MutateNN: Mutation Testing of Image Recognition Models Deployed on Hardware Accelerators

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***Abstract*—With the research advancement of Artificial Intelligence in the last years, there are new opportunities to mitigate real-world problems and advance technologically. Image recognition models in particular, are assigned with perception tasks to mitigate complex real-world challenges and lead to new solutions. Furthermore, the computational complexity and demand for resources of such models has also increased. To mitigate this, model optimization and hardware acceleration has come into play, but effectively integrating such concepts is a challenging and error-prone process.**

In order to allow developers and researchers to explore the robustness of deep learning image recognition models deployed on different hardware acceleration devices, we propose `MutateNN`, a tool that provides mutation testing and analysis capabilities for that purpose. To showcase its capabilities, we utilized 21 mutations for 7 widely-known pre-trained deep neural network models. We deployed our mutants on 4 different devices of varying computational capabilities and observed discrepancies in mutants related to conditional operations, as well as some unstable behaviour with those related to arithmetic types.

I. Introduction

With the popularity of perception AI increasing nowadays, Deep Neural Networks (DNNs) are assigned with perception tasks for complex, sophisticated and even safety-critical systems, such as autonomous vehicles. Furthermore, the necessity of optimizing these models, while also enabling hardware acceleration, becomes vital in order to achieve high performance and meet the strict standards of systems as the ones aforementioned. A recent study [7] however, has shown that GPU bugs are amongst the main faults in DNNs, indicating that the process of integrating hardware acceleration in DNNs, is not straightforward.

Although many advances and standards have been defined to increase effectiveness in the process, managing to implement and apply optimizations to DNNs remains a challenging task and an open problem [2]. Tools such as OpenAI's Triton [15] and Apache TVM's TOPI [1] provide the necessary tools for the developers to build such optimizations with focus on integrating hardware acceleration, but the process requires strong knowledge of parallel programming and DNNs in-depth, and therefore are prone to software development bugs.

To assist developers identify the robustness of such optimizations specifically when deploying on different hardware acceleration devices, we propose a tool based on mutation testing for DNNs, called MutateNN. The system generates mutants out of pre-trained image classification models, imitating errors introduced by the developers in the optimization process, aiming to determine their effect across different hardware acceleration devices. The tool orchestrates the mutation generation an deployment process, following a configuration-based recipe, through which it is capable of building mutations targeting specific hardware acceleration devices, performing deployment and inference and applying pairwise comparison of the outputs in order to detect potential discrepancies. It is noteworthy however that, although MutateNN is inspired by the mutation testing concept applied in conventional software, the system deviates for the paradigm, given that the aim is not to test the effectiveness of specific test suites, but discover the error-proneness of the system, when faults are unintentionally introduced. This is valuable for DNNs, as the behaviour of such systems is not imperatively defined by design. Furthermore, discovering problematic behaviours and error-proneness is a difficult and non-straightforward procedure. Furthermore, MutateNN can by used industrially by developers to test the model architecture and structure robustness, by simulating specific erroneous scenarios that can potentially be introduced on model deployment and optimization phases, to observe abnormal model behaviour and take measures to mitigate it, especially in systems used in environments where there is little margin of error.

To demonstrate the capabilities of MutateNN, we selected 7 widely-known image recognition models. The models were all pre-trained with ImageNet [3] dataset. We generated 21 mutations, related to model graph, tensor management, arithmetic types and kernel operations, and we performed inference in 4 devices of varying computational capabilities. We observed up to 100% differences across mutants related to conditional operations, in particular those modifying the conditional operator (e.g., less-than to less-than-equal). We also observed an unexpectedly severe performance degradation when we changed arithmetic types with ones of lower precision.

II. System Architecture

MutateNN consists of three main components: the *Model Variants Generator*, the *Execution Module*, and the *Analysis Module*. It utilizes a configuration-based approach, capable of generating, deploying, performing inference and analyzing a batch of model mutations. The system architecture is presented in Figure 1. The system is built on top of *TVM* compiler stack [1], which allows heavy parameterization of the models and deployment on multiple different hardware acceleration devices.

a) Model Variants Generator Module: In order to test perception AI model robustness, MutateNN allows the gen-

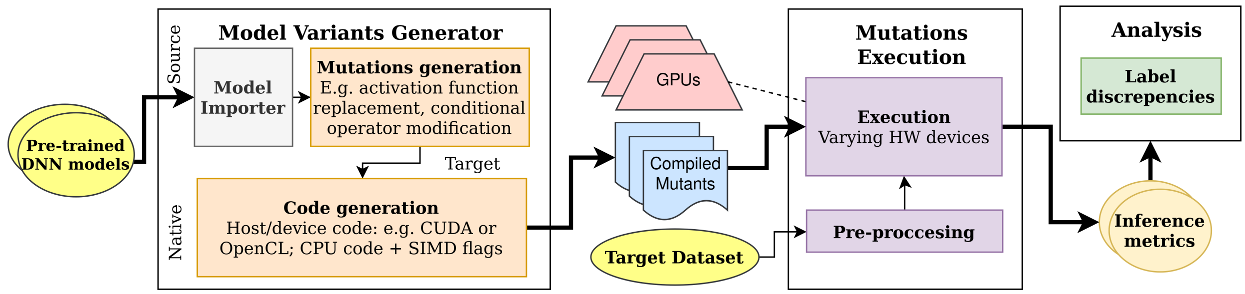

Fig. 1. Architecture of `MutateNN`: (1) *Model Variants Generator* for generating different mutations and compiling them to device code; (2) *Mutations Execution* that executes the various mutants on images from a target dataset; and (3) *Analysis* that compares inference metrics between mutant executions and reporting discrepancies.

eration of a number of model mutations, focusing on model 1) graph structure, 2) tensor management and computations, 3) arithmetic operations and 4) GPU kernel-based elements, such as stores. The mutations supported are selected on the basis of the elements involved in order for developers to apply optimizations to a model and it is error-prone for developers to introduce errors in the process of optimization. Considering all these aspects, we implemented a number of graph and tensor-level mutations representative to each of these categories on the respective intermediate representations (IRs) using TVM passes. The IR is then lowered in device code. An example of the effect of a mutation in the device code, can be observed on Figure 2. `MutateNN` generates mutants based on the definitions set in its configuration file, and stores it in compressed format, so that they can be loaded, deployed and executed at a later stage in the process.

b) Mutations Execution Module: Once the tool completes the mutant generation process, `MutateNN` loads and deploys a mutant to a hardware acceleration device for model inference. The system utilizes Remote Process Communication (RPC) in order to execute inference of a model to a remote hardware acceleration device. Once the model is loaded, `MutateNN` prepares the dataset under test, applies the necessary pre-processing on each dataset image performs inference against the model mutant, generating the top-K inference result along with the execution time. It then stores each output to a separate file for further examination by the analysis module.

c) Analysis Module: Once inference operations are complete for the whole experiment set, then `MutateNN` applies analysis to determine discrepancies across different mutant executions. The system applies pairwise comparison against the inference outputs generated by different devices for the respective mutant under test. The system supports a number of comparison metrics, such as top inference output label comparison, Levenshtein distance and Kendall's Tau. The reporting results are generated in a summary JSON file, enabling further processing. The analysis module also has an intelligent way of distinguishing crashes in dataset inference outputs, even they are implicit (i.e., the model has not crashed, but its performance is severely degraded).

```
if (((int)get_local_id(0)) < 16) {
    placeholder_shared[(((((int)get_local_id(2)) * 16) +
        ((int)get_local_id(0))))] = placeholder1[
            (((((((int)get_group_id(2)) * 576) +
            (((int)get_local_id(2)) * 96)) +
            ((((int)get_local_id(0)) >> 2) * 24)) +
            (rc_outer * 4)) + (((int)get_local_id(0)) & 3)))
        ];
}
```

```
if (((int)get_local_id(0)) <= 16) {
    placeholder_shared[(((((int)get_local_id(2)) * 16) +
        ((int)get_local_id(0))))] = placeholder1[
            (((((((int)get_group_id(2)) * 576) +
            (((int)get_local_id(2)) * 96)) +
            ((((int)get_local_id(0)) >> 2) * 24)) +
            (rc_outer * 4)) + (((int)get_local_id(0)) & 3)))
        ];
}
```

Fig. 2. Mutation of a conditional operator from less-than (top) to less-than-equal (bottom) in the device kernel code (OpenCL) for a fused operation in MobileNetV2.

III. Implementation

`MutateNN` is available publicly on GitHub, at https://www.github.com/luludak/MutateNN. It is implemented in 1551 lines of Python code (including 353 lines of third-party open-source code for preprocessing, and 72 lines for third-party comparison algorithms, all publicly available), utilized a highly parameterizable configuration. `MutateNN` is implemented on top of `Apache TVM` [1], a performance-oriented DNN compiler stack that enables extensive, manual and automatic DNN optimization and deployment in a variety of hardware acceleration devices of different software backends and architectures.

a) Model Variants Generator: The Variants Generator utilizes both the Relay and Tensor-level IR passes of `Apache TVM`'s API. `MutateNN` is implemented so that its end users can define their own operators or functions to replace, via the configuration. To demonstrate this part, we present two samples of code, part of the implementation of TIR pass (Figure 3), demonstrating the mutation of conditional operators, and Relay IR pass (Figure 4), demonstrating the replacement of activation functions. The users are able to define their own function mutations, based on their model architecture. In addition, the system allows them to instruct where in the code this mutations will occur, and to which extent, by defining the exact positions to be mutated for the model under test in the configuration.

b) Mutations Supported: In detail, the system supports four types of mutations: (1) graph-based, by applying operations on the DNN model's graph, such as changing an activation function (e.g., converting ReLU to Sigmoid), (2) tensor management-based, by mutating operations related to handling of tensors, such as conditional operations that might be part of a custom optimization implementation (e.g., changing the less-than (LT) operator to less-than-equal (LTE) in a conditional expression), (3) arithmetic types- based, by modifying types (e.g., converting *Float32* variables to *Int16*) and (4) GPU kernel related-operations, such as multiplying the value stored in a GPU variable (store) and thread extent modification. The module eventually generates the model mutant to a linked library for the respective mutant and compresses it, but it also generates the Relay IR and TIR sources, as well the device code in high-level source for inspection purposes. We can see two examples of this code in Figures 3 and 4. The implementation logic for each mutation category, is described as follows: Regarding (1), the system applies either a replacement of function calls in the model graph in Relay IR, or injects function calls to apply specific operations, such as tensor transposition. In the latter case, the system also ensures that axis parameters are properly defined by performing analysis on graph metadata, so that the mutant preserves validity and compiles. An indicative example is shown on Figure 5. Regarding (2), the system follows the logic presented on Figure 3. It traverses the TIR code Abstract Syntax Tree (AST), and when it detects a specific source operator that is marked for replacement in a conditional statement, it replaces it with an operator indicated for that purpose in the documentation. In addition, it can apply mathematical operations to left and right operands, such as adding a specific value. Regarding (3), the ststem traverses the AST of the TIR, and it replaces all occurrences from a source type to a target one. Finally, regarding (4), the system once again traverses the TIR AST, but it applies mathematical operations upon inline values used by TIR artifacts for kernel generation, such as store values.

c) Inference Analysis: The analysis module is built based on a folder exploration algorithm, allowing the system to perform scalable analysis, by identifying all the folders containing executions The system then compares the specific mutant of one device to the same mutant on another to detect discrepancies. The system also supports a wide variety of pairwise comparison algorithms, such as top-1 comparison, Levenshtein Distance, and Kendall's Tau. For the sake of simplicity, we choose the first option in our experiments by default. Once pairwise comparison is performed for all sets of mutations and devices, the system generates a JSON file, containing, amongst a number of analysis metadata, the difference percentage of outputs for a dataset executed on a specific mutant across two devices. It also generates a separate JSON file which contains

```
if op in elems["if_then_else_stmts"]:

    # Detect original conditional operator instance based on config.
    if (isinstance(op.condition, eval(mutation_data["original"]))):
        # Instantiate mutation operator based on config.
        mutation_type = eval(mutation_data["mutation"])
        op.condition = mutation_type(op.condition.a, op.condition.b)

        # Perform replacement.
        return filter_mutations(tvm.tir.IfThenElse(op.condition, \
            op.then_case, op.else_case, op.span), mutation_data)
```

Fig. 3. Implementation of the operator mutation generation in TIR pass.

```
# Load original and mutation function name to replace in graph.
original_func_name = mutation_data["original_func_name"]
mutated_func_name = mutation_data["mutated_func_name"]
if(call.op.name == original_func_name):
    return tvm.relay.Call(tvm.relay.op.get(mutated_func_name), \
        new_args)
```

Fig. 4. Implementation of the activation function replacement mutation generation in Relay IR pass.

```
%122 = nn.bias_add(%121, %onnx::Conv_562) /* ty=Tensor[(1, 384, 14, 14), float32] */;
%123 = clip(%122, a_min=0f, a_max=6f) /* ty=Tensor[(1, 384, 14, 14), float32] */;
%124 = transpose(%123, axes=[0, 1, 3, 2]) /* ty=Tensor[(1, 384, 14, 14), float32] */;
%125 = nn.conv2d(%124, %onnx::Conv_564, padding=[0, 0, 0, 0], kernel_size=[1, 1]) /*
```

Fig. 5. Injected tensor transposition in Relay IR.

only the cases that presented discrepancies. The analysis module is also able to detect a crash in an output bundle by requiring the source and target dataset batches to have the same size of outputs. The system also detects implicit crashes or extreme model performance degradation, by monitoring the occurrences of very similar results. Once the error threshold defined in `MutateNN` configuration is passed, the analysis terminates for this output bundle.

IV. Related Work

Existing work has primarily focused towards exploring DNN model correctness, applying adversarial testing [10], [18]. In terms of mutation testing, DeepMutation [9] and DeepMutation++ [5] generate model mutants to assess the test data input quality for convolutional and recurrent neural networks, respectively. In addition, contributions such as LEMON [17] and CRADLE [11] explore mutation testing and fault localization from models sourced from different deep learning (DL) frameworks. In total, such systems focus on testing the effectiveness of adversarial inputs or specific model aspects such as DL frameworks, but do not explore the effects of potential computational environment aspects, such as hardware acceleration. In relation to DNN faults, a taxonomy of faults has been created [7], which reveals that GPU issues are a primary cause of DNN model faults. However, DNN developers and researchers utilize custom optimization methods that integrate hardware acceleration, by using tools such as Triton [15] and TVM TOPI [1]. Furthermore, the implementation and deployment of optimizations to hardware acceleration devices is an error-prone task. To the best of our knowledge, `MutateNN` is the first work that attempts to mitigate this problem, by considering the importance of the aforementioned work and using inspiration from mutation testing frameworks to highlight potential problems in the process.

A. Experimental Setup

We considered seven widely used image recognition models of various sizes: MobileNetV2 [13], ResNet152 [4], AlexNet [8], ShuffleNet [19], EfficientNet [16], DenseNet121 [6] and InceptionV2 [14]. All models are pre-trained on ImageNet [3], considering we focus on the deployment process and we used the ImageNet object detection test dataset [12] as our experiments base dataset.

We also utilized 4 high-end to low-end GPU accelerators: an Intel-based server featuring an Nvidia Tesla K40c GPU (*Server #1*), a Nvidia Titan Xp (*Server #2*), a Nvidia AGX Xavier featuring an Nvidia Volta GPU (*Xavier*), and a mobile-class Hikey 970 board featuring an Arm Mali-G72 GPU (*Hikey*).

For our mutations set, we select 21 mutations, applying tensor transpositions and additional mathematical computations to a variety of layers, replacement of activation functions and operational layers, modification of conditional statements, change of types to different ones with lower accuracy and modification of kernel-based elements, such as variable (store) values. To maximize the mutation effect, and contrary to the conventional software testing practice of introducing only mutants randomly to a small part of the system, we deliberately mutated the occurrences of all matching cases identified on each mutant. In detail the mutations we applied are split into 6 main categories: 1) transposition of key layer tensors, 2) application of arithmetic operations in key layer tensors, 3) replacement of arithmetic types to affect tensor value precision, 4) replacement of activation functions and important layer operations, 5) modification of kernel variables and 6) modifications of conditional statements.

The selection of mutations, was done in compliance with an established taxonomy of real faults in DNNs [7], with focus on simulating key aspects related to deployment. Briefly, the taxonomy identified that tensor and layer structure and properties can be error-prone, as well as GPU errors. We aim to simulate the tensor errors in categories (1) - (3), (4) focuses on layer errors and (5) simulates errors related to kernel code executed in GPUs. Category (6) is also related to GPU executed code, as with systems such as `TVM TOPI` [1] and `Triton` [15], developers can describe complex optimization operations manually. Furthermore, we aim to explore the error-proneness of this procedure. In detail:

1) The transposition of key layers include the transposition of *Conv2D* and *Dense* layer and weight tensors, as well as batch normalization layers.
2) The application of arithmetic operations include the application of exponent and rounding operations on batch normalization layers.
3) The replacement of arithmetic types include the replacement of *Float32* to *Float16*, *Int32* and *Int16*.
4) The replacement of layers and operations include the transformation of *ReLU* to *Sigmoid*, as well as *Add* operation to *Subtract*.
5) The modification of variable (store) values in kernels, by applying minor changes to values.
6) The modification of conditional statements, involve the replacements across a set conditional expression conditions ($<$, $>$, $<=$, $>=$), as well as the modifications of values of any of the conditional expression operands.

In total, we utilize 21 different mutations. The aim, is to imitate real-world faults and discover to what extent DNNs are vulnerable to such errors. However, this set of mutations is indicative, and the system can be utilized to generate new mutants with respect to the related configuration.

B. Preliminary Results

We observed considerable discrepancies across devices for operators related to conditional expressions. In particular, the mutant of changing less-than (LT) to less-than-equal (LTE) operator in conditional expressions, revealed a wide variety of results, as presented in Figure 6. We observe that, although Shufflenet and AlexNet were proven the most robust systems for this mutant, EfficientNet, MobileNetV2 and InceptionV2 presented heavy discrepancies across devices, while the mutant crashed for almost all devices for DenseNet121 and ResNet152.

Another notable observation, was the mutant adding an offset value (0.5) to the right operand of LT conditional expressions, where once again models presented a variation of discrepancies, of up to 100% across devices. The results can be observed in detail in Figure 7. It is noteworthy that the deviations of this mutant follow a similar pattern with the aforementioned change in the less-than conditional operator, but is expected to an extent, as the two mutants are semantically similar - leading to a variant in approximation threshold in the mutated condition.

We also observed that all numeric type conversions led to either model crash, or heavy model degradation, meaning that the models produced the same output for a large amount of completely different inputs. We considered this case as a crash as well. This result is interesting, as a change to a type (e.g., *Float32* to *Float16*) was expected to lead to a performance degradation, but not to complete model crash, given that there are standard methods that apply this concept for optimization purposes, such as quantization.

The models were proven to be robust on the rest of the mutants, with the exception of the mutant converting less-than to greater-than operand in conditional statements led to crashes for most of the models, with the exception of AlexNet, where 96.3% to 98.8% differences were observed. Also, applying exponent computation to convolution and dense layer outputs crashed most of the models, except EfficientNet, which presented very small differences (0.1% to 0.43%). Converting *ReLU* to *Sigmoid* activation function layers also led the generated mutants to crash.

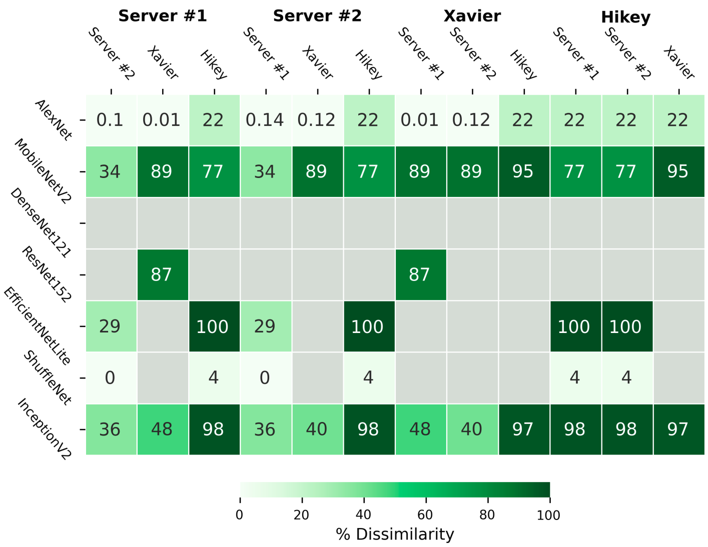

Fig. 6. Dissimilarities across devices of the mutant changing LT to LTE in conditional statements for all the DNNs under test (grey color indicates model crash).

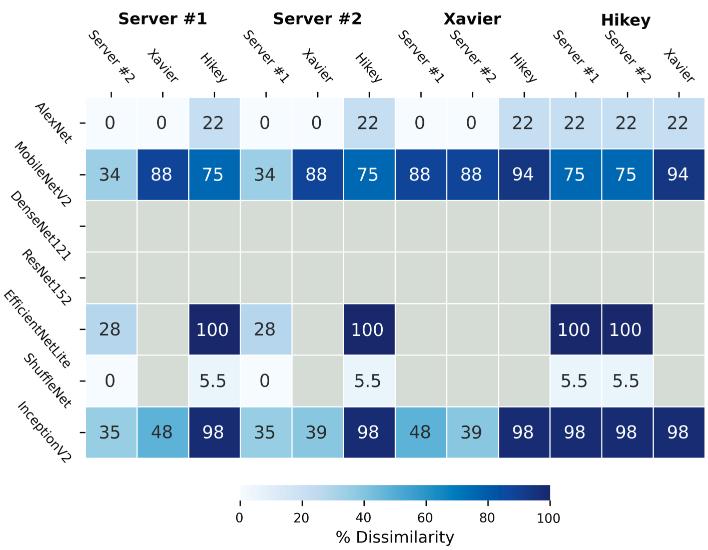

Fig. 7. Dissimilarities across devices of the mutant changing conditional statement threshold by adding to right operand the value of 0.5 on LT conditional expressions for all the DNNs under test (grey color indicates model crash).

V. Conclusion

We present MutateNN, a tool that enables mutation testing of DNN image recognition models. The tool supports mutations related to model graph, tensor management, arithmetic types and kernel memory management. We demonstrated the potential of our tool by running preliminary experiments of 7 perception AI models, generating 21 mutations for each and executing in 4 hardware acceleration devices of varying capabilities. We observed up to 100% output label deviations in 4 mutants, related primarily to threshold approximations and conditional operators. We also observed a number of unexpected crashes in relation to numeric types, which are subject to further investigation in future work.

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APPENDIX

MutateNN is a comprehensive suite for compiling, optimizing, executing and analyzing pretrained DNNs under different computational environment settings. In total, the tool supports:

- Downloading and building Deep Neural Networks.
- Generating mutants from a variety of settings for testing purposes, given many parameterization capabilities.
- Generating device code for execution on different hardware acceleration devices supporting different frameworks such as OpenCL and CUDA.
- Executing inference on those devices for a dataset of inputs, following the necessary pre-processing, dependent on each DNN model.
- Performing analysis against all mutation configurations, for all devices, by supporting a variety of pairwise comparison operators, such as top-1 output label comparison, and Kendall's Tau.
- Allowing debug execution and different optimizations applications on DNN models.

The suite utilizes Apache TVM[1]. The mutation transformations are programmed on Relay[**?**], TVM's graph Intermediate Representation (IR), and TIR, the Tensor-level IR.

VI. INSTALLATION

The system requires TVM to be installed. We also use `Python v3.x.x` (tested with `3.6.x-3.10.x`) and `Pip` as the package installer.

In addition, the system requires a number of pip packages. You can find them in the `requirements.txt` file

VII. INSTRUCTIONS

1) Install Python and Pip on your system. Python comes with linux distributions usually, but this is not always the case for Pip. You can install it by running `sudo apt install python3-pip`
2) Download and install TVM: For instructions of how to install TVM, please refer to the TVM related guide for developers[1]. We tested MutateNN using *TVM v0.13.0*.
3) Follow the installation from source instructions, and based on the experiments you want to run, enable the respective flags in the `<tvm_folder>/build/config.cmake`. For our experiments, we followed different settings per-device, but consider enabling the `USE_LLVM` and `USE_OPENCL` or `USE_CUDA` flags, depending on your configuration.
4) Install necessary Python packages by executing the command: `pip install -r requirements.txt`
5) Download necessary models, if you wish to run them locally. Alternative, you can instruct the MutateNN to download them for you. Although system utilizes already provided models for Keras and PyTorch, we utilized some TF and TFlite models from the GitHub repository of TensorFlow for slim Models.
6) You can also download the models manually, place them in the models folder defined in `models_out_relative` parameter, and defining `"type": "local"` in the configuration file. By default, use models from the official TensorFlow repo[2]. The supported format for the models is ONNX.

[1]https://tvm.apache.org/docs/install/from_source.html#developers-get-source-from-github

VIII. CONFIGURATION

The configuration of the system is included into the 'config.json' file. Each section is self-explanatory and defines which part it concerns.

Important notes:

- You can utilize the TVM debugger, by setting `debug_enabled: true` to collect additional inference metadata and execution traces.
- You can set different TVM optimization settings, by modifying the `opt_level` variable from 0 to 4, with optimization level increasing.
- You can set the mutations you want to generate, by modifying the `mutations` entry of the object.
- You can specify the occurrence numbers that you want your mutation to be applied, by modifying 'positions' parameter in mutations. You can see examples of it on the configuration file provided.
- Device settings have been cleared out to preserve anonymity. If you wish, you can set up your own TVM RPC server on your own device and run everything following the instructions in TVM documentation[3]. You can then define your device in the system configuration and perform inference.

IX. EXAMPLE CASE

In order to verify your installation and be able to run the framework with your own configuration, we have setup the configuration to build the system utilizing 7 models under test: MobileNetV2 [13], DenseNet121 [6], ResNet152 [4], [**?**], AlexNet [8], EfficientNetLite [16], ShuffleNet [19], and InceptionV2 [14]. You can download, run and evaluate the models accordingly. All models are obtained from the slim official repository, are pre-trained against ImageNet [3] and perform classification tasks against 1000 labels.

We also provide a small test dataset, consisting of 5 public domain images, obtained from unsplash[4]. To demonstrate device comparison, we have generated 3 simulations on different devices for MobileNetV2, which can be found on `/generated/MobileNetV2/simple_run`. You can instruct MutateNN to build, run and evaluate the existing dataset against these device outputs, by setting `build`,

[2]https://github.com/tensorflow/models/tree/master/research/slim

[3]https://tvm.apache.org/docs/tutorial/cross_compilation_and_rpc.html

[4]https://unsplash.com/images/stock/public-domain

execute and evaluate to true in theMobileNetV2 model entry of the configuration file.

Each model configuration entry also contains a number of necessary parameters, such as the input layer name and size, the output layer, etc, which are necessary for the model preparation, deployment, execution and evaluation.

Once you set up the tool, you can execute MutateNN by running: python3 main.py. An example of an execution instance terminal output, containing model build, execution and analysis, is presented on figure8.

A. Model Build & Mutants Generation

Inside config.json, you can set the mutations you want to generate, by modifying the mutations entry of the object. You can instruct MutateNN to generate mutants on Relay IR, or in the Tensor-level IR. A number of supported mutations are already provided, but they can be modified and parameterized, based on the user needs.

The system will generate the models in the folder defined in config.json in a tar package, along with a folder providing their generated Relay, TIR representations, but also their GPU host and kernel code, for inspection and debugging purposes.

In total, the framework will generate the models compiled on TVM, utilizing the opt=2 optimization setting by default which performs basic graph-level optimizations to the models, such as inference simplification, operator fusion and constant folding.

B. Execution

Your system will then execute, generating a folder with experiments. The structure followed is the following, using MutateNN folder (<script_folder>) as the base folder:

- Build: /<models_out_relative>/<model_variant>_<opt_setting>.tar
- Execution: <exec_out_relative>/mutations/ts_<epoch_time_of_run>/<predictions>.txt
- Evaluation: <evaluation_out_relative>

Based on existing configuration, inference generates the top-5 predictions, along with the execution time per-prediction at the bottom. In addition, you will find an execution_log.txt file in the aforementioned folder, containing info about the run.

The console will indicate the status of the running model and update accordingly, as shown in Figure 8.

C. Analysis

Once execution is complete, analysis will be executed. This will be done in 3 ways:

- Comparing results per-device (if provided), in JSON files.
- Analyze CSV and JSON files, containing metadata related to the execution.
- Comparing results per-multiple executions (if provided).

The system will then generate the following files inside each evaluation folder:

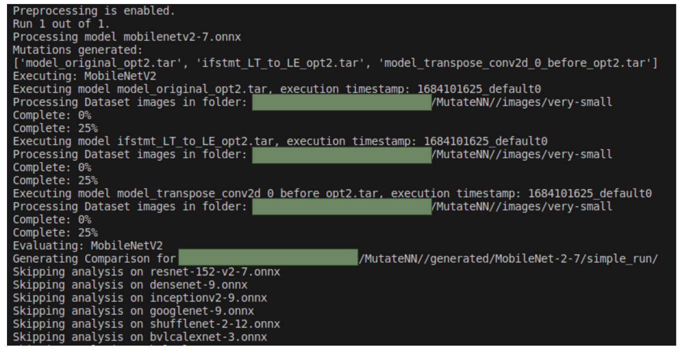

Fig. 8. Log of MutateNN performing all operations (build, execute, evaluate) simultaneously, for MobileNetV2.

- device_evaluation.json, containing results per-device comparison in a pairwise manner.
- device_discrepancies.json containing only the cases where dissimilarities are observed.
- output_stats_total.csv, containing inference time data and performance of statistical analysis against execution times (using One Way ANOVA). This is an implementation related to analyzing inference times, which is not included in this work but is intended for future work usage.

Finally, you can also try your own model, given you provide the right files and settings. Configuration provides exactly the details requested for a model to be loaded from a backend, compiled using a specific optimization and GPU backend and be run for inference, respectfully.

D. Error Logging

In case of an error, the suite will generate a file related to the specific execution instance, by generating a file containing all the necessary data in <script_folder>/error_log/<model>/ts_<epoch_time_of_problematic_run>/error_log.txt.