree of optimization without system software techniques. The degree of optimization will be much higher with appropriate system software techniques, time, and efforts; however, such resources are scarce even in large companies. Results of E4 show the importance of initial design choices as well.

V. CONCLUSIONS

From the experiences of on-device AI products, we show that the stream processing paradigm may significantly improve performance and productivity. By deploying NNStreamer, we have achieved improvements for on-device AI applications: higher throughput, more straightforward developments with more features and less effort, and improved code quality. Traditional multimedia developers may also employ arbitrary neural network models in their pipelines with NNStreamer.

The lessons learned during the development and deployment of NNStreamer include:

- Stream processing paradigm works appropriately for on-device AI systems and makes their implementation much more straightforward. However, optimizing pipelines still requires some degree of technique and experience. Placing and configuring queues, branching and merging, and choosing proper filters for given operations have been sometimes not so trivial.
- Showing that a new framework improves performance and efficiency alone is not enough for products or platforms to adopt it. As long as conventional implementations meet functional requirements, product engineers are reluctant to adopt a new framework even if costs per application grow excessively. We have integrated the work into the software platform along with APIs, user manuals, automated build and deployment systems, test cases, and sample applications. We have written first versions of applications and systems, including hardware adaptations with product engineers. Then, showing higher productivity, performance, and efficiency has worked.
- Analyzing pipeline performance is often complicated and requires specialized tools for visualization and profiling. Training developers with such tools may be required.
- For a framework helping applications, developer relations of both public and in-house is crucial. Besides, for in-house developers, releasing it as an open-source helps break down silos.
- Open sourcing a framework along with opened processes and governance may appear to incur more workloads. However, such workloads include better documentation, rules, policies, broader test cases, and public CI/CD systems, which help improve the overall code quality. Besides, we have received more bug and test reports, usage cases, documentation, and code updates.

This work is being deployed for various commercial products and platforms and is actively and continuously developed with various future goals. NNStreamer is the standard on-device AI framework of Tizen, which is the OS for a wide range of devices. We are also deploying NNStreamer for Android products. Developers may install ready-to-use binary packages for Android Studio (JCenter), Ubuntu (PPA), OpenEmbedded (layer), macOS (Homebrew), and Tizen Studio (pre-installed).

BROADER IMPACT

Initially, we have designed NNStreamer for autonomous vehicles. We have soon discovered that it is applicable for any devices that process neural networks for online data: i.e., analyzing live video streams. Then, we have successfully deployed NNStreamer to Tizen 5.5 (2019.10) and 6.0 (2020.5) as its standard machine learning framework and API. Tizen is an operating system for general consumer electronics, including mobile phones, TV sets, wearable devices, robotic vacuums, refrigerators, smart ovens, IoT devices, and so on. For example, the first product using Tizen 5.5, Galaxy Watch 3, uses NNStreamer for its on-device AI applications.
We do not have any contracts or relations with such affiliations. With NNStreamer compatible with ROS and OpenEmbedded/Yocto, we are providing NNStreamer to robotics communities as well. We have opened the developmental processes and released source codes and binary packages for various platforms as an open-source project. Therefore, anyone may adopt NNStreamer freely for their research or products and contribute to NNStreamer. We already have a few third party companies applying NNStreamer for their own products and prototypes.

We have found a significant concern for on-device AI projects. Machine learning experts are usually not interested in writing optimized or maintainable codes for embedded devices. Moreover, often, system programers are also not interested in analyzing and re-implementing codes written by such experts. With NNStreamer, an easy-to-use pipeline framework for AI projects, we hope to close the gaps between the two parties by adopting pipeline topology as a communication protocol. Note that this is not necessarily limited to on-device AI projects but also applicable to general server/workstation-based AI projects.

We expect that NNStreamer will help improve the productivity of AI researchers in general. However, the learning curve of describing appropriate pipelines exists, and profiling pipeline performance issues require proper tools and some experiences along with some understandings in queueing theory. Fortunately, when we have trained developers who have just received their bachelor’s degrees in computer science, their learning curves have not been too steep. They have started writing appropriate pipelines within a few days and optimized pipelines within a couple of weeks. To further assist novice developers, we are implementing pipeline visualization tools and provide pipeline performance profiling tools.

NNStreamer extensions for Protobuf and Flatbuf provide standard representations of tensor streams to interconnect heterogeneous pipelines of MediaPipe and DeepStream. We can construct pipelines across sensor nodes, edge and mobile devices, workstations, and cloud servers of different stakeholders, which are often referred as “Edge-AI”.

Stream processing does not need to be restricted to inferences, but can be extended for training. We are implementing NNTrainer so that we can apply on-device training with NNStreamer for personalization (adapting a pre-trained neural network for specific users) with personal data kept in the device. The initial version of NNTrainer is already being deployed for personalization services of next-generation products along with NNStreamer pipelines. Besides, stream processing does not need to be restricted to on-device AI application, but can be extended to cloud or server-based AI applications.

There are a few services developed by other affiliations preparing server-based AI services with NNStreamer as well as on-device AI systems and devices of different affiliations. We do not have any contracts or relations with such affiliations except for sharing the same GitHub repository and communicating with them via public channels. We gather additional requirements from developers of such affiliations and accept contributions from them as well. In the course of such open collaboration we could have the following benefits:

- We have been further required to consider the extensibility, which allowed NNStreamer to be adopted to new products in the affiliation that the authors have not imagined.
- We have received extensive usage examples and test results from users across various affiliations, which helps improve the functionalities and the robustness.
- We have received bug fixes, example applications, new features, and documentations from different affiliations.
- Developers have become more enthusiastic with open source software developmental environments. In such environments, daily work including the codes and documents are exposed to the public and the developers are supposed to communicate with developers from different affiliations.

We could enjoy such benefits opening not only the source code, but also the whole developmental and policy making processes. We hope that we could get more contributors and users for the NNStreamer project and, someday, we could have voting members and committers in its technical steering committee from various affiliations. Then, we expect that such higher degree of public inter-affiliation collaboration will help improve both functional and non-functional properties of NNStreamer and its sub-projects greatly.

### Availability

Readers may visit our GitHub pages to get the full source code and its history, sample application code, binary packages, documentations. We welcome everyone to join NNStreamer’s public events, to contribute code commits, to use NNStreamer for any purposes, or to discuss via various channels.

- Web page: [https://nnstreamer.ai](https://nnstreamer.ai)
- GitHub main: [https://github.com/nnstreamer/nnstreamer](https://github.com/nnstreamer/nnstreamer)
- Gitter: [https://gitter.im/nnstreamer](https://gitter.im/nnstreamer)
- Slack: [http://nnstreamer.slack.com](http://nnstreamer.slack.com)
- Mailing list: [https://lists.lfai.foundation/g/nnstreamer-technical-discuss](https://lists.lfai.foundation/g/nnstreamer-technical-discuss)

- Tizen: Machine Learning APIs are NNStreamer APIs.
- Ubuntu PPA: ppa:nnstreamer/ppa
- Android Studio: JCenter “nnstreamer”
- Yocto/OpenEmbedded Layer: meta-neural-network
- MacOS Homebrew: nnstreamer (#5926)

- Sample: [https://github.com/nnstreamer/nnstreamer-example](https://github.com/nnstreamer/nnstreamer-example)
- ROS extension: [https://github.com/nnstreamer/nnstreamer-ros](https://github.com/nnstreamer/nnstreamer-ros)

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