Copyright Notice

Features

Lightweight

Low-latency

Privacy

Improved power consumption

Efficient model format

Pre-trained models

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Components in TensorFlow Lite

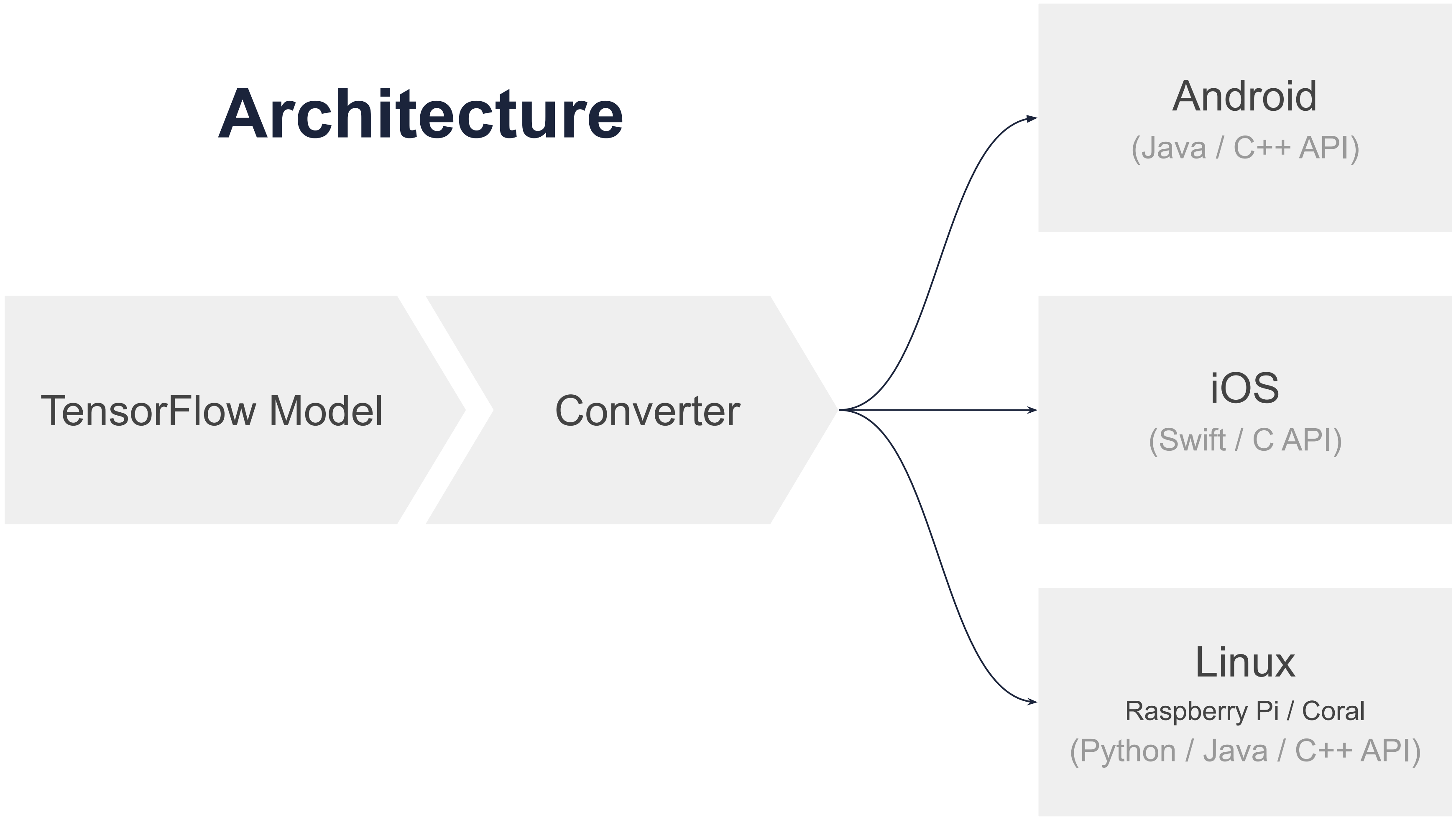
Converter
(to TensorFlow Lite format)

- Transforms TensorFlow models into a form efficient for reading by the interpreter
- Introduces optimizations to improve binary size model performance and/or reduce model size.

Interpreter
Core

- Diverse platform support, (Android, iOS, embedded Linux and microcontrollers)
- Platform APIs for accelerated inference

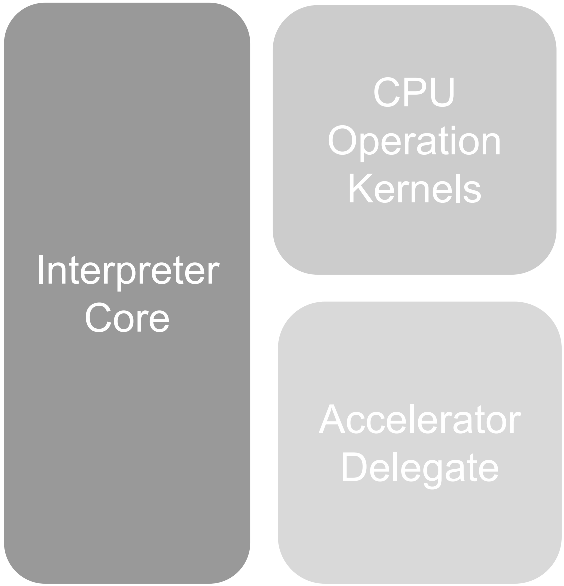
Architecture

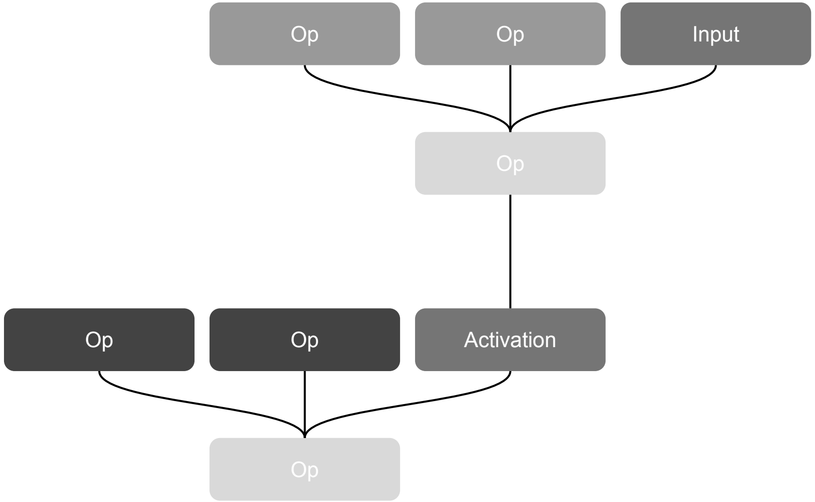


Performance

Acceleration	Available
Software	NN API (also a delegate)
Hardware	Edge TPU
	GPU
	CPU Optimizations (ARM and x86)

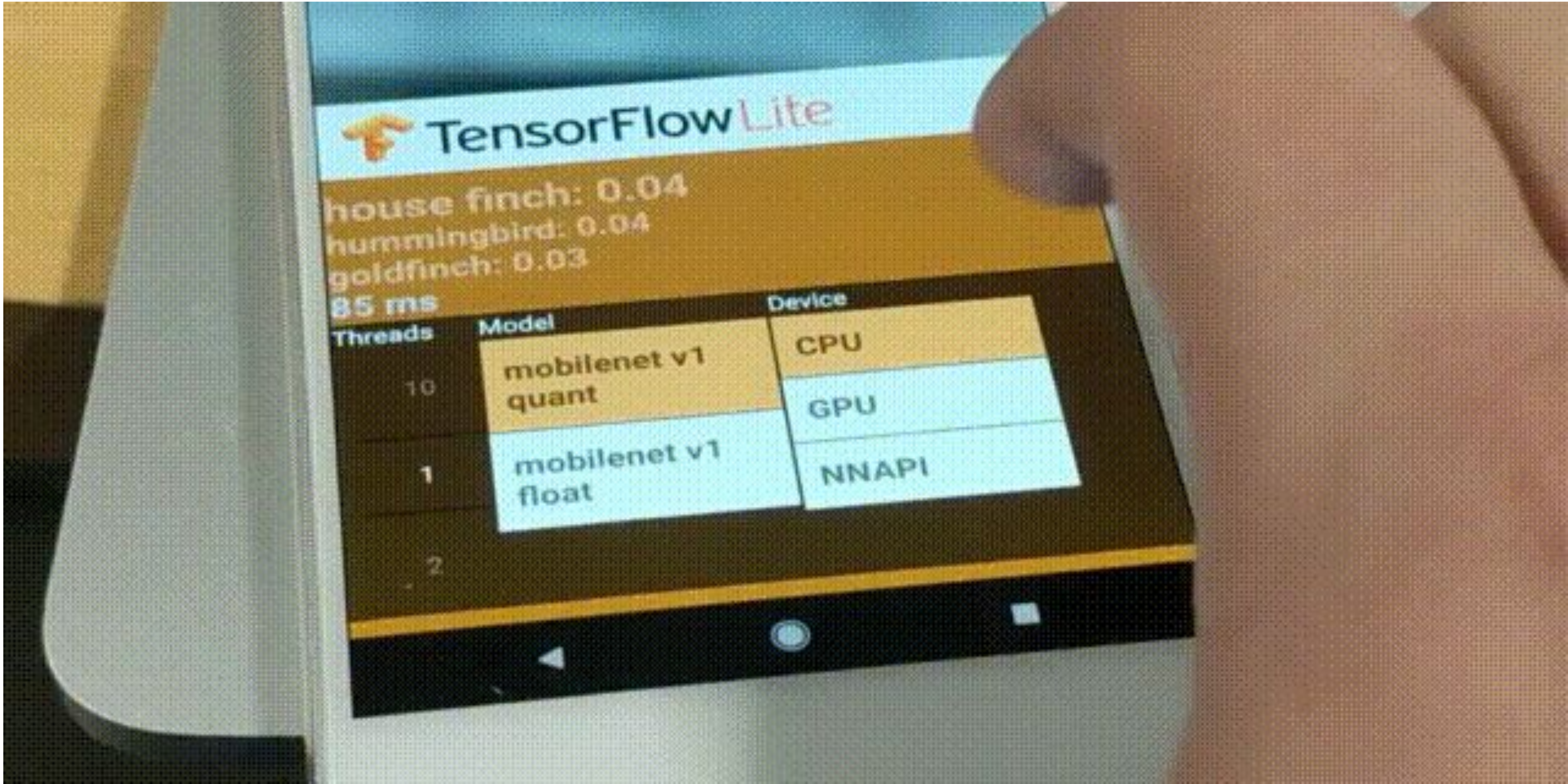
Delegates


Interpreter
Core
CPU
Operation
Kernels
Accelerator
Delegate


Op
Op
Input
Op
Op
Op
Activation
Op

https://www.youtube.com/watch?v=QSbAUxWfxQw

https://www.tensorflow.org/lite/performance/gpu



Techniques

- Quantization
- Weight pruning
- Model topology transforms
  - Tensor Decomposition
  - Distillation

Why Quantize?

- All available CPU platforms are supported
- Reducing latency and inference cost
- Low memory footprint
- Allow execution on hardware restricted-to or optimized-for fixed-point operations
- Optimized models for special purpose HW accelerators (TPUs)

Putting it all together

1 — 2 — 3 — 4

1. Jump start

Use Pretrained or Retrained Models

2. Custom model

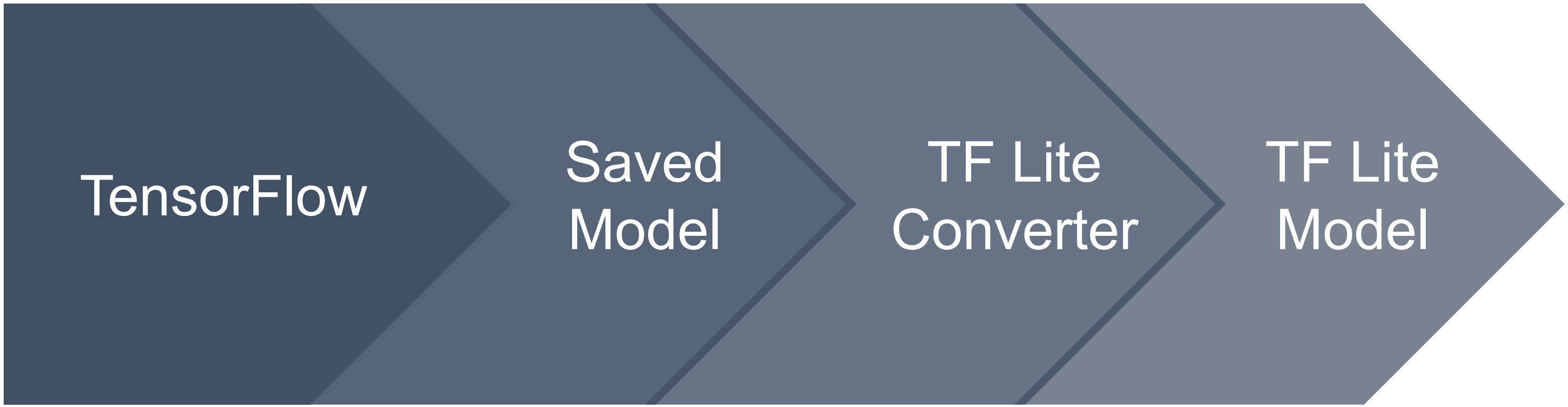
Develop & deploy a custom model

3. Performance

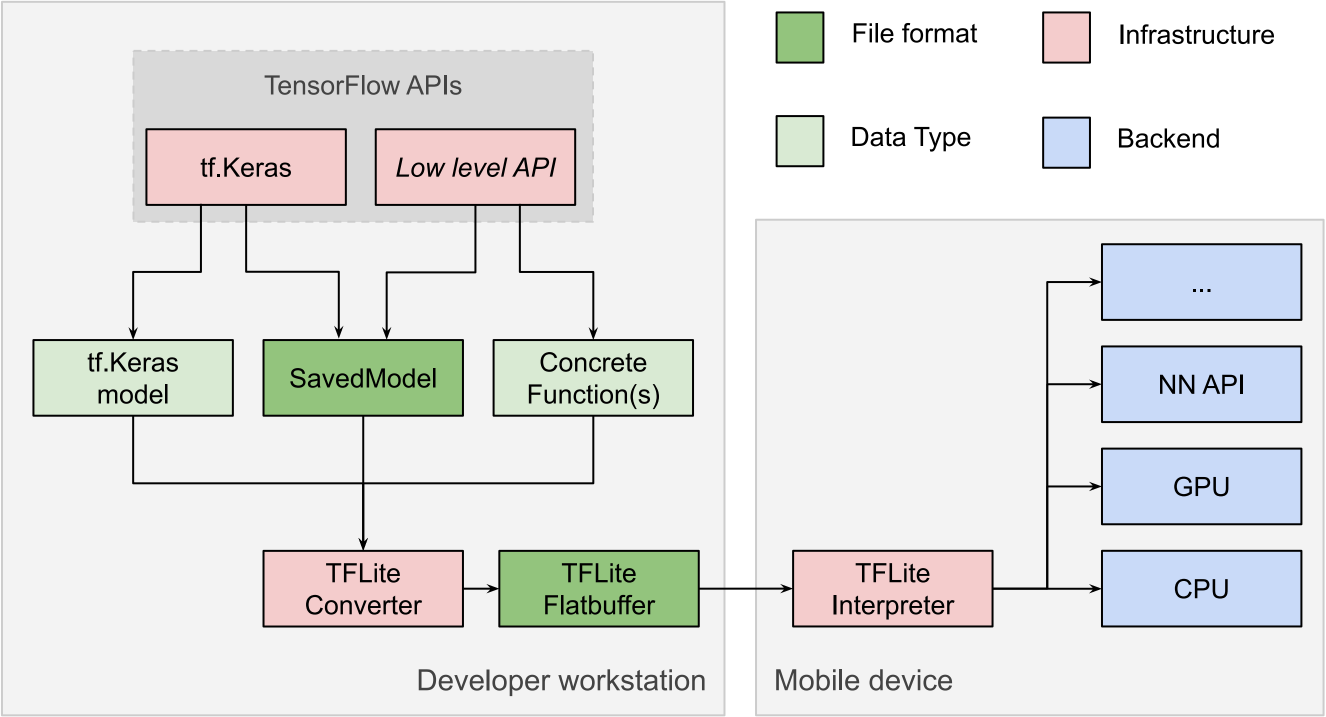
Explore options, validate & accelerate models.

4. Optimize

Model Optimization Toolkit


TensorFlow
Saved Model
TF Lite Converter
TF Lite Model

TensorFlow Lite Converter



Parameters for conversion

Inputs

SavedModel (preferred)	`tf.lite.TFLiteConverter.from_saved_model(...)`	
Keras a model instance HDF5 file	`tf.lite.TFLiteConverter.from_keras_model(...)`	**Output** TFLite model
Concrete function(s)	`tf.lite.TFLiteConverter.from_concrete_functions(...)`	

Python API (preferred)

SavedModel

- The standard for serializing a TensorFlow model
- A MetaGraph to hold metadata
- Holds snapshot of the trained model (with model weights and computation)
- No model building code required
- Supports model versioning

Inspecting with SavedModel's CLI

```
!saved_model_cli show --dir /tmp/mobilenet/1 \
                      --tag_set serve \
                      --signature_def serving_default
```

Inspecting with SavedModel's CLI

```
The given SavedModel SignatureDef contains the following input(s):
  inputs['input_1'] tensor_info:
      dtype: DT_FLOAT
      shape: (-1, 224, 224, 3)
      name: serving_default_input_1:0
The given SavedModel SignatureDef contains the following output(s):
  outputs['act_softmax'] tensor_info:
      dtype: DT_FLOAT
      shape: (-1, 1000)
      name: StatefulPartitionedCall:0
Method name is: tensorflow/serving/predict
```

Exporting a SavedModel from Keras

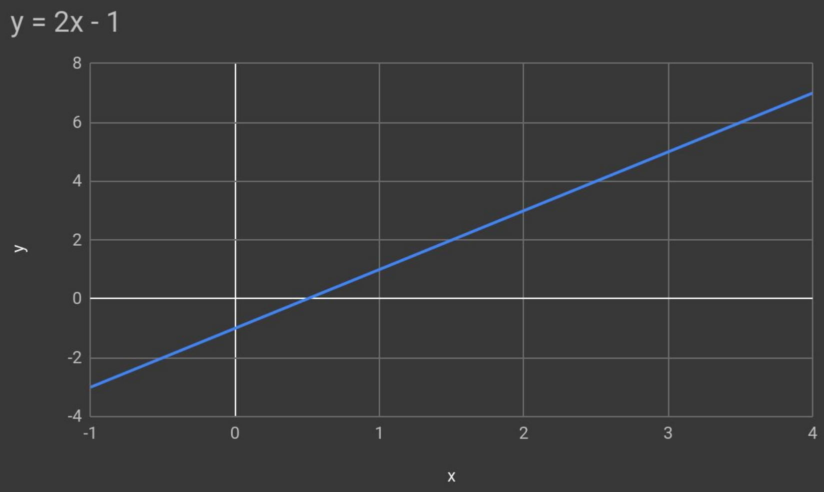
```
pretrained_model = tf.keras.applications.MobileNet()
tf.saved_model.save(pretrained_model, '/tmp/saved_model/1/')
```

Example 1


```
import tensorflow as tf

# Store data for x and y
x = [-1, 0, 1, 2, 3, 4]
y = [-3, -1, 1, 3, 5, 7]


# Create a simple Keras model.
model = tf.keras.models.Sequential(
    [tf.keras.layers.Dense(units=1, input_shape=[1])])
model.compile(optimizer='sgd', loss='mean_squared_error')
model.fit(x, y, epochs=500)
```



Example 1


```
import pathlib

# Export the SavedModel
export_dir = '/tmp/saved_model'
tf.saved_model.save(model, export_dir)

# Convert the model
converter = tf.lite.TFLiteConverter.from_saved_model(export_dir)
tflite_model = converter.convert()

# Save the model
tflite_model_file = pathlib.Path('/tmp/foo.tflite')
tflite_model_file.write_bytes(tflite_model)
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tflite_model_file.write_bytes(tflite_model)
```

Example 2


```python
import tensorflow as tf
import pathlib

# Load the MobileNet tf.keras model.
model = tf.keras.applications.MobileNetV2(weights="imagenet", input_shape=(224, 224, 3))
# Saving the model for later use by tflite_convert
model.save('model.h5')

# Convert the model.
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()

# Save the model
tflite_model_file = pathlib.Path('/tmp/foo.tflite')
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```

Command-line usage

```
#!/usr/bin/env bash

# Saving with the command-line from a SavedModel
tflite_convert --output_file=model.tflite --saved_model_dir=/tmp/saved_model

# Saving with the command-line from a Keras model
tflite_convert --output_file=model.tflite --keras_model_file=model.h5
```

Command-line usage

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# Saving with the command-line from a SavedModel
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```

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tflite_convert --output_file=model.tflite --keras_model_file=model.h5
```

Post-training quantization

- Reduced precision representation with 3x lower latency
- Little degradation in model accuracy
- Optimization modes
  - ↕ Default (both size and latency)
  - ↓ Size
  - ↓ Latency
- Efficiently represents an arbitrary magnitude of ranges
- Quantization target specification (FP32/INT8)

Image credits

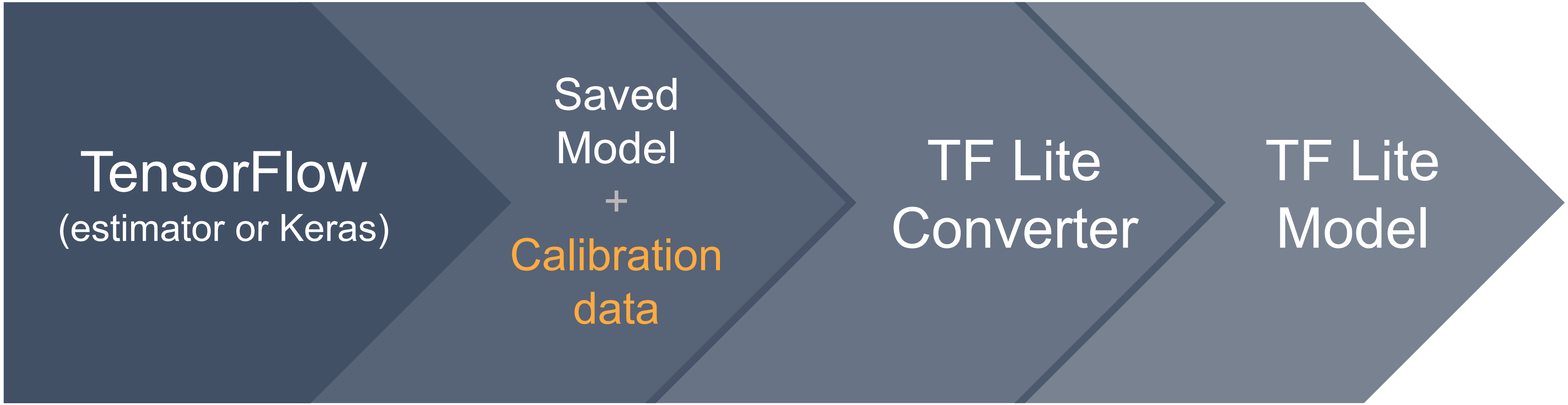
```
import tensorflow as tf

converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_dir)

converter.optimizations = [tf.lite.Optimize.OPTIMIZE_FOR_SIZE]

tflite_quant_model = converter.convert()
```

Post-training integer quantization



```
# Define the generator
def generator():
  data = tfds.load(...)
  for _ in range(num_calibration_steps):
    image, = data.take(1)
    yield [image]

converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_dir)

# Set the optimization mode
converter.optimizations = [tf.lite.Optimize.DEFAULT]

# Pass the representative dataset to the converter
converter.representative_dataset = tf.lite.RepresentativeDataset(generator)
```

```
# Define the generator
def generator():
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# Pass the representative dataset to the converter
converter.representative_dataset = tf.lite.RepresentativeDataset(generator)
```

```
...
# Set the optimization mode
converter.optimizations = [tf.lite.Optimize.OPTIMIZE_FOR_LATENCY]

# Pass the representative dataset to the converter
converter.representative_dataset = tf.lite.RepresentativeDataset(generator)

# Restricting supported target op specification to INT8
converter.target_spec.supported_ops = [tf.lite.OpsSet.TFLITE_BUILTINS_INT8]
```

Learn more about supported ops:

https://www.tensorflow.org/lite/guide/ops_compatibility

TF-Select to overcome unsupported ops

TF-Select

https://www.tensorflow.org/lite/guide/ops_select

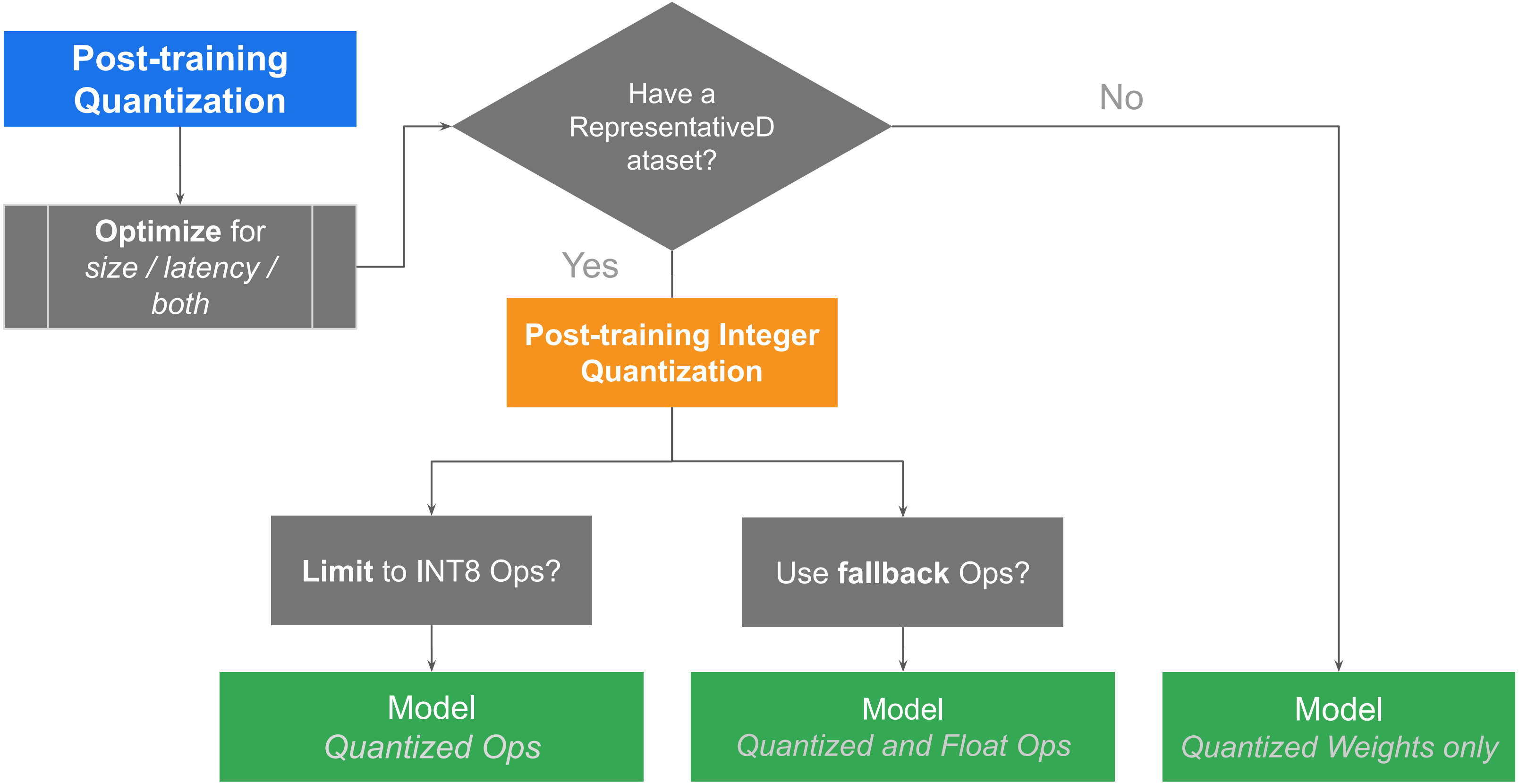
```
import tensorflow as tf

converter = tf.lite.TFLiteConverter.from_saved_model(saved_model_dir)

converter.target_ops = [tf.lite.OpsSet.TFLITE_BUILTINS,
                        tf.lite.OpsSet.SELECT_TF_OPS]

tflite_model = converter.convert()
```

Optimizing your models in a nutshell



TensorFlow Lite Interpreter in Python

```python
# Load TFLite model and allocate tensors
interpreter = tf.lite.Interpreter(model_content=tflite_model)
interpreter.allocate_tensors()

# Get input and output tensors.
input_details = interpreter.get_input_details()
output_details = interpreter.get_output_details()

# Point the data to be used for testing and run the interpreter
interpreter.set_tensor(input_details[0]['index'], input_data)
interpreter.invoke()
tflite_results = interpreter.get_tensor(output_details[0]['index'])
```

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```

Running models

Pretrained models

Image classification

Object detection

Smart reply

Pose estimation

Segmentation

TensorFlow Hub

Classification modules

Feature vector modules

Embedding modules

Not what you're looking for?

Build a custom model!

Getting a basic model running

Get started

1

Build a model

Create a simple model for (y = 2x - 1) from simulated data and train it

2

Export & Convert

Generate the SavedModel and convert it to TFLite

3

Verify

Perform evaluation on random data to verify the results

4

Deploy

Deploy the converted model on a mobile device (Android/iOS)

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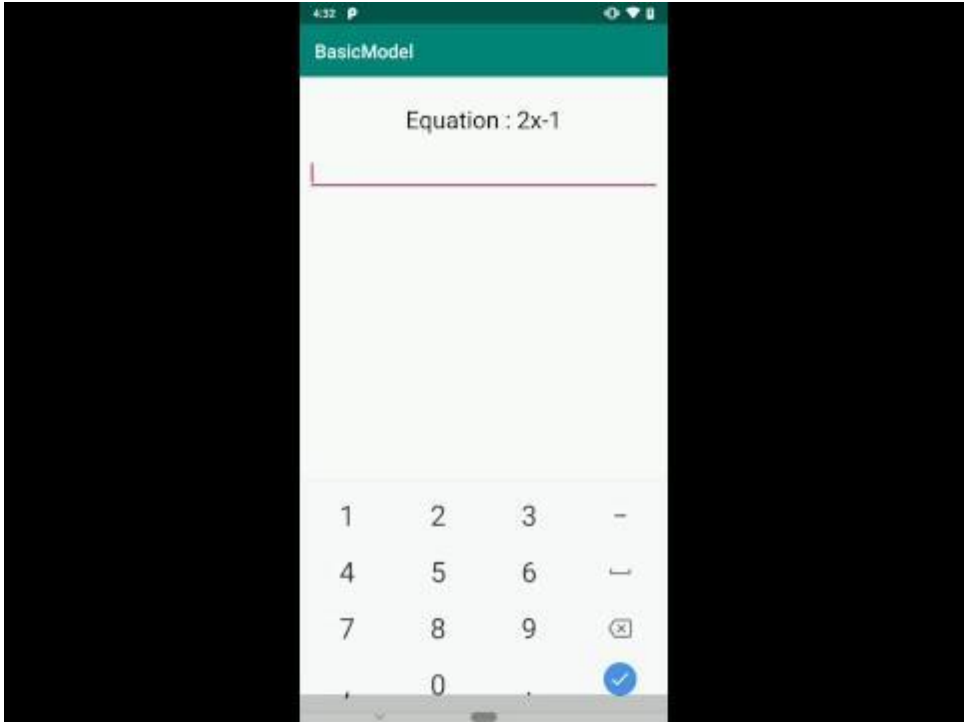
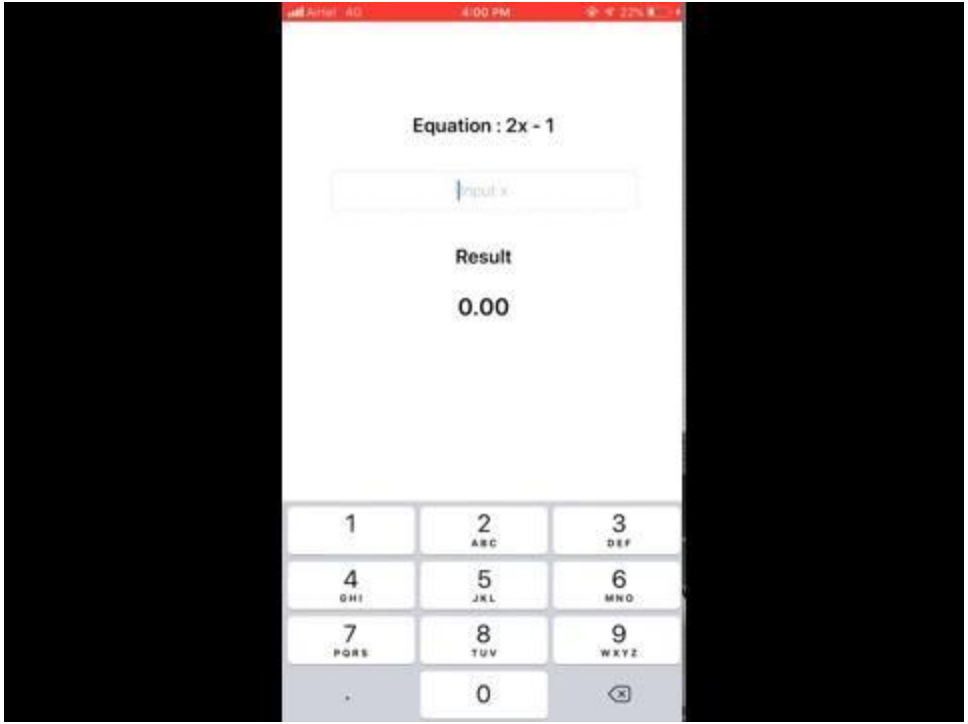
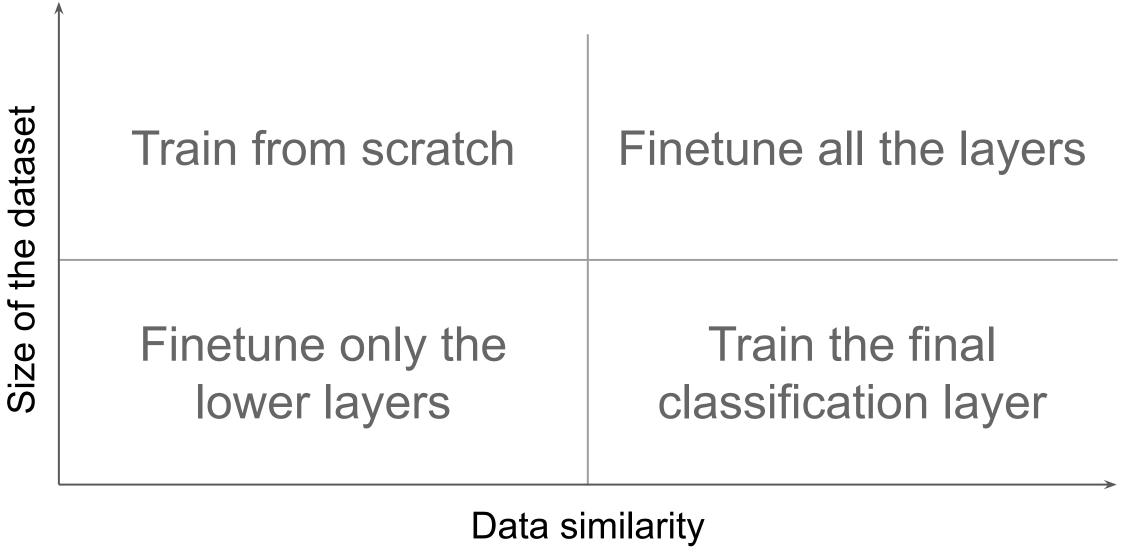
Android

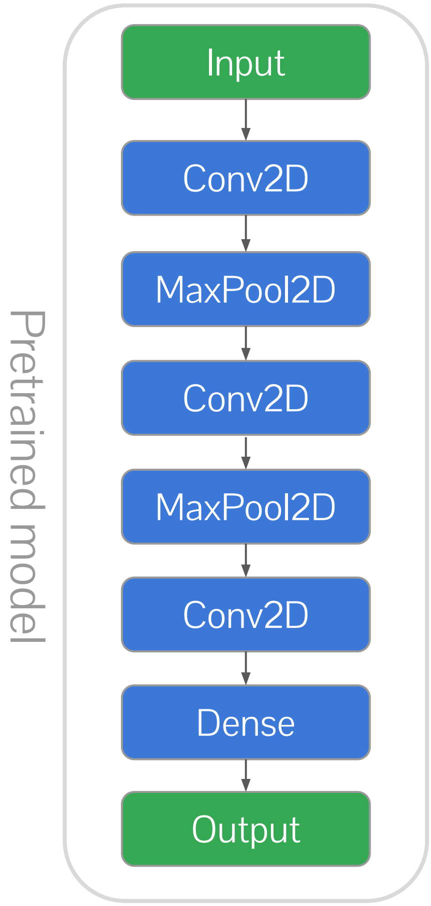


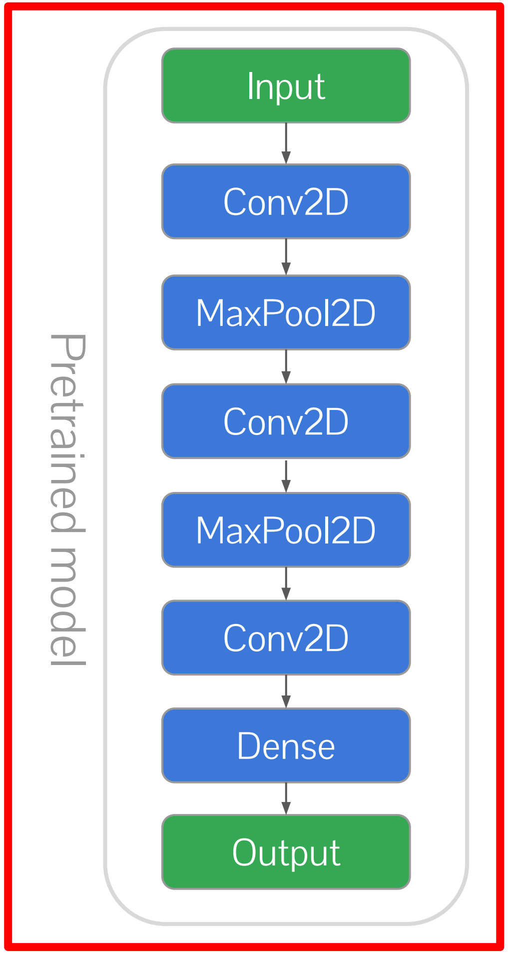
iOS



Transfer Learning




Pretrained model
Input
Conv2D
MaxPool2D
Conv2D
MaxPool2D
Conv2D
Dense
Output



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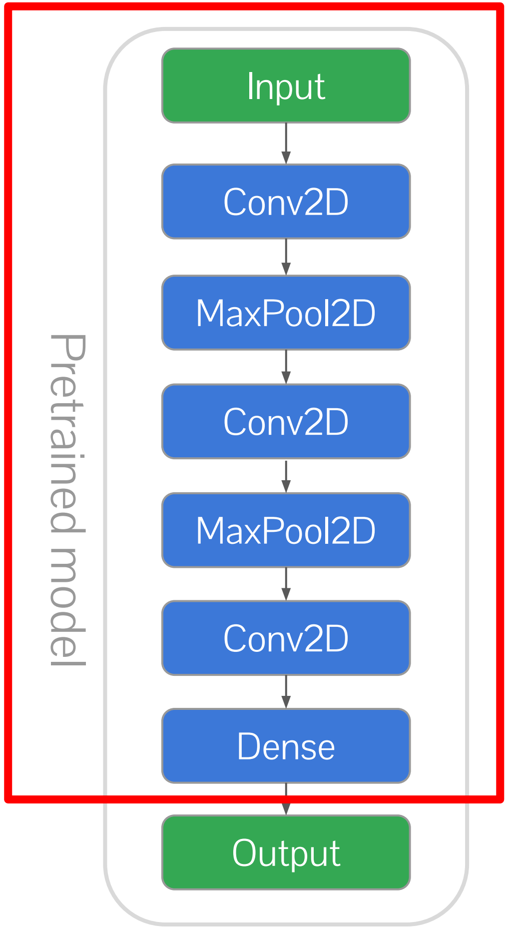
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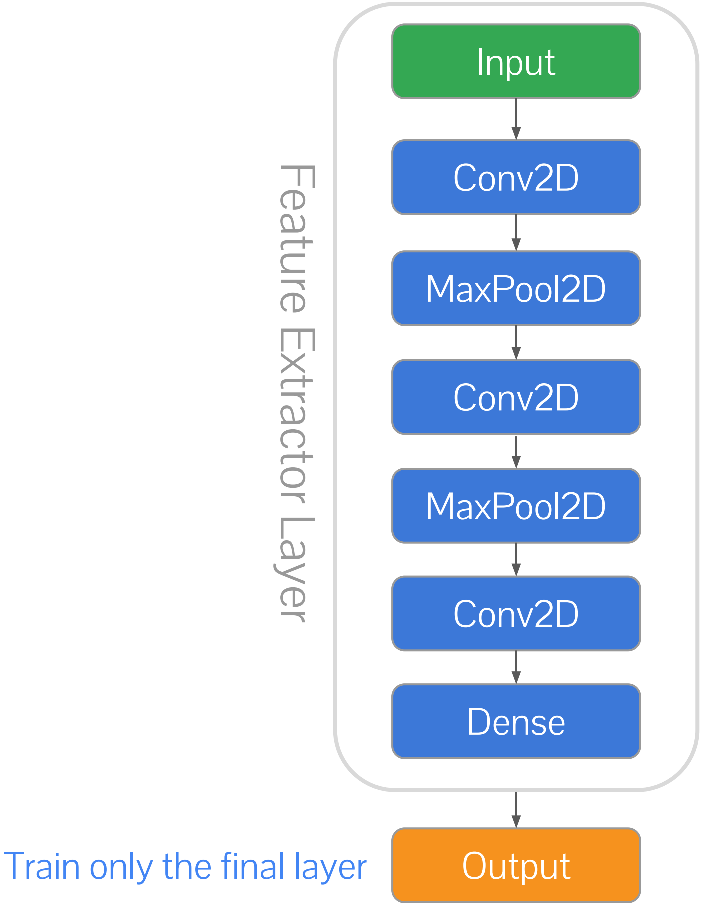
Feature Extractor Layer
Input
Conv2D
MaxPool2D
Conv2D
MaxPool2D
Conv2D
Dense
Output
Train only the final layer

Transfer Learning on Cats vs Dogs with TensorFlow Hub

Get started

1

Prepare the dataset

Download the Cats vs. Dogs tf.Dataset, split into sets (train, val, test), and preprocess

2

Transfer Learning

Choose a feature vector module (MobileNet V2) from TFHub and perform transfer learning

3

Export & Convert

Export the trained model to SavedModel and convert it to TFLite

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