

LAB TASK 2

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Q1. MNIST Dataset

Code with arguments:

```
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.model_selection import train_test_split
import pickle
import os

# =====
# JAR 1: DATA
# Purpose: Load, Preprocess, and Split Data
# =====
print("--- JAR 1: DATA ---")
# Load existing MNIST dataset
(X_full, y_full), (X_test_orig, y_test_orig) =
keras.datasets.mnist.load_data()

# Combine to demonstrate custom splitting
X_total = np.concatenate((X_full, X_test_orig))
y_total = np.concatenate((y_full, y_test_orig))

# Preprocessing: Normalize images to [0, 1]
X_total = X_total.astype("float32") / 255.0
X_total = np.expand_dims(X_total, -1) # Shape: (70000, 28, 28, 1)

# ARGUMENT FOR SPLITTING:
# We use 'stratify=y_total' to ensure the Train and Test sets have the
# exact same proportion of digits (0-9). This prevents bias.
X_train, X_test, y_train, y_test = train_test_split(
    X_total, y_total,
    test_size=0.2,
    random_state=42,
    stratify=y_total # <-- STRATIFIED SPLIT
)

# One-hot encode labels
y_train_cat = keras.utils.to_categorical(y_train, 10)
y_test_cat = keras.utils.to_categorical(y_test, 10)

print(f"Data loaded and split. Train shape: {X_train.shape}, Test
shape: {X_test.shape}")

# =====
# JAR 2: TASK
# Purpose: Define the Input and Output goal
# =====
```

```

print("\n--- JAR 2: TASK ---")
# Input: 28x28 grayscale images
# Output: Probability distribution over 10 classes (Digits 0-9)
input_shape = (28, 28, 1)
num_classes = 10
print(f"Task: Image Classification. Input: {input_shape} -> Output:
{num_classes} Classes")

# =====
# JAR 3: MODEL
# Purpose: The Mathematical Architecture
# =====
print("\n--- JAR 3: MODEL ---")
model = keras.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(), # Flatten 2D image to 1D vector
    layers.Dense(128, activation="relu"), # Hidden layer
    layers.Dense(num_classes, activation="softmax") # Output layer
])
model.summary()

# =====
# JAR 4: LOSS
# Purpose: Error Function
# =====
print("\n--- JAR 4: LOSS ---")
# We use Categorical Crossentropy because our targets are one-hot
encoded.
loss_fn = "categorical_crossentropy"
print(f"Loss Function selected: {loss_fn}")

# =====
# JAR 5: LEARNING
# Purpose: Optimization Algorithm to minimize Loss
# =====
print("\n--- JAR 5: LEARNING ---")
# Optimizer: Adam (Adaptive Moment Estimation)
optimizer_algo = "adam"
model.compile(loss=loss_fn, optimizer=optimizer_algo,
metrics=["accuracy"])

# Training the model
batch_size = 128
epochs = 5
history = model.fit(X_train, y_train_cat, batch_size=batch_size,
epochs=epochs, validation_split=0.1)

# =====
# JAR 6: ACCURACY (Evaluation)
# Purpose: Test on unseen data
# =====
print("\n--- JAR 6: ACCURACY ---")
test_loss, test_acc = model.evaluate(X_test, y_test_cat, verbose=0)
print(f"Test Accuracy: {test_acc * 100:.2f}%")

# =====
# PICKLE & SIZE CHECK

```

```

# =====
print("\n--- PICKLE SAVE & SIZE CHECK ---")

# Save the training history variable using Pickle
filename = "training_history_variable.pkl"
with open(filename, "wb") as f:
    pickle.dump(history.history, f)

# Check size
file_size = os.path.getsize(filename)
file_size_mb = file_size / (1024 * 1024)

print(f"Variable saved to: {filename}")
print(f"File Size: {file_size_mb:.5f} MB")

```

Output Screenshot:

The screenshot shows a Jupyter Notebook environment with the following details:

- File Structure:** A sidebar on the left shows a tree view of files and folders.
- Code Cell:** The main area contains Python code for saving a training history and checking its size.
- Output:**
 - Printed message: "Variable saved to: training_history_variable.pkl"
 - Printed message: "File Size: 0.00024 MB"
 - Model Summary:
 - Layers: flatten_3 (Flatten), dense_6 (Dense), dense_7 (Dense)
 - Output Shapes: (None, 784), (None, 128), (None, 10)
 - Parameters: 0, 100,480, 1,290
 - Total params: 101,770 (397.54 KB)
 - Trainable params: 101,770 (397.54 KB)
 - Non-trainable params: 0 (0.00 B)
 - Learning Metrics (Epoch 1/5 to 394/394):
 - 4s 8ms/step - accuracy: 0.8237 - loss: 0.6419 - val_accuracy: 0.9379 - val_loss: 0.2180
 - 4s 5ms/step - accuracy: 0.9481 - loss: 0.1868 - val_accuracy: 0.9550 - val_loss: 0.1525
 - 2s 5ms/step - accuracy: 0.9636 - loss: 0.1302 - val_accuracy: 0.9629 - val_loss: 0.1254
 - 2s 5ms/step - accuracy: 0.9728 - loss: 0.0957 - val_accuracy: 0.9666 - val_loss: 0.1090
 - 2s 5ms/step - accuracy: 0.9785 - loss: 0.0790 - val_accuracy: 0.9693 - val_loss: 0.0994
 - Test Accuracy: 97.03%
 - Pickle Save & Size Check:
 - Variable saved to: training_history_variable.pkl
 - File Size: 0.00024 MB

Hyperparameters & Training Explanation:

- **Epochs (5):** The number of times the model sees the entire dataset. We chose 5 because MNIST is simple and converges quickly; too many epochs might lead to overfitting.
- **Batch Size (128):** The model doesn't update weights after every single image (which is slow/noisy) or after the whole dataset (which requires huge memory). It updates after every 128 images. This is a balance between speed and stability.
- **Learning Rate (Adam default):** This controls how big of a "step" the optimizer takes to correct errors. We used the Adam optimizer because it automatically adjusts this rate during training, making it efficient for beginners.
- **6 JARS:**
 - Data: The fuel (images).
 - Task: The goal (classify digits).
 - Model: The math (Neural Network layers).
 - Loss: The error metric (difference between prediction and actual).
 - Learning: The correction mechanism (Optimizer/Backpropagation).
 - Accuracy: The final report card (Evaluation on test set).
- **Pickle Size**
The pickle file saves the history variable (accuracy/loss logs).

Q2. Data Acquisition

Objective

To understand and implement data acquisition and dataset preparation using the Edge Impulse platform for object classification, including data collection, labeling, and train–test split.

Platform Used

- Edge Impulse Studio (Web Platform)
- Target device: Raspberry Pi 5 (configured in Edge Impulse)[As we can see in the edge impulse target device in upper right side]
- Data type: Image data

In this lab, the objective was to collect real-world image data using Edge Impulse, label the data correctly, and prepare it for machine learning by splitting it into training and testing datasets.

Objects Collected

The following 6 object classes were collected:

1. Desktop
2. Laptop

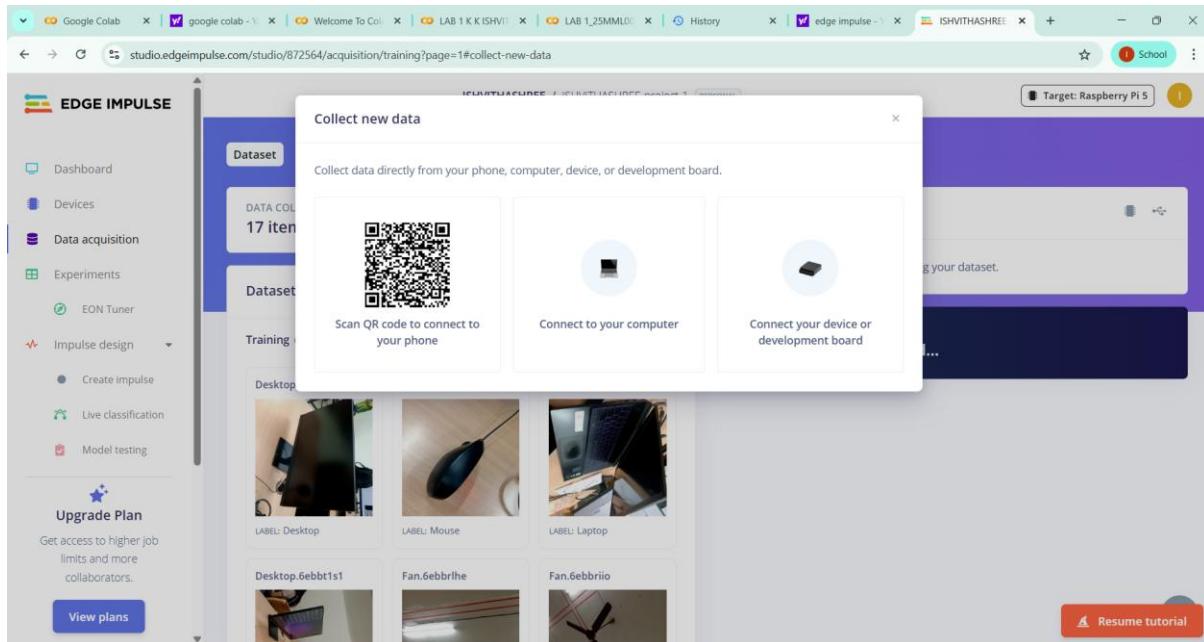
3. Chair
4. Keyboard
5. Mouse
6. Fan

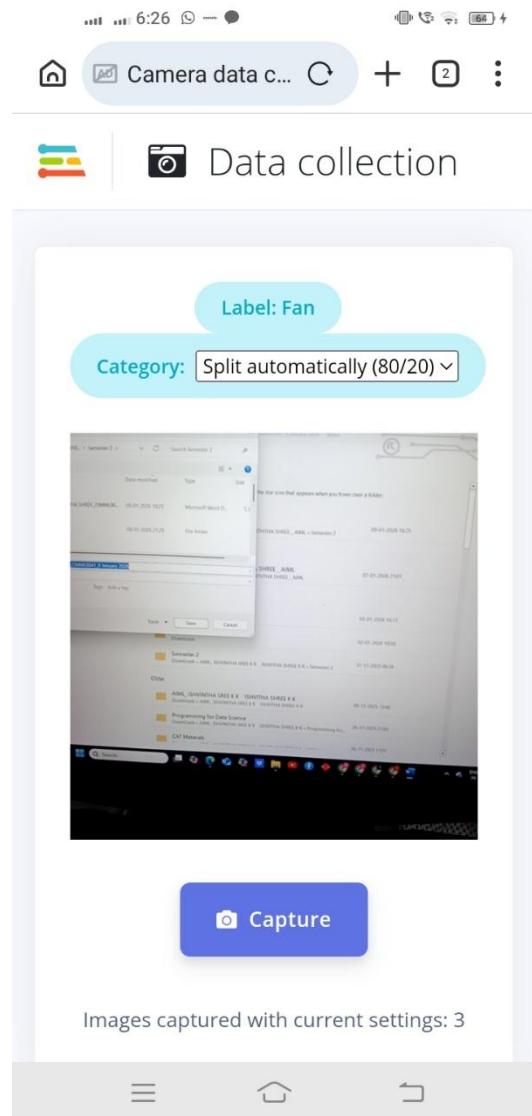
Each object was captured from multiple angles and orientations to improve dataset diversity.

Steps :

Step 1: Project Setup

- Created a new project in Edge Impulse Studio.
- Selected the target device and navigated to the Data Acquisition section and connect to phone.





Step 2: Data Collection

- Uploaded image samples for each object class.
- Multiple images were captured for each object under different viewpoints.
- Each image was manually labeled with the correct class name.

Step 3: Dataset Organization

- A total of 30 image samples were collected.
- The dataset was automatically divided into: Training set: 80% , Testing set: 20%
- This split ensures proper model training and unbiased evaluation.

Step 4: Verification Using Data Explorer

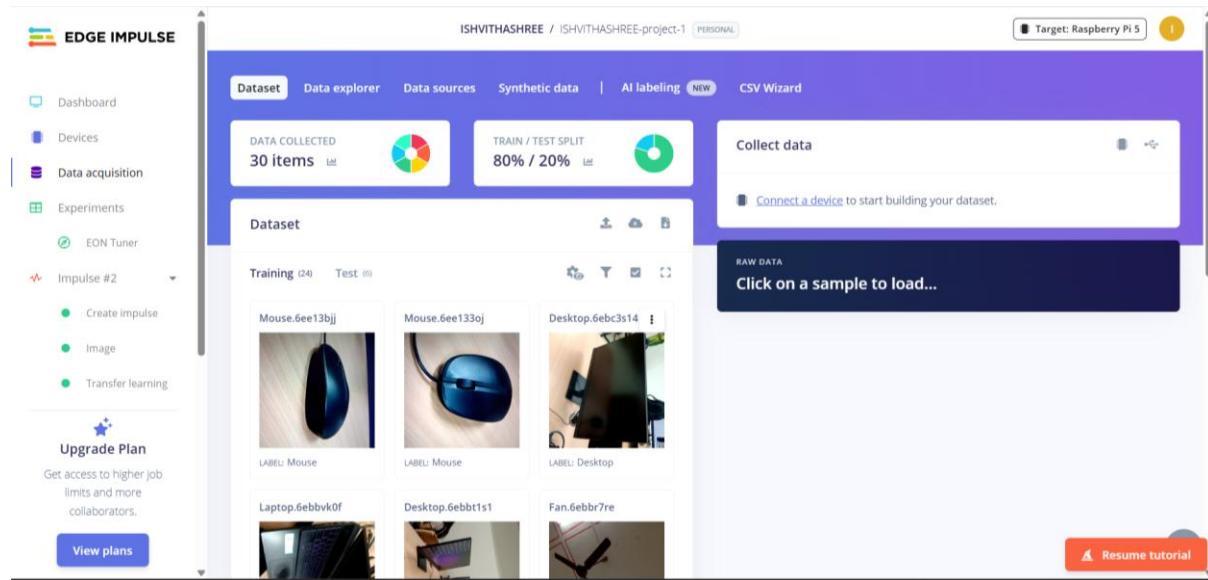
- Verified uploaded images and labels using the Dataset view.
- Confirmed correct separation of training and testing samples.
- Ensured no label mismatch or data duplication.

Observation

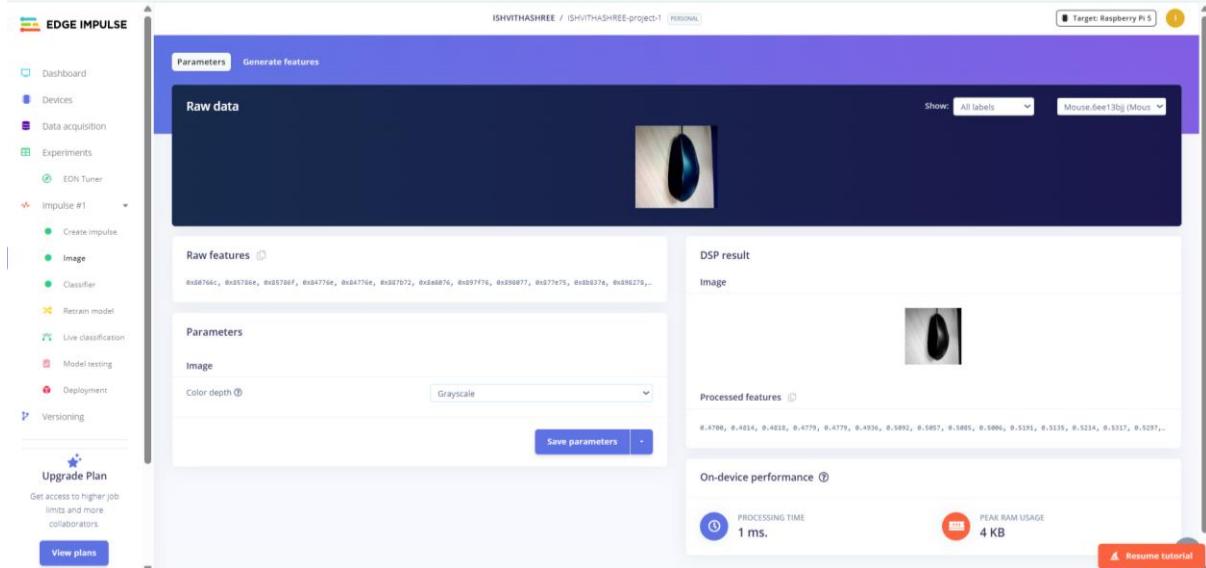
- Edge Impulse provides an intuitive interface for data acquisition and labeling.
- Collecting images from different angles improves model generalization.
- Proper train–test split is essential for reliable performance evaluation.

Result

A labeled image dataset containing 6 object classes was successfully created and organized in Edge Impulse, ready for feature extraction and model training.

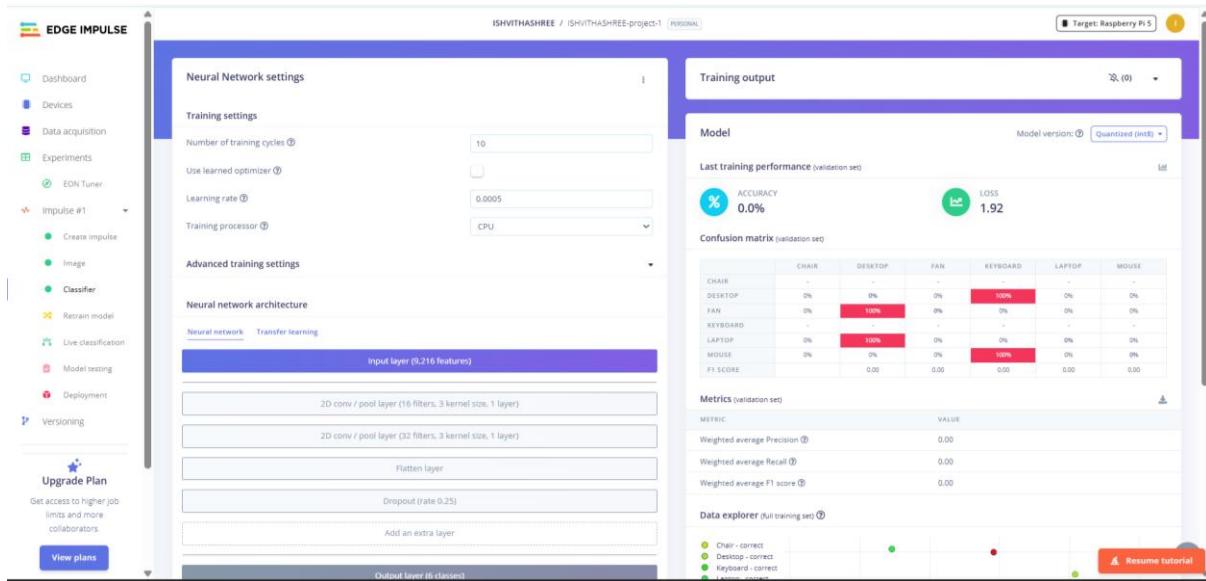


Edge Impulse #1 → Classification:



The screenshot shows the Edge Impulse web interface for a project titled "ISHVITHASHREE / ISHVITHASHREE-project-1". The left sidebar includes options like Dashboard, Devices, Data acquisition, Experiments, EON Tuner, Impulse #1 (Create impulse, Image, Classifier, Retrain model), Live classification, Model testing, Deployment, and Versioning. An "Upgrade Plan" section is also present.

The main area displays "Raw data" with a preview image of a blue object. Below it, "Raw features" are listed as a series of hex values. The "Parameters" section includes "Image" settings (Color depth: Grayscale) and a "Save parameters" button. To the right, the "DSP result" shows a processed image of the same blue object. The "On-device performance" section indicates a processing time of 1 ms and peak RAM usage of 4 KB.



This screenshot shows the "Neural Network settings" and "Training output" sections of the Edge Impulse interface.

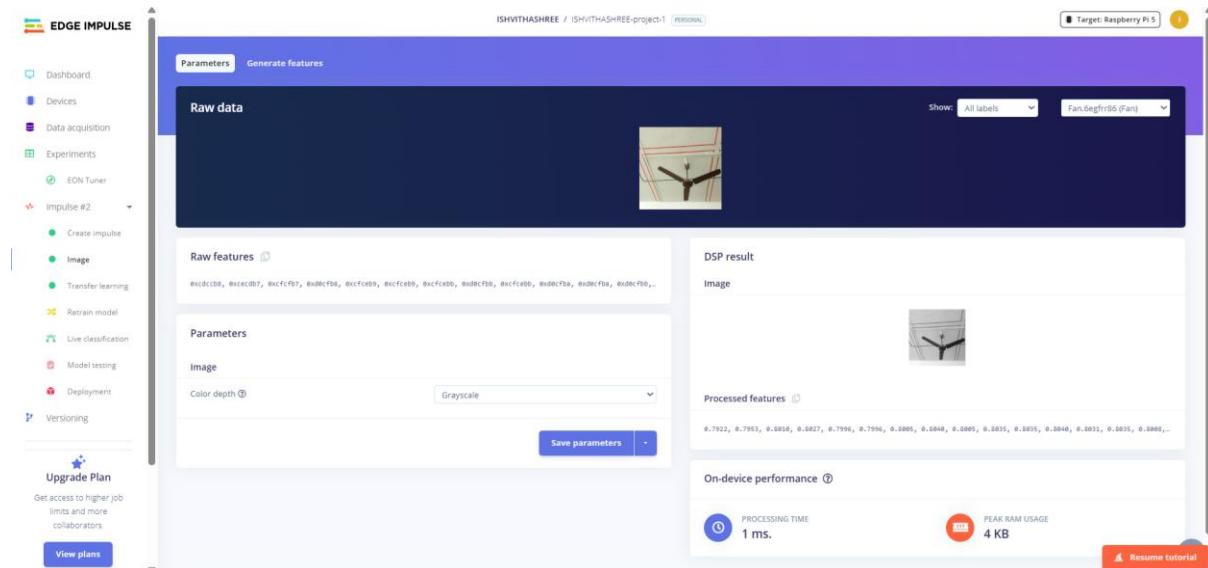
Neural Network settings: Includes "Training settings" (Number of training cycles: 10, Use learned optimizer, Learning rate: 0.0005, Training processor: CPU) and "Advanced training settings" (Neural network architecture: Transfer learning). The architecture section shows layers: "input layer (9,216 features)", "2D conv / pool layer (16 filters, 3 kernel size, 1 layer)", "2D conv / pool layer (32 filters, 3 kernel size, 1 layer)", "Flatten layer", "Dropout (rate 0.25)", and "Add an extra layer".

Training output: Shows the "Model" (Last training performance (validation set): Accuracy 0.0%, Loss 1.92) and a "Confusion matrix (validation set)". The confusion matrix table is as follows:

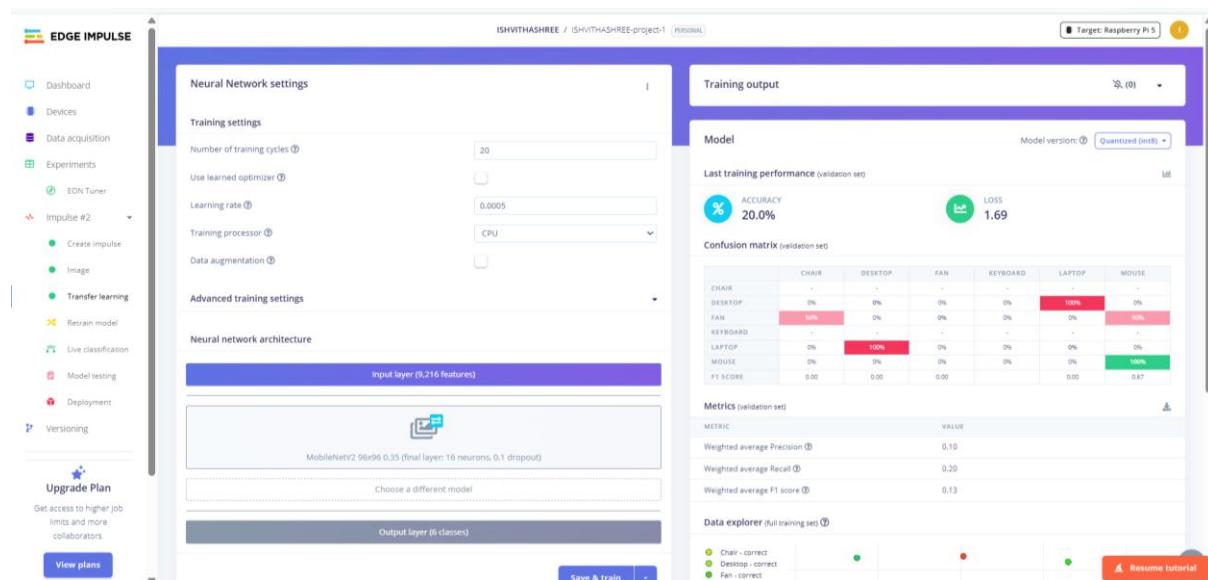
	CHAIR	DESKTOP	FAN	KEYBOARD	LAPTOP	MOUSE
CHAIR	-	-	-	-	-	-
DESKTOP	0%	0%	0%	100%	0%	0%
FAN	0%	100%	0%	0%	0%	0%
KEYBOARD	-	-	-	-	-	-
LAPTOP	0%	100%	0%	0%	0%	0%
MOUSE	0%	0%	0%	100%	0%	0%
F1 SCORE	0.00	0.00	0.00	0.00	0.00	0.00

Below the confusion matrix are "Metrics (validation set)" (Weighted average Precision: 0.00, Weighted average Recall: 0.00, Weighted average F1 score: 0.00) and a "Data explorer (full training set)" section.

Edge Impulse #2 → Transfer Learning:



This screenshot shows the 'Generate features' step in the Edge Impulse workflow. It displays a live feed of a fan from a camera, labeled 'Raw data'. Below it, 'Raw features' are listed as a series of hex codes. The 'Parameters' section includes settings for 'Image' (Color depth: Grayscale) and a 'Save parameters' button. To the right, the 'DSP result' shows a processed image of the fan, and 'On-device performance' metrics indicate a processing time of 1 ms and peak RAM usage of 4 KB.



This screenshot shows the 'Train model' step. On the left, 'Neural Network settings' include training cycles (20), optimizer (learned), learning rate (0.0005), and processor (CPU). The 'Advanced training settings' section is collapsed. On the right, the 'Training output' panel shows the 'Model' tab with 'Last training performance' metrics: Accuracy 20.0% and Loss 1.69. A 'Confusion matrix' table details the model's performance across six classes: CHAIR, DESKTOP, FAN, KEYBOARD, LAPTOP, and MOUSE. The 'Metrics' section lists weighted average Precision (0.10), Recall (0.20), and F1 score (0.13). The 'Data explorer' shows a scatter plot of training set data points for Chair, Desktop, and Fan categories.

Conclusion

This lab helped in understanding the end-to-end data acquisition workflow using Edge Impulse, including dataset creation, labeling, and preparation for edge-based machine learning applications.

Using Edge Impulse, I collected and labeled image data for six objects, organized them into training and testing sets.