# Exploring Effects of Computational Parameter Changes to Image Recognition Systems

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#### Abstract

Image recognition tasks typically use deep learning and require enormous processing power, thus relying on hardware accelerators like GPUs and FPGAs for fast, timely processing. Failure in real-time image recognition tasks can occur due to incorrect mapping on hardware accelerators, which may lead to timing uncertainty and incorrect behavior. Owing to the increased use of image recognition tasks in safetycritical applications like autonomous driving and medical imaging, it is imperative to assess their robustness to changes in the computational environment as parameters like deep learning frameworks, compiler optimizations for code generation, and hardware devices are not regulated with varying impact on model performance and correctness. In this paper we conduct robustness analysis of four popular image recognition models (MobileNetV2, ResNet101V2, DenseNet121 and InceptionV3) with the ImageNet dataset, assessing the impact of the following parameters in the model's computational environment: (1) deep learning frameworks; (2) compiler optimizations; and (3) hardware devices.

We report sensitivity of model performance in terms of output label and inference time for changes in each of these environment parameters. We find that output label predictions for all four models are sensitive to choice of deep learning framework (by up to 57%) and insensitive to other parameters. On the other hand, model inference time was affected by all environment parameters with changes in hardware device having the most effect. The extent of effect was not uniform across models.

#### Introduction

The first step in achieving environmental perception in autonomous vehicles (AV) is to detect objects using object detection algorithms that is central for recognizing and localizing objects such as pedestrians, traffic lights/signs, other vehicles, and barriers in the AV vicinity. Typically object detection algorithms use Deep Neural Networks (DNNs) for image recognition and localisation, as they can learn and extract more complex features.

Much of the existing literature for assessing robustness and safety of image recognition has focused on testing the DNN structure and addressing bias in the training dataset through adversarial testing and data augmentation (Zhang

	Framework	Model Source	Device	Classification	Inf. time
	PyTorch	PyTorch	GPU 1	Cyclist	80ms
- A B	PyTorch	TensorFlow	GPU 1	Cat	75ms
40	PyTorch	PyTorch	GPU 2	Cyclist	150ms
1	TensorFlow	TensorFlow	GPU 1	Cyclist	85ms
True label: Cyclist	TensorFlow	PyTorch	GPU 1	Cyclist	90ms
Ref. inf. time: 80ms	TensorFlow	TensorFlow	GPU 2	Cyclist	130ms

Figure 1: Example showing how varying factors can impact the classification accuracy of an image recognition model.

et al. 2018; Tian et al. 2018; Guo et al. 2021). Existing techniques have failed to consider safety violations caused by interactions of the DNN with the underlying computational environment: both software and hardware. This can include the Deep Learning (DL) frameworks (e.g., TensorFlow, Py-Torch, etc), compiler optimizations for device code generation (e.g., operator fusion, loop unrolling), and the hardware accelerators they run on (e.g.GPUs). As an illustrative example, consider an image recognition model to classify the image in Figure 1 with a true label "Cyclist" and reference inference times of 80ms with PyTorch and 85ms with TensorFlow. The figure illustrates how changing the DL framework or device (italicized in the table) can impact the output label and/or model inference time.

In this paper, we conduct an empirical study to evaluate the robustness of image recognition models in the presence of changes in the computational environment. We consider the following parameters in the computational environment: (1) Source DL framework for the DNN model; (2) Compiler optimizations; and finally (3) GPU accelerator devices. We assess the robustness of four widely used image recognition models with respect to the output label and inference time when changing each of these environment parameters. It is important to check changes in the output label, as it directly affects model correctness. On the other hand, inference time is an important consideration for timing safety in real-time perception systems within applications like self-driving cars where there is a performance requirement for object detection models to return results within a fixed time (Dreossi et al. 2019).

Overall, we find that varying DL frameworks significantly impacts output label and inference time of the model. Varying hardware accelerators and compiler optimization do not

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affect model output but have a significant effect on inference time. In summary, we make the following contributions:

- Assess robustness of image recognition model *outputs* with respect to changes in the computational environment: DL frameworks, compiler optimizations, and hardware accelerators;
- 2. Assess robustness of model *inference time* with respect to changes in the computational environment: DL frameworks, compiler optimizations, and hardware accelerators;

## Background

Figure 2 gives an overview of the typical layers in the deep learning systems stack (Turner et al. 2018). Much of the existing work has focused on testing and robustness with respect to the top two layers, *Datasets* and *Models*. In this paper, we consider robustness with respect to the bottom three layers that make up the computational environment required for executing a given DL model, that includes the deep learning framework, related systems software, and the underlying hardware. We describe the relevant parts of the computational environment in the sections below. In addition, we provide a brief overview of image recognition models that is the focus of this study.

## **Deep Learning Frameworks**

Deep Learning Frameworks, shown as the third layer in Figure 2, provide utilities such as model declaration, training and inference to machine learning engineers. For our study, we use four DL frameworks that are widely used in the community: Keras, PyTorch, TensorFlow (TF), and TensorFlow Lite (also known as TFLite). We use these frameworks as sources for the image recognition models, as each has its own native definition for the models. We briefly describe each of the four frameworks below.

**Keras** (Chollet et al. 2015) is a high-level DL framework, providing APIs for effective deep learning usage. Keras acts as an interface for TensorFlow, and we aim to observe potential overheads and bug introductions from the extra layer of complexity.

**PyTorch** (Paszke et al. 2019) is an open source machine learning framework based on the Torch library and developed by Meta AI team. It supports hardware acceleration for tensor computing operations.

**TensorFlow (TF)** (Abadi et al. 2015) is an open-source DL framework, developed by Google, and widely used for training and inference of DNNs.

**TensorFlow Lite (TFLite)** (Abadi et al. 2015) is a lightweight version of TensorFlow and part of the original TensorFlow library, providing framework focused only on the inference of neural networks on mobile and lightweight devices.

**Framework Conversion** Conversion of models between DL frameworks can be a complex task, and thus many frameworks redefine common DNN architectures natively, and often training said model from scratch. We refer to such models as a "*native model*", and models that have been converted to another DL framework as a "*converted model*".



Figure 2: Relevant layers in the deep learning systems stack.

Systems such as ONNX (onn 2022) and MMdnn (Liu et al. 2020) attempt to provide common intermediate formats for translation between DL frameworks, however these processes can still be error prone, and have issues around support for bespoke operators. Note that the DL framework used to design and train a model may not be the same as that used to deploy the model. Hence, it is worth exploring potential errors that may be introduced during framework translation. We only consider two framework translations in our experiments: (1) TF to TFLite; and (2) PyTorch to TFLite. This is because TFLite is a deployment-only framework and thus is more likely to be the final software environment that developers convert their models to.

We will explore other framework conversions in our future work.

## Systems Software: Apache TVM

Apache TVM (Chen et al. 2018a) is an end-to-end machine learning compiler framework for CPUs, GPUs, and accelerators. It generates optimized code for specific DNN models and hardware backends, allows us to import DNN models from a range of DL frameworks, and provides profiling utilities such as per-layer inference times. A simplified representation of Apache TVM can be seen in Figure 3. TVM's support of several DL frameworks, optimization settings, and hardware accelerators made it a suitable choice explore varying different environment parameters in our experiments. TVM provides direct importers for models from most popular DL frameworks, which load said models as a TVM computation graph.

The first level of optimization available in TVM is graphlevel optimizations, which is the focus of this study. These optimizations impact the full model and include operator fusion (e.g., batch normalization, activation functions), elimination of common subexpressions, and potentially unsafe optimizations such as fast math.

TVM also supports optimizations for a given operation type (e.g., convolutional layers, matrix-multiplications) such as loop tiling, loop re-ordering, unrolling, vectorization, auto-tuning (Chen et al. 2018b), and auto-scheduling (Zheng et al. 2020), among others.

TVM also supports third-party libraries such as cuDNN (Chetlur et al. 2014) and the Arm Compute Library (Com 2022).



Figure 3: Overview of DNN compilation in Apache TVM.

# **The Perception AI Models**

A common benchmark for Perception AI models is the ImageNet image classification dataset (Russakovsky et al. 2015), which requires assigning one of a possible 1000 class labels to RGB images of size  $224 \times 224$  pixels. For solving Perception AI problems, such as classification and semantic segmentation, convolutional neural networks (CNNs) are commonly used, which are DNNs characterized by convolutional layers. Transformers-based architectures (Vaswani et al. 2017) have begun to provide competitive results in the past two years (Dai et al. 2021; Zhai et al. 2022), however are still maturing. Thus for our evaluation we explore four widely used CNN models: MobileNetV2 (Sandler et al. 2018), ResNet101V2 (He et al. 2015), DenseNet121 (Huang, Liu, and Weinberger 2016), and InceptionV3 (Szegedy et al. 2015). These models are widely known and extensively used for classification and semantic segmentation operations, as well as being the "backbone network" for other tasks such as object detection (Chiu et al. 2020).

All four models have native definitions within the DL frameworks under study.

#### **Related Work**

Existing work has primarily focused on robustness of the dataset and model architecture layers (top two layers), shown in Figure 2. DeepXPlore (Pei et al. 2017) applies whitebox testing, by measuring neuron coverage, identifying similar DNNs for cross-reference and generating adversarial inputs to detect faults. This work has been extended by DLFuzz that attempts to minutely mutate inputs to improve neuron coverage (Guo et al. 2021). DeepHunter (Xie et al. 2019) applies fuzzing (i.e., generation of random, invalid and unexpected inputs) to DNNs, aiming to maximize coverage of the system and potentially discover faults. DeepTest (Tian et al. 2018), a tool that modifies images using linear & affine transformations, generates inputs simulating different weather conditions and real-world phenomena to test the robustness and validity of DNNs to changing weather conditions in autonomous driving. Deep-Road (Zhang et al. 2018) uses GAN-based metamorphic testing to generate inputs that simulate extreme weather conditions, such as heavy rain and snow. DeepBillboard (Zhou et al. 2020) explores the potential of physical world adversarial testing utilizing Billboard inputs. For a more comprehensive overview of adverarial examples for images, we refer the readers to a survey (Shorten and Khoshgoftaar 2019).

Robustness with respect to layers in the computational environment, seen in Figure 2, has received little attention.

With respect to the DL Frameworks layer, some attempts have been made to explore the effect of DL frameworks towards model performance. In particular, some benchmarking analysis has been conducted towards training and inference time analysis and performance (Shi et al. 2016; Liu et al. 2018; Mahmoud et al. 2019). In addition, a survey (Wu et al. 2022) explores various parameters and their effect towards model accuracy and execution time. However, both contributions utilize experiment sets of limited of model numbers, DL frameworks, input dataset and variety of hardware acceleration devices, providing useful results but in a small scale. Our contribution aims to extend this work against real-world, challenging conditions and scenarios, exploring the effects of a challenging dataset, plus a wide variety of models and hardware acceleration devices capabilities, a setup much closer to real-world environments of safety-critical systems.

In addition, CRADLE (Pham et al. 2019) attempts to detect and localise inconsistencies between models sourced from different DL frameworks by comparing their outputs and analysing model execution. LEMON (Wang et al. 2020) is a framework that generates model mutations to detect discrepancies in DL frameworks used in Neural Networks. Both CRADLE and LEMON aim to detect faults in DL frameworks by comparing it to other frameworks. Impact of changing DL framework on model performance is not considered in these paper and that is the focus in our work.

For the systems software layer in Figure 2, a recent study (Shen et al. 2021) examined bugs introduced by different deep learning compilers. Incorrect optimization code logic accounted for 9% of the bugs introduced by compilers. Other compiler bugs presented in the study include misconfiguration, type problem, API misuse, incorrect exception handling, incompatibility. In our study, we examine the effect of changing compiler optimisations on model performance. We will examine the effect of other compiler bugs in our future work.

Finally, for the hardware layer in Figure 2, (Humbatova et al. 2020) created a taxonomy of faults encountered in DNNs used in object Detection. The authors surveyed commits, issues and pull requests from 564 GitHub projects and 9,935 posts from Stack Overflow and interviewed 20 researchers and practitioners. The study revealed GPU related bugs to be one of the five main categories faults in deep learning tasks like object detection. The study, however, did not explore the impact of these bugs on model performance. The other four categories of faults were API, Model, Tensors and Inputs and Training that relate to the top two layers in Figure 2. In this paper, we are primarily interested in the effect of changes in the bottom three layers of the stack that make up the computational environment on model performance, in terms of output and model inference time. This has not been systematically explored in the literature.

#### Experiments

We consider four different CNN (image recognition) models: MobileNetV2, ResNet101V2, DenseNet121, and InceptionV3. Each model is evaluated in the TVM compiler framework (v0.8.0), imported via ONNX (onn 2022), with

Table	1: Accuracy	of native n	nodels on th	he Image	Net dataset.
	1				

Framework DNN Model	PyTorch	Keras	TF	TFLite
ResNet101	81.9	76.4	77.0	77.0
InceptionV3	77.3	77.9	78.0	78.0
MobileNetV2	72.2	71.3	71.9	71.9
DenseNet121	74.4	75.0	N/A	N/A

all possible combinations of values for each of the following environment parameters:

- **DL Frameworks:** We consider Keras, TF, TFLite, and Py-Torch as sources for our models. We selected these frameworks as they are widely used in the deep learning community (Khan et al. 2019). The accuracy of the native version of each model is shown in Table 1. We verify that each model in correctly imported into TVM by comparing the output labels with the source framework.
- **Framework Conversion:** We examine the effect of framework conversion on model robustness. In particular, we convert native models from PyTorch and TF to TFLite models, and examine labelling differences introduced by the conversion.
- **Compiler Optimizations:** We explored the impact of different levels of TVM graph-level compiler optimization: basic, default, and extended variants.

**Basic** (00) applies only "inference simplification", which generates simplified expressions with the same semantic equivalence as the original DNN.

**Default** ( $\circ$ 2) applies all optimizations of  $\circ$ 0, and in addition fusion of operators such as ReLU activation functions, as well as constant folding.

**Extended** ( $\circ$ 4) applies all optimizations from Default and a number of additional ones. For example: enabling "fast math" (which allows the compiler to break strict IEEE standard compliance for float operations if it could improve performance), allowing modification of data layouts, and eliminating subexpressions with multiple occurrences.

- **Devices:** We used four different hardware devices, featuring GPU accelerators of varying capabilities. More specifically, we used:
  - **Server:** Intel-based server featuring an Nvidia Tesla K40c (GK11BGL) GPU;
  - **Xavier:** Nvidia AGX Xavier featuring an Nvidia Volta GPU;
  - **Local:** Laptop featuring an Intel(R) GEN9 HD Graphics NEO;
  - **Hikey:** Hikey 970 board featuring an Arm Mali-G72 GPU;

Note that Server represents a high-end Nvidia GPU, Xavier a mid-end Nvidia GPU, Local a low-end Intel GPU, and Hikey a mobile-class Arm GPU. For the Nvidia devices we use TVM to generate CUDA code, and for the Hikey and Intel GPUs we generate OpenCL code. In total, we evaluate 276 model variants from 4 Models \* (4 DL Frameworks + 2 DL Framework Conversions) \* 4 Devices \* 3 Optimizations – (12 Keras native models)). We subtract 12 Keras native models, since we were unable to compile the InceptionV3 model on any device or under any optimization setting. We discuss challenges faced in compiling and executing certain configurations in the Execution Issues Section .

**Dataset** We use the ImageNet Large Scale Visual Recognition Challenge 2017 (ILSVRC2017) (Russakovsky et al. 2015) image classification test dataset for our experiments, consisting of 5500 RGB images, of size  $224 \times 224$  pixels. The task is to produce an output label classifying the image, out of 1000 possible labels (all our models were pre-trained on the ImageNet dataset, see Table 1 for their accuracy).

#### **Robustness Measurements**

Our experiments are aimed at evaluating (1) Robustness of Model Output, and (2) Robustness of Model Execution Time. We describe these measurements below.

**1. Robustness of Model Output** For every image input in the ImageNet (Russakovsky et al. 2015) test dataset, we record the top-ranked output label for every combination of environment parameters. We then conduct pairwise comparison of the labels for the same image input while varying each environment parameter in turn. For instance, over a single image, we would compare the output label from InceptionV3 from Keras against that of PyTorch while keeping the device and compiler optimization constant. We then compute total dissimilarity in labels across all images in the dataset for every pairwise environment parameter variation.

**2. Robustness of Model Execution Time** We use the term *model execution time* to mean model inference time which is the processing time of the network model without including the time to load images and any pre-processing that may be needed. We record model execution time for every image in the dataset and with every model configuration. We repeated executions 10 times and recorded average time per image. We compare execution times for model configurations across all images in the dataset using box plots and mean execution time.

## **Execution Issues**

All environment parameter combinations could not be executed with all models due to the following incompatibility issues:

1. The DenseNet121 model from TF and TFLite resulted in incorrect output labels for most images. The output labels remained constant regardless of image, even when running within TensorFlow itself. Although we sourced the model from the TensorFlow website, we believe that the model has been deprecated, and thus does not behave as expected. This is because it no longer appears in the list of pre-trained models within the TensoFlow repository<sup>1</sup>. 2. InceptionV3 sourced from Keras was problematic, in the sense

<sup>&</sup>lt;sup>1</sup>https://github.com/tensorflow/models/tree/master/research/ slim#pre-trained-models

that we were unable to succesfully import it into TVM. We attempted using TVM's Keras model importer, as well as importing the model via ONNX, however in both cases the import failed. We did not experience this issue with any other version of InceptionV3.

3. For ResNet101 sourced from PyTorch, we selected the V1 version the model instead of V2 as the V2 version was not provided in the official PyTorch repository. The version difference may have a larger effect on model inference time when we compare across DL frameworks. We therefore ask the readers to take this into consideration for results involving ResNet101 sensitivity to DL framework.

4. Regarding MobileNetV2, we experienced problems when executing it on the Xavier device, as we received a CUDA\_ERROR\_INVALID\_PTX error. We do not consider this device configuration for MobileNetV2 in our experiments.

# Results

For each image recognition model, we discuss robustness of (1) output label prediction and (2) model inference time in the presence of changes in the the DL framework from which models are sourced, compiler optimizations, and hardware devices.

## **Robustness of Model Output (1)**

We vary one environment parameter at a time (while fixing the others) – the DL framework, compiler optimization level, GPU device – and examine their impact on output label prediction. Table 1 shows the accuracy of native models on the ImageNet test dataset. To take InceptionV3 as an example, all frameworks get approximately 78% accuracy, however this does not mean that thy will be correct for the same 78%. Thus in the worst case, we would expect two frameworks would only agree on 56% of labels (i.e., 44% dissimilarity).

**Varying Deep Learning framework** We present results for the four models under study in Figure 4, with the TVM compiler optimization level set to *Default* (-02), and the hardware acceleration device set to Server.

We then vary the DL frameworks one at a time to compute sensitivity of model output label to that framework. Figures 4a–4d show that models are acutely sensitive to the DL framework they are sourced from. Changes in the framework has a significant impact on output label, with MobileNetV2 exhibiting most discrepancy in output labels, in the range of 49 - 57% for different DL frameworks. We analyse each model below:

- **InceptionV3** (Figure 4a) we observe a 33% discrepancy between PyTorch versus both TF and TFLite. No discrepancies were observed for TF versus TFLite; the same was true with other models.
- **MobileNetV2** (Figure 4b) we observe a 49% dissimilarity between Keras versus the other three frameworks and a 57% dissimilarity for PyTorch versus TF and TFLite. We hypothesize that lower complexity and size of MobileNetV2 makes it less robust to changes in the framework.

- **ResNet101V2** (Figure 4c) Keras has a 19% dissimilarity against TF and TFLite. PyTorch resulted in a 40% dissimilarity against all the other frameworks.
- **DenseNet121** (Figure 4d) we find a 26% dissimilarity for PyTorch versus Keras. Owing to the execution issues with TF/TFLite (discussed in Execution Issues section), we do not report dissimilarities when changing to these frameworks.

Overall, TF and TFLite models always produce the same output, which suggests that the official TFLite models are successfully converted TF models, and contain the same parameters. This is further confirmed by their achieving the same accuracy as seen in Table 1. However, when comparing against Keras and PyTorch, we observe significant differences. The extent of difference varies widely among the models, with MobileNetV2 being most sensitive to DL framework changes (see Figures 4b).

**Impact of DL Framework Conversion** We explore the impact of framework conversion on model output by converting models from PyTorch and TF to TFLite, and evaluating the converted models in TVM. For TF-to-TFLite, we were able to convert directly, whereas for PyTorch we had to convert to ONNX, then to TF, then to TFLite. We then compare the output labels between the native and converted models, i.e. if any errors were introduced by converting the model. The results are presented in Figure 5. We observed 37% discrepancies in output label when converting the ResNet101 model from PyTorch to TFLite, meaning that, for models converted from TF to TFLite, discrepancies are fewer and are in the range of 2% (ResNet101) to 10% (MobileNetV2).

Analysis of Output Label Sensitivity Small changes in output labels when varying DL frameworks might be expected, since each framework has a specific implementation of the model and has been trained independently.

However, the extent of change in output labels (0-57%) across images in the test dataset observed in all 4 models when changing DL frameworks is surprising. To gain a better insight, for 10 images from the test dataset producing different labels, we took a closer look at the convolutional layers within one of the models, DenseNet121, sourced from different frameworks. We compared layer activation tensors between the models to identify the layers involved in the label discrepancy. We use an error threshold for comparing elements within the tensors.

Figures 6a and 6b show the number of tensor elements that are different between corresponding layer activations<sup>2</sup> in DenseNet121 sourced from Keras, versus PyTorch for two images that produce different labels on them. We also show the effect of choosing different error threshold values. We find for both images with label discrepancies, layers 3 and 11, followed by layers 8, 6, and 10 have the highest number of differing tensor elements between the DenseNet121 variants. A similar trend was found in the other 8 images with discrepancies that we investigated. For the DenseNet121

<sup>&</sup>lt;sup>2</sup>We show a subset of 12 convolutional layers from the model.



Figure 4: Pairwise comparison of output label dissimilarities (%) between DL frameworks for our 4 models, running on Server, with *Default* optimization level.



Figure 5: DL Framework Conversions Dissimilarities (%).



Figure 6: Convolution activations comparison for DenseNet121.

model, Keras versus PyTorch, we find the aforementioned layers are worth investigating further for identifying source of model output sensitivity.

**Varying Compiler Optimizations** We varied the optimization level within the TVM framework between *Basic*, *Default*, and *Extended*. We kept the framework and device constant for assessing sensitivity to optimization level.

We found that varying compiler optimization levels causes no discrepancies in output labels for all four models.

The lack of discrepancies/sensitivity is notable, since the *Extended* (-04) level enables unsafe math optimization that allows code violating IEEE float conventions to be generated. Note that these potential unsafe perturbations were minor enough that all four models were resilient to them. It is, however, worth considering robustness checks with respect to optimization levels in safety-critical domains, in case unsafe optimizations result in undesirable model outputs.

**Varying Hardware Accelerator** With a fixed DL framework and compiler optimization (-02), we compiled each of the four image recognition models on the four hardware devices: Server, Xavier, Hikey, and Local.

We found output label prediction for all four models with the ImageNet dataset was unaffected by changes in the hardware device and programming paradigm (OpenCL for Intel/Arm devices, and CUDA for Nvidia devices). This demonstrates that label predictions in our experiment are robust to device changes, at least when using Apache TVM as the code generator. In our future work, we plan to explore the impact of varying the backend library, for example cuDNN (Chetlur et al. 2014) and the Arm Compute Library (Com 2022).

## 2. Robustness of Model Inference Time

We vary one environment parameter at a time while fixing the others to check their impact on model inference time.

**Varying Deep Learning Framework** We fixed the optimization setting to Default and device to Server and examined deviation in model inference times across models sourced from different DL frameworks. Results for MobileNetV2 are presented in Figure 7.

It is worth noting that we observe considerable differences in inference times across model configurations. The extent of difference depends on the model. We find MobileNetV2 is most sensitive to DL framework changes (similar to output label), with inference times varying by 4-16%. InceptionV3 was most robust to DL framework changes with an average difference of 8% for changes between PyTorch and TF/T-FLite. Finally, it is worth noting that a large difference of upto  $5\times$  was observed onResNet101 between PyTorch and other frameworks. This is because ResNet101 uses PyTorch version1, unlike other frameworks using version 2.

**Varying Compiler Optimization** With device fixed to Server and framework to Keras, we vary optimization levels between *Basic*, *Default*, and *Extended*, examining the effect on model inference times. We find changing optimization levels has a sizeable effect on inference times.

Execution times generally improved with increased optimization as we moved from Basic to Extended, up to 121.4% across optimizations in all models. There are,



Figure 7: Comparison of inference times (%) across DL Frameworks for MobileNetV2 on Server with *Default* optimization.



Figure 8: Device execution times difference (%) on *InceptionV3*, *TensorFlow*, *Default Optimization*.

however, some exceptions. For instance, MobileNetV2 using PyTorch was 11% slower on Hikey device when using Default versus the Basic optimization. This suggests that increased optimization does not always result in speedup and in some cases can degrade performance.

Varying Hardware Accelerator We measured model inference on different hardware devices while fixing the DL framework and optimization level. Figure 8 shows the results when evaluating InceptionV3 model sourced from TensorFlow with Default optimization. We compute average inference time across all images in the test set and use this in comparing between devices. As expected, model inference times vary considerably with devices, based on their processing power and memory. Maximum execution time difference was observed between Server and Hikey (62782%) on InceptionV3 and the minimum difference was 41%, between Xavier and Local devices in ResNet101V2, utilizing Default optimization. Inference time difference with device change is most significant on InceptionV3 (upto  $627 \times$ ) owing to its larger size and memory requirements. When running on low-end device like Hikey as opposed to Server, we believe the smaller memory can cause cache misses resulting in significant inference time penalty.

# **Threats To Validity**

There are five threats to validity in our experiments based on the dataset, models, model pre-processing, compiler framework and inference time.

First, we only evaluate robustness using four image recognition models that are widely used. Results are model dependent as seen in our experiments and will likely vary on other models. We plan on conducting a more extensive evaluation in the future.

Second, we use the ImageNet (Russakovsky et al. 2015) image classification test dataset for our experiments. This widely used dataset is a common benchmark which we believe adequately stresses the different model configurations in terms of both output label and inference time. Other datasets may yield different robustness results on the models considered.

Third, model pre-processing is crucial for model performance (Camacho-Collados and Pilehvar 2017). In our experiments, we use the recommended pre-processing for each model and DL framework. Results may vary for other preprocessing settings.

The fourth threat is introduced by the use of the TVM compiler framework and importing models into it. To ensure that errors are not introduced in this process, for each model we validated the output labels for 100 random image samples from their source framework against the output label given by the model after importing into TVM.

The final threat is in inference time measurement. To ensure time deviations (especially in the first or "cold" run) are taken into account, we repeat inferences for each image 10 times and use the average inference time across 10 runs.

## Discussion

We make the following observations based on our results:

**Sensitivity to DL framework** Changing the DL framework used to generate the model can have a considerable effect on both the output label, and surprisingly, the model inference time. The extent of this impact depends on other environment parameters. Among the four models, MobileNetV2 had 57% dissimilarity in output labels when Py-Torch source is changed to TF/TFLite. Other models also had significant sensitivity to DL framework, up to 57%.

Inference time impact varied from 1-16% (not including ResNet101 PyTorch version).

**Sensitivity to Framework Conversion** Framework conversion between TF or PyTorch to TFLite can have an effect on output labels for some models. ResNet101V2 was most sensitive to conversion from PyTorch to TFLite with 37% disssimilarity in output labels. InceptionV3 was the most robust to framework conversion with respect to output labels, with a change between 0 and 4%.

Sensitivity to Compiler Optimization Compiler optimizations had no effect on output labels, but as expected have a considerable effect on model inference time, ranging from 1% to 16% across models. This is not surprising as different optimization settings have a direct effect on code efficiency.

Sensitivity to Hardware Devices Changing hardware devices had no impact on output labels from all four models but had a considerable effect on inference time, ranging from 1.2 to  $628 \times$  and owing to the wide range in device capabilities used in our experiments. The device change impact was most seen on InceptionV3, with *Default* optimization. For instance, when we change from Server to Hikey device, we find inference time is  $87 \times$  slower on MobileNetV2,  $227 \times$  slower on ResNet101,  $285 \times$  slower on DenseNet121 and  $628 \times$  slower on InceptionV3.

In safety-critical applications, the consequences of the above sensitivities can be crucial. Therefore it is essential that framework, compiler, and hardware communities, along with the developers of DNN models are aware of these sources of error, and test their systems for robustness to computational environment changes. Currently, there is no regulation or benchmarking of DNN model performance for environment parameter configurations. The results from our experiments indicate that assessing sensitivity to environment parameters is an important consideration during model development and use.

#### References

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