Data Collection

```
1 import os
 2 import cv2
 3 import numpy as np
4 import pandas as pd
 5 import zipfile
 6 from tensorflow.keras.utils import to_categorical
 7
8 # Define the path for the zip file and extraction directory
9 zip_path = '/content/GTSRB_Final_Training_Images.zip'
10 extract_dir = '/content/GTSRB/Final_Training/Images'
11
12
13 # Extract the dataset if not already extracted
14 if not os.path.exists(extract_dir):
      with zipfile.ZipFile(zip_path, 'r') as zip_ref:
          zip ref.extractall(r"/content/")
16
17
18 # Path to GTSRB training data
19 train_root = extract_dir
20
 1 import os
 2
 3 # Check if extraction was successful
 4 if os.path.exists(extract dir):
      print(" Extraction successful. Checking dataset structure...")
      print("Classes found:", os.listdir(extract_dir)) # Should list class fc
 7 else:
      print(" Extraction failed. Check the ZIP file.")
   Extraction successful. Checking dataset structure...
   Classes found: ['00018', '00026', '00038', '00003', '00041', '00024', '0003
 1 import os
 3 dataset_path = "/content/GTSRB/Final_Training/Images"
 5 # Verify folder contents
 6 print("Checking dataset structure...")
 7 for folder in os.listdir(dataset_path):
      folder_path = os.path.join(dataset_path, folder)
      nrint(f" \folder\ - \folder\ if oc nath icdir(folder nath) else \File\}
```

```
10
11 # Pick a class and check images inside
12 sample_class = os.listdir(dataset_path)[0] # First class folder
13 sample_class_path = os.path.join(dataset_path, sample_class)
14
15 print(f"\n Checking images inside {sample_class}...")
16 print(os.listdir(sample_class_path)[:5]) # Show first 5 files
```

```
→ Checking dataset structure...
     00018 - Folder
     00026 - Folder
     00038 - Folder
     00003 - Folder
     00041 - Folder
     00024 - Folder
     00030 - Folder
     00029 - Folder
     00004 - Folder
     00000 - Folder
     00016 - Folder
     00027 - Folder
     00017 - Folder
     00008 - Folder
     00032 - Folder
     00015 - Folder
     00011 - Folder
     00006 - Folder
     00033 - Folder
     00019 - Folder
     00023 - Folder
     00031 - Folder
     00012 - Folder
     00035 - Folder
     00021 - Folder
     00010 - Folder
     00034 - Folder
     00037 - Folder
     00042 - Folder
     00039 - Folder
     00028 - Folder
     00009 - Folder
     00022 - Folder
     00001 - Folder
     00007 - Folder
     00013 - Folder
     00002 - Folder
     00005 - Folder
     00025 - Folder
     00020 - Folder
     00040 - Folder
     00036 - Folder
     00014 - Folder
     Checking images inside 00018...
    ['00009_00016.ppm', '00015_00001.ppm', '00029_00009.ppm', '00008_00009.ppm'
 1
      Load and preprocess images
 3 def load_gtsrb_dataset(root_dir, img_size=(32, 32)):
       images, labels = [], [] # FIXED
 4
```

```
5
       for class id in sorted(os.listdir(root dir)):
           class_path = os.path.join(root_dir, class_id)
6
7
           if os.path.isdir(class path):
               for img_file in os.listdir(class_path):
8
                   if img_file.endswith(".ppm"):
9
                       img path = os.path.join(class path, img file)
10
                       img = cv2.imread(img_path)
11
12
                       if img is not None:
13
                           img = cv2.resize(img, img_size)
14
                           img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
15
                           images.append(img)
                           labels.append(int(class_id))
16
17
       return np.array(images), np.array(labels)
18
19 # Load data
20 X_raw, y_raw = load_gtsrb_dataset(train_root)
21 print(f"Loaded {len(X raw)} images, shape: {X raw.shape}")
22
23 #
     Display class-wise distribution
24 label counts = np.bincount(y raw)
25 label_df = pd.DataFrame({
       "ClassId": np.arange(len(label_counts)),
26
      "Image Count": label_counts
27
28 })
29 print("\nClass-wise Image Distribution:")
30 print(label_df.to_string(index=False))
31
```

→ Loaded 39209 images, shape: (39209, 32, 32, 3)

Class-wise Image Distribution: ClassId Image Count

ISS-W1S	5
.assId	Image Count
0	210
1	2220
2 3	2250
3	1410
4	1980
5	1860
6	420
7	1440
8	1410
9	1470
10	2010
11	1320
12	2100
13	2160
14	780
15	630
16	420
17	1110
18	1200
19	210
20	360
21	330
22	390
23	510
24	270
25 26	1500
26	600
27	240
28	540 270
29	270
30	450
31 32	780 240
33	689
34	420
35	1200
36	390
37	210
38	2070
39	300
40	360
40	240
41	240
42	240

Data Cleaning

```
1 import glob
 3 # Clean using CSV ROI data
 4 def load and crop with roi(root dir, img size=(32, 32)):
       images, labels = [], []
 5
 6
 7
       # Get all class CSVs
       csv_files = glob.glob(os.path.join(root_dir, "*", "GT-*.csv"))
 8
 9
10
       for csv_path in csv_files:
            df = pd.read_csv(csv_path, sep=';')
11
12
            class dir = os.path.dirname(csv path)
13
            for _, row in df.iterrows():
14
                img_path = os.path.join(class_dir, row['Filename'])
15
                img = cv2.imread(img_path)
16
17
18
                if img is not None:
19
                    # Crop using ROI
20
                    x1, y1, x2, y2 = row['Roi.X1'], row['Roi.Y1'], row['Roi.X2'
                    cropped = img[y1:y2, x1:x2]
21
                    resized = cv2.resize(cropped, img size)
22
23
                    resized = cv2.cvtColor(resized, cv2.COLOR_BGR2RGB)
                    images.append(resized)
24
25
                    labels.append(row['ClassId'])
26
27
       return np.array(images)/255.0, np.array(labels)
28
      Load cleaned dataset
29 #
30 X_cleaned, y_cleaned = load_and_crop_with_roi(train_root)
31 print(f" Cropped and resized {len(X_cleaned)} images, shape: {X_cleaned.sha
32
\rightarrow
     Cropped and resized 39209 images, shape: (39209, 32, 32, 3)
```

Data Transformation

```
1 from sklearn.model selection import train test split
 2 from tensorflow.keras.utils import to_categorical
 3 import requests
 4 import numpy as np
 6 # One-hot encode labels
 7 y encoded = to categorical(y cleaned)
 8 print(f" Labels one-hot encoded: shape = {y encoded.shape}")
10 # Train/Test Split
11 X_train, X_test, y_train, y_test = train_test_split(
12
       X_cleaned, y_encoded, test_size=0.2, stratify=y_cleaned, random_state=4
13)
14 print(f" Split: {X_train.shape[0]} train, {X_test.shape[0]} test")
15
16 # Real-time Weather API Integration
17 API KEY = "4690348b38a4f5520d615776d7e9e01d"
18 CITY = "Texas"
19 API_URL = "https://api.openweathermap.org/data/2.5/weather"
20
21 def get_weather():
22
       try:
23
           params = {"q": CITY, "appid": API_KEY, "units": "metric"}
24
           response = requests.get(API_URL, params=params)
25
           data = response.json()
26
           if response.status_code == 200:
27
               temp = data["main"].get("temp", 20.0)
28
               humidity = data["main"].get("humidity", 50)
29
               print(f" Temp: {temp}°C, Humidity: {humidity}%")
30
               return temp, humidity
31
       except Exception as e:
           print(" Weather API error:", e)
32
33
       return 20.0, 50
34
35 # Fetch real-time weather (assumed constant for training batch)
36 temperature, humidity = get_weather()
37 weather_train = np.array([[temperature, humidity]] * len(X_train))
38 weather_test = np.array([[temperature, humidity]] * len(X_test))
39
40 print(f" Weather metadata shape (train): {weather_train.shape}")
41
     Labels one-hot encoded: shape = (39209, 43)
\rightarrow
     Split: 31367 train, 7842 test
     Temp: 29.97°C, Humidity: 35%
     Weather metadata shape (train): (31367, 2)
```

1 # Augmentation

```
1 # After Step 3 is done — you already have these
2 # X_train, y_train, weather_train
3 # (All numpy arrays)
4
5 # INSERT AUGMENTATION HERE
6 import random
7
8 def add_fog(image):
       fog_layer = np.full_like(image, 200, dtype=np.uint8)
       return cv2.addWeighted(image, 0.7, fog_layer, 0.3, 0)
10
11
12 def add_rain(image, drop_count=100):
13
       rainy = image.copy()
      h, w, _ = image.shape
14
15
       for _ in range(drop_count):
           x1, y1 = random.randint(0, w), random.randint(0, h)
16
           x2, y2 = x1 + random.randint(-2, 2), <math>y1 + random.randint(10, 20)
17
           cv2.line(rainy, (x1, y1), (x2, y2), (200, 200, 200), 1)
18
       return cv2.addWeighted(image, 0.8, rainy, 0.2, 0)
19
20
21 def add_glare(image):
      glare = image.copy()
22
23
      h, w = glare.shape[:2]
      cx = random_randint(w//3, 2*w//3)
24
25
      cy = random.randint(h//3, 2*h//3)
       r = random.randint(5, 15)
26
27
      overlay = glare.copy()
28
       cv2.circle(overlay, (cx, cy), r, (255, 255, 255), -1)
29
       return cv2.addWeighted(glare, 0.8, overlay, 0.2, 0)
30
31 # Augment 25% of training data
32 augment_fraction = 0.25
33 num aug = int(len(X train) * augment fraction)
34 indices = random.sample(range(len(X_train)), num_aug)
35
36 X_{aug}, y_{aug} = [], []
37
38 for idx in indices:
       img = (X_train[idx] * 255).astype(np.uint8)
39
40
       label = y train[idx]
      effect = random.choice(["fog", "rain", "glare"])
41
42
      if effect == "fog":
43
44
           aug_img = add_fog(img)
45
      elif effect == "rain":
```

```
46
            aug_img = add_rain(img)
47
       else:
48
           aug_img = add_glare(img)
49
50
       X_aug.append(aug_img / 255.0)
       y aug.append(label)
51
52
53 # Final combined training data
54 X_train_aug = np.concatenate((X_train, np.array(X_aug)), axis=0)
55 y_train_aug = np.concatenate((y_train, np.array(y_aug)), axis=0)
56 weather_train_aug = np.concatenate((weather_train, weather_train[:len(X_aug
57
58 print(f" Augmented {len(X_aug)} images. Final training shape: {X_train_aug.
59
\rightarrow
     Augmented 7841 images. Final training shape: (39208, 32, 32, 3)
 1 # Display Augmented Images
 1 import cv2
 2 import numpy as np
 3 import matplotlib.pyplot as plt
 4 import random
 6 # --- Weather effect functions ---
 7 def add_fog(image):
       fog_layer = np.full_like(image, 200, dtype=np.uint8)
       return cv2.addWeighted(image, 0.7, fog_layer, 0.3, 0)
 9
10
11 def add_rain(image, drop_count=100):
12
       rainy = image.copy()
13
       h, w, _ = image.shape
       for _ in range(drop_count):
14
            x1, y1 = random.randint(0, w), random.randint(0, h)
15
            x2, y2 = x1 + random.randint(-2, 2), <math>y1 + random.randint(10, 20)
16
            cv2.line(rainy, (x1, y1), (x2, y2), (200, 200, 200), 1)
17
18
       return cv2.addWeighted(image, 0.8, rainy, 0.2, 0)
19
20 def add_glare(image):
       glare = image.copy()
21
       h, w = glare.shape[:2]
22
       cx = random.randint(w // 3, 2 * w // 3)
23
       cy = random.randint(h // 3, 2 * h // 3)
24
       radius = random.randint(5, 15)
25
       overlay = glare.copy()
26
       cv2.circle(overlay, (cx, cy), radius, (255, 255, 255), -1)
27
28
       return cv2.addWeighted(glare, 0.8, overlay, 0.2, 0)
```

```
29
30 # --- Sharp image filter ---
31 def is_clear_image(img, threshold=100.0):
      gray = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)
32
       return cv2.Laplacian(gray, cv2.CV_64F).var() > threshold
33
34
35 def get_one_clear_image(X):
36
      for i in range(len(X)):
           img = (X[i] * 255).astype(np.uint8)
37
           if is_clear_image(img):
38
39
               return img
40
       return None
41
42 # --- Select and visualize one image with 4 versions ---
43 base_img = get_one_clear_image(X_cleaned)
44
45 if base img is not None:
      fog = add_fog(base_img)
46
47
       rain = add_rain(base_img)
      glare = add_glare(base_img)
48
49
       images = [base_img, fog, rain, glare]
50
      titles = ["Original", "Fog", "Rain", "Glare"]
51
52
53
      plt.figure(figsize=(16, 4))
      for i in range(4):
54
55
           plt.subplot(1, 4, i+1)
56
           plt.imshow(images[i])
57
           plt.title(titles[i])
58
           plt.axis("off")
59
60
      plt.tight_layout()
61
      plt.suptitle("Simulated Weather Effects on Clear Traffic Sign", fontsiz
62
      plt.show()
63 else:
      print(" No clear image found in the dataset.")
64
65
```











Model Training (CNN + Weather Input)

```
1 from tensorflow.keras.models import Model
 2 from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, Flatten, De
 3
 4 def build_weather_aware_model(img_shape=(32, 32, 3), weather_shape=(2,), num
 5
      # CNN Branch for images
      cnn_input = Input(shape=img_shape)
 6
      x = Conv2D(32, (3, 3), activation='relu')(cnn_input)
 7
      x = MaxPooling2D((2, 2))(x)
8
      x = Conv2D(64, (3, 3), activation='relu')(x)
9
      x = MaxPooling2D((2, 2))(x)
10
11
      x = Flatten()(x)
      cnn_output = Dense(128, activation='relu')(x)
12
13
      cnn output = Dropout(0.5)(cnn output)
14
      # DNN Branch for weather metadata
15
      weather_input = Input(shape=weather_shape)
16
17
      weather_dense = Dense(8, activation='relu')(weather_input)
18
19
         Fusion
```

```
merged = Concatenate()([cnn_output, weather_dense])
20
      final_output = Dense(num_classes, activation='softmax')(merged)
21
22
      model = Model(inputs=[cnn_input, weather_input], outputs=final_output)
23
      model.compile(optimizer='adam', loss='categorical_crossentropy', metrics
24
      return model
25
26
27 #
     Build the model
28 model = build_weather_aware_model()
29 model.summary()
30
```



Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 32, 32, 3)	0	-
conv2d (Conv2D)	(None, 30, 30, 32)	896	input_layer[0][0]
max_pooling2d (MaxPooling2D)	(None, 15, 15, 32)	0	conv2d[0][0]
conv2d_1 (Conv2D)	(None, 13, 13, 64)	18,496	max_pooling2d[0]
max_pooling2d_1 (MaxPooling2D)	(None, 6, 6, 64)	0	conv2d_1[0][0]
flatten (Flatten)	(None, 2304)	0	max_pooling2d_1[
dense (Dense)	(None, 128)	295,040	flatten[0][0]
input_layer_1 (InputLayer)	(None, 2)	0	_
dropout (Dropout)	(None, 128)	0	dense[0][0]
dense_1 (Dense)	(None, 8)	24	input_layer_1[0]
concatenate (Concatenate)	(None, 136)	0	dropout[0][0], dense_1[0][0]
dense_2 (Dense)	(None, 43)	5,891	concatenate[0][0]

Total params: 320,347 (1.22 MB)
Trainable params: 320,347 (1.22 MB)
Non-trainable params: 0 (0.00 B)

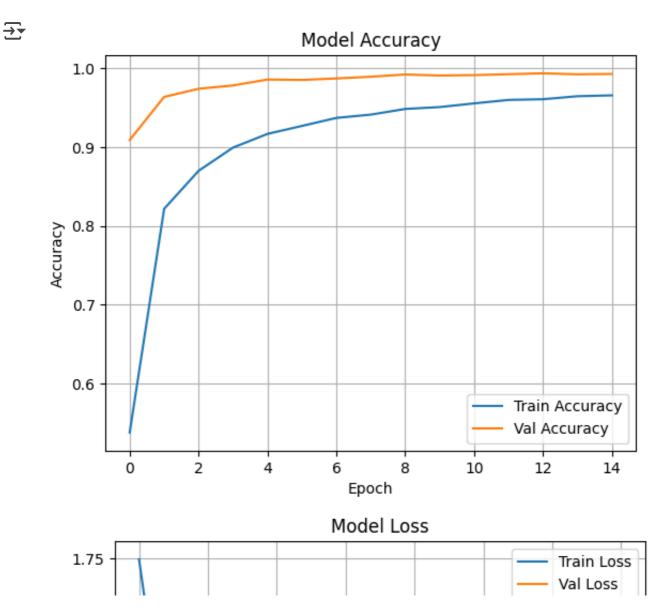
Training the Model

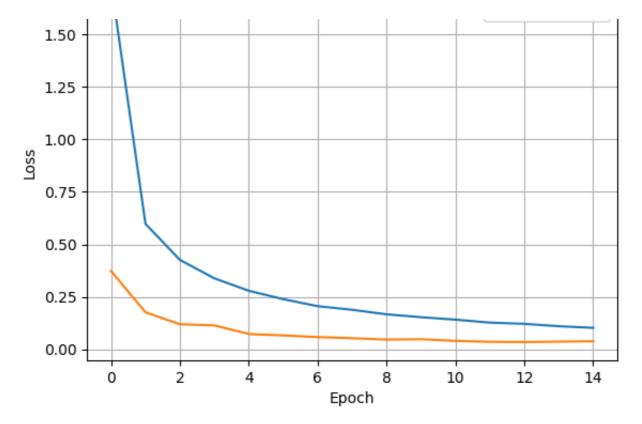
```
1 history = model.fit(
2
      [X train_aug, weather_train_aug], y_train_aug,
3
     epochs=15,
      batch_size=64,
4
5
      validation_data=([X_test, weather_test], y_test)
6)
 Epoch 1/15
  613/613 -
                            —— 53s 82ms/step – accuracy: 0.3261 – loss: 2.766
  Epoch 2/15
  613/613 -
                              - 83s 84ms/step - accuracy: 0.8020 - loss: 0.667
  Epoch 3/15
                            — 81s 82ms/step - accuracy: 0.8654 - loss: 0.439
  613/613 -
  Epoch 4/15
                            — 84s 84ms/step - accuracy: 0.8983 - loss: 0.345
  613/613 —
  Epoch 5/15
  613/613 -
                              - 80s 81ms/step - accuracy: 0.9154 - loss: 0.283
  Epoch 6/15
  613/613 —
                             --- 84s 85ms/step - accuracy: 0.9254 - loss: 0.248
  Epoch 7/15
  613/613 -
                              - 79s 80ms/step - accuracy: 0.9341 - loss: 0.213
  Epoch 8/15
  613/613 -
                            —— 83s 81ms/step – accuracy: 0.9435 – loss: 0.179
  Epoch 9/15
  613/613 —
                             — 81s 79ms/step - accuracy: 0.9462 - loss: 0.172
  Epoch 10/15
  613/613 -
                              - 50s 81ms/step - accuracy: 0.9527 - loss: 0.147
  Epoch 11/15
  613/613 —
                              — 50s 81ms/step — accuracy: 0.9571 — loss: 0.138
  Epoch 12/15
  613/613 -
                              - 80s 79ms/step - accuracy: 0.9581 - loss: 0.130
  Epoch 13/15
                            — 83s 80ms/step - accuracy: 0.9603 - loss: 0.123
  613/613 -
  Epoch 14/15
  613/613 -
                             — 82s 80ms/step - accuracy: 0.9646 - loss: 0.110
  Epoch 15/15
  613/613 -
                              - 48s 79ms/step - accuracy: 0.9669 - loss: 0.102
```

Plot Accuracy and Loss

```
1 import matplotlib.pyplot as plt
2
3 # Accuracy
```

```
4 plt.plot(history.history['accuracy'], label='Train Accuracy')
 5 plt.plot(history.history['val_accuracy'], label='Val Accuracy')
 6 plt.title('Model Accuracy')
 7 plt.xlabel('Epoch')
 8 plt.ylabel('Accuracy')
 9 plt.legend()
10 plt.grid(True)
11 plt.show()
12
13 # Loss
14 plt.plot(history.history['loss'], label='Train Loss')
15 plt.plot(history.history['val_loss'], label='Val Loss')
16 plt.title('Model Loss')
17 plt.xlabel('Epoch')
18 plt.ylabel('Loss')
19 plt.legend()
20 plt.grid(True)
21 plt.show()
22
```





#

1 # 6.1. Evaluate on Test Set

```
1 # Final evaluation
2 from sklearn.metrics import accuracy_score, classification_report, confusion
3 import seaborn as sns
4 import matplotlib.pyplot as plt
5 import numpy as np
7 # Predict on entire test set
8 y_pred_probs = model.predict([X_test, weather_test])
9 y_pred = np.argmax(y_pred_probs, axis=1)
10 y_true = np.argmax(y_test, axis=1)
11
12 # Accuracy
13 acc = accuracy_score(y_true, y_pred)
14 print(f"\no Final Test Accuracy: {acc * 100:.2f}%")
15
16 # h Classification Report
17 print("\n Classification Report:")
18 print(classification_report(y_true, y_pred))
20 # Confusion Matrix
21 cm = confusion_matrix(y_true, y_pred)
```

```
22
23 plt.figure(figsize=(12, 10))
24 sns.heatmap(cm, annot=False, fmt='d', cmap='Blues')
25 plt.title("Confusion Matrix")
26 plt.xlabel("Predicted Label")
27 plt.ylabel("True Label")
28 plt.tight_layout()
29 plt.show()
```

4s 17ms/step

Classification Report:

→ 246/246 -

	TOTT REPOT OF			
	precision	recall	f1-score	support
0	0.98	0.98	0.98	42
1	0.99	0.99	0.99	444
2	0.99	0.99	0.99	450
3	0.98	0.99	0.98	282
4	1.00	0.99	1.00	396
5	0.99	0.98	0.99	372
6	1.00	1.00	1.00	84
7	0.98	1.00	0.99	288
8	0.99	0.99	0.99	282
9	0.99	1.00	0.99	294
10	0.99	1.00	0.99	402
11	1.00	0.98	0.99	264
12	1.00	1.00	1.00	420
13	1.00	1.00	1.00	432
14	0.99	1.00	1.00	156
15	0.98	1.00	0.99	126
16	1.00	1.00	1.00	84
17	0.99	1.00	0.99	222
18	0.99	1.00	1.00	240
19	0.98	1.00	0.99	42
20	1.00	0.97	0.99	72
21	1.00	0.98	0.99	66
22	0.99	1.00	0.99	78
23	1.00	1.00	1.00	102
24	1.00	1.00	1.00	54
25	0.99	0.99	0.99	300
26	0.98	0.98	0.98	120
27	1.00	1.00	1.00	48
28	1.00	0.98	0.99	108
29	1.00	0.98	0.99	54
30	0.98	0.99	0.98	90
31	0.99	0.99	0.99	156
32	1.00	1.00	1.00	48
33	1.00	1.00	1.00	138
34	1.00	1.00	1.00	84
35	1.00	1.00	1.00	240
36	1.00	1.00	1.00	78

8 9

```
37
                                                                                              0.95
                                                                1.00
                                                                                                                            0.98
                                                                                                                                                                42
                                     38
                                                                1.00
                                                                                              1.00
                                                                                                                            1.00
                                                                                                                                                             414
                                                                0.98
                                     39
                                                                                              0.98
                                                                                                                            0.98
                                                                                                                                                                60
                                     40
                                                                0.96
                                                                                              1.00
                                                                                                                            0.98
                                                                                                                                                                72
                                     41
                                                                1.00
                                                                                              1.00
                                                                                                                            1.00
                                                                                                                                                                48
                                     42
                                                                1.00
                                                                                              1.00
                                                                                                                            1.00
                                                                                                                                                                48
                   accuracy
                                                                                                                            0.99
                                                                                                                                                          7842
               macro avq
                                                                0.99
                                                                                              0.99
                                                                                                                            0.99
                                                                                                                                                          7842
                                                                0.99
                                                                                              0.99
                                                                                                                            0.99
       weighted avg
                                                                                                                                                          7842
                                                                                                Confusion Matrix
1 # 6.2. Save Model
1 model.save("weather_augmented_traffic_sign_model.keras")
2 print(" Final model saved as weather_augmented_traffic_sign_model.keras")
                                                                                                                                                                                                                                300
          Final model saved as weather_augmented_traffic_sign_model.keras
             - 10
1 # 6.3. Make a Few Predictions
        Lak
12
1 # Predict on first 10 test samples
2 y_pred_probs = model.predict([X_test[:10], weather_test[:10]])
3 y_pred = np.argmax(y_pred_probs, axis=1)
4 y_true = np.argmax(y_test[:10], axis=1)
6 # Compare predictions vs true
7 for i in range(10):
                 print(f"Image {i+1}: Predicted = {y_pred[i]}, Actual = {y_true[i]}")
       1/1
                                                                              - 0s 50ms/step
       Image 1: Predicted = 28, Actual = 28
       Image 2: Predicted = 2, Actual = 2
       Image 4: Predicted = 1, Actual = 25, Actual = 25
       Image 5: Predicted = 38, Actual = 38
       Image 6: Predicted = 9, Actual = 9
       Image 7: Predicted = 31, Actual = 31
```

Image 8: Predicted = 12, Actual = 12 Image 9: Predicted = 1, Actual = 1 Image 10: Predicted = 4, Actual = 4

1 # 6.4. Visual Display

```
1 import matplotlib.pyplot as plt
2
3 plt.figure(figsize=(12, 4))
4 for i in range(10):
5    plt.subplot(2, 5, i + 1)
6    plt.imshow(X_test[i])
7    plt.title(f"Pred: {y_pred[i]}, True: {y_true[i]}")
8    plt.axis("off")
9 plt.tight_layout()
10 plt.show()
```



Pred: 28, True: 28



Pred: 9, True: 9



Pred: 2, True: 2



Pred: 31, True: 31



Pred: 1, True: 1



Pred: 12, True: 12



Pred: 25, True: 25



Pred: 1, True: 1



Pred: 38, True: 38



Pred: 4, True: 4



```
1 import tensorflow as tf
 2 import time
 3 import numpy as np
 5 \text{ batch size} = 1
 6 X_batch = X_test[:batch_size]
 7 weather batch = weather test[:batch size]
 9 # Define the prediction function with tf.function
10 @tf.function
11 def predict_fn(inputs):
12
       return model(inputs, training=False)
13
14 # Warm-up to avoid initialization overhead
15 for in range(5):
16
       _ = predict_fn([X_batch, weather_batch])
17
18 # Measure over multiple iterations for accuracy
19 iterations = 100
20 start_time = time.perf_counter() # Higher precision timing
21 for _ in range(iterations):
       _ = predict_fn([X_batch, weather_batch])
23 total_time = time.perf_counter() - start_time
24
25 # Calculate FPS
26 if total_time > 0: # Avoid division by zero
       fps = (batch_size * iterations) / total time
27
28
       print(f"Optimized FPS for {batch_size} frames (over {iterations} iterat
29 else:
30
       print("Execution too fast to measure accurately with current setup.")
       fps_per_run = float('inf') # Indicates extremely high FPS
31
→ Optimized FPS for 1 frames (over 100 iterations): 630.92
```

```
1 import tensorflow as tf
 2 import time
 3 import numpy as np
 5 \text{ batch size} = 4
 6 X_batch = X_test[:batch_size]
 7 weather_batch = weather_test[:batch_size]
 9 # Define the prediction function with tf.function
10 @tf.function
11 def predict_fn(inputs):
12
       return model(inputs, training=False)
13
14 # Warm-up to avoid initialization overhead
15 for _ in range(5):
16
       _ = predict_fn([X_batch, weather_batch])
17
18 # Measure over multiple iterations for accuracy
19 iterations = 100
20 start_time = time.perf_counter() # Higher precision timing
21 for _ in range(iterations):
       _ = predict_fn([X_batch, weather_batch])
23 total_time = time.perf_counter() - start_time
24
25 # Calculate FPS
26 if total_time > 0: # Avoid division by zero
       fps = (batch_size * iterations) / total time
27
28
       print(f"Optimized FPS for {batch_size} frames (over {iterations} iterat
29 else:
30
       print("Execution too fast to measure accurately with current setup.")
       fps_per_run = float('inf') # Indicates extremely high FPS
31
→ Optimized FPS for 4 frames (over 100 iterations): 1560.52
  1 import cv2
  2 import numpy as np
  3 import matplotlib.pyplot as plt
  4 import requests
  5 from tensorflow.keras.models import load model
  6 from IPython.display import display
  7 import zipfile
  8 import os
  9 import tempfile
 10
 11 # Load the trained model
 12 try:
        model = load_model("weather_augmented_traffic_sign_model.keras")
 13
```

```
print("Model loaded successfully.")
14
15 except Exception as e:
       print(f"Error loading model: {e}")
17
       raise
18
19 # Real-time Weather API Integration
20 API KEY = "4690348b38a4f5520d615776d7e9e01d"
21 CITY = "Texas"
22 API_URL = "https://api.openweathermap.org/data/2.5/weather"
23
24 def get_weather():
25
       try:
26
           params = {"q": CITY, "appid": API_KEY, "units": "metric"}
27
           response = requests.get(API URL, params=params)
28
           response.raise_for_status()
29
           data = response.json()
30
           temp = data["main"].get("temp", 20.0)
           humidity = data["main"].get("humidity", 50)
31
           print(f"Weather in {CITY}: Temp: {temp}°C, Humidity: {humidity}%")
32
33
           return temp, humidity
34
       except Exception as e:
           print(f"Weather API error: {e}")
35
36
           return 20.0, 50
37
38 # Preprocess an image
39 def preprocess_image(img_path, img_size=(32, 32)):
       img = cv2.imread(img path)
40
41
       if img is None:
42
           raise ValueError(f"Failed to load image: {img_path}")
43
       img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
44
       img = cv2.resize(img, img_size)
45
       img = img / 255.0
46
       return img
47
48 # Predict traffic sign class
49 def predict_traffic_sign(img_path):
50
       try:
           img = preprocess_image(img_path)
51
52
           img = np.expand_dims(img, axis=0)
53
           temperature, humidity = get weather()
           weather_data = np.array([[temperature, humidity]])
54
           prediction = model.predict([img, weather_data], verbose=0)
55
56
           predicted_class = np.argmax(prediction, axis=1)[0]
57
           confidence = np.max(prediction) * 100
           return predicted_class, confidence, img[0]
58
59
       except Exception as e:
60
           raise ValueError(f"Prediction error for {img_path}: {e}")
61
```

```
62 # Visualize the result
63 def display_result(img, predicted_class, confidence, img_name):
       plt.figure(figsize=(6, 6))
       plt.imshow(img)
65
       plt.title(f"Image: {img_name}\nPredicted Class: {predicted_class}\nCor
66
67
       plt.axis("off")
       plt.show()
68
69
70 # Process images from zip file
71 def process zip file(zip path):
72
        if not os.path.exists(zip_path):
            print(f"Zip file not found at: {zip_path}")
73
74
            return
75
       with tempfile.TemporaryDirectory() as temp dir:
76
 77
                with zipfile.ZipFile(zip_path, 'r') as zip_ref:
78
                    zip ref.testzip() # Check for corruption
 79
                    zip_ref.extractall(temp_dir)
                print(f"Extracted zip file to temporary directory: {temp_dir}"
80
81
                supported_extensions = ('.png', '.jpg', '.jpeg', '.ppm')
 82
83
                image found = False
84
                for root, _, files in os.walk(temp_dir):
 85
                    for file in files:
                        if file.lower().endswith(supported_extensions):
86
 87
                            image_found = True
88
                            img path = os.path.join(root, file)
89
                            try:
                                print(f"\nProcessing image: {file}")
90
91
                                predicted_class, confidence, processed_img = r
92
                                print(f"Prediction: Class {predicted_class}, (
93
                                display_result(processed_img, predicted_class,
 94
                            except Exception as e:
95
                                print(f"Error processing {file}: {e}")
 96
                if not image_found:
97
                    print("No supported images (.png, .jpg, .jpeg, .ppm) founc
            except zipfile.BadZipFile:
98
                print(f"Error: The file {zip_path} is not a valid zip file or
99
100
            except Exception as e:
                print(f"Error extracting or processing zip file: {e}")
101
102
103 # Main function to handle input and prediction
104 def main():
105
       print("Please enter the name of the zip file in the notebook's director
       zip_name = input().strip()
106
107
        if not zip_name:
108
            print("No file name provided. Exiting.")
109
            return
```

zip_path = os.path.join(os.getcwd(), zip_name) 110 process_zip_file(zip_path) 111 112 113 # Run the prediction 114 main()

Model loaded successfully.

Please enter the name of the zip file in the notebook's directory (e.g., tr traffic images.zip

Extracted zip file to temporary directory: /tmp/tmp7v31q07s

Processing image: IMG-20250405-WA0048.png Weather in Texas: Temp: 30.97°C, Humidity: 35% Prediction: Class 30, Confidence: 95.86%

Image: IMG-20250405-WA0048.png

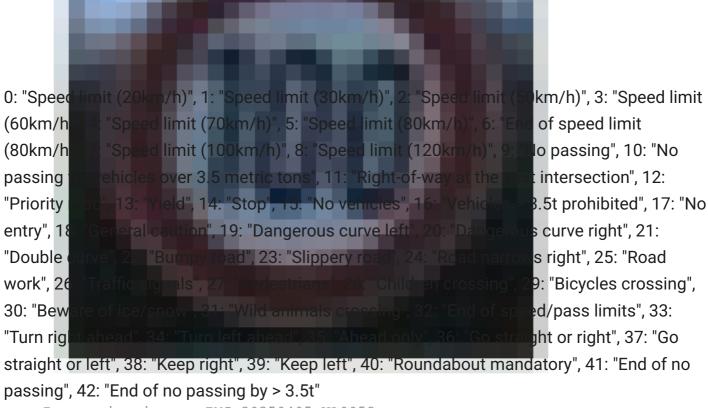
Predicted Class: 30 Confidence: 95.86%



Processing image: IMG-20250405-WA0047.png Weather in Texas: Temp: 30.97°C, Humidity: 35% Prediction: Class 7, Confidence: 100.00%

Image: IMG-20250405-WA0047.png Predicted Class: 7

Confidence: 100.00%



Processing image: IMG-20250405-WA0058.png Weather in Texas: Temp: 30.97°C, Humidity: 35% Prediction: Class 21, Confidence: 98.90%

> Image: IMG-20250405-WA0058.png Predicted Class: 21

> > Confidence: 98.90%

