The LeNet-5 CNN Architecture, developed by Yann LeCun in 1998, is one of the pioneering convolutional neural networks (CNNs).

- The architecture was developed to recognize handwritten and machine-printed characters, a function that showcased the potential of deep learning in practical applications.
- This architecture used backpropagation for training CNNs.
- Suitable for smaller datasets due to limited capacity.

LeNet-5 has a total of 7 layers, excluding the input layer.

- These layers include convolutional layers, pooling (subsampling) layers, and fully connected layers.
- It uses **tanh** activation functions (as opposed to ReLU in modern architectures).

Let us know Layer-by-Layer Description:

1. **Input Layer**: Accepts a 32x32 grayscale image as input. (Images from datasets like MNIST are padded from 28x28 to 32x32 to fit this architecture.)
2. **Convolutional Layer 1 (C1)**:
    - Applies 6 filters of size 5x5.
    - Produces an output of 6 feature maps each of size 28x28.
3. **Pooling Layer 1 (S2)**:
    - Averages values in 2x2 regions with a stride of 2.
    - Reduces the spatial dimensions from 28x28 to 14x14.
4. **Convolutional Layer 2 (C3)**:
    - Applies 16 filters of size 5x5.
    - Produces an output of 16 feature maps each of size 10x10.
5. **Pooling Layer 2 (S4)**:
    - Averages values in 2x2 regions with a stride of 2.
    - Reduces the spatial dimensions from 10x10 to 5x5.
6. **Fully Connected Layer 1 (F5)**: Flattens the feature maps and passes them through a dense layer with 120 units.
7. **Fully Connected Layer 2 (F6)**: Passes the output from the previous layer to another dense layer with 84 units.
8. **Output Layer**:
    - Contains 10 units, representing the 10 digit classes (0–9).
    - Uses a softmax function for classification.

Parameter Sharing

LeNet-5 utilizes shared weights in the convolutional layers to reduce the number of trainable parameters.

Here's a more structured representation of the **LeNet-5 CNN Architecture** in a table format:

Layer	Type	Input Size	Output Size	Kernel/Filter Size	Number of Filters	Activation	Remarks
Input Layer	-	32x32x1	32x32x1	-	-	-	Grayscale image input
C1	Convolutional	32x32x1	28x28x6	5x5	6	Tanh	Extracts features using 6 filters
S2	Average Pooling	28x28x6	14x14x6	2x2	-	Tanh	Reduces dimensions by half
C3	Convolutional	14x14x6	10x10x16	5x5	16	Tanh	Extracts more complex features
S4	Average Pooling	10x10x16	5x5x16	2x2	-	Tanh	Further reduces dimensions
F5	Fully Connected	5x5x16 (Flattened)	120	-	-	Tanh	Dense layer with 120 neurons
F6	Fully Connected	120	84	-	-	Tanh	Dense layer with 84 neurons
Output Layer	Fully Connected	84	10	-	-	Softmax	Produces class probabilities

To know more:

- https://www.datasciencecentral.com/lenet-5-a-classic-cnn-architecture/
- https://medium.com/@siddheshb008/lenet-5-architecture-explained-3b559cb2d52b

Image Classification with the CIFAR-10 Dataset Using the LeNet-5 CNN Architecture

```
# Step 1: Importing the necessary libraries

import tensorflow as tf
from tensorflow.keras import datasets, layers, models
from tensorflow.keras.utils import to_categorical
import matplotlib.pyplot as plt
```

```
# Step 2: Loading and pre-processing of the CIFAR-10 dataset

(train_images, train_labels), (test_images, test_labels) = datasets.cifar10.load_data()
```

```
# Step 3: Normalizing pixel values to be between 0 and 1

train_images = train_images / 255.0
test_images = test_images / 255.0
```

- One-hot encoding converts categories into a numeric format, enabling models to process them.
- Assigning numeric values (e.g., 1, 2, 3) to categories implies an ordinal relationship that may not exist.
- One-hot encoding removes this unintended relationship by treating each category as independent.
- In classification tasks, the softmax activation function is often used in the output layer.
- One-hot encoding creates a binary vector with a "1" for the true class and "0" elsewhere, which aligns with the softmax output's probability distribution.
- one-hot encoding ensures categorical variables are appropriately represented without introducing unintended relationships or biases, making it an essential preprocessing step for classification tasks.

```
# Step 4: One-hot encode the labels.
# This step is required to use the loss function "categorical_crossentropy"

train_labels = to_categorical(train_labels, 10) # here 10 is for- It ensures the output one-hot enc
test_labels = to_categorical(test_labels, 10)
```

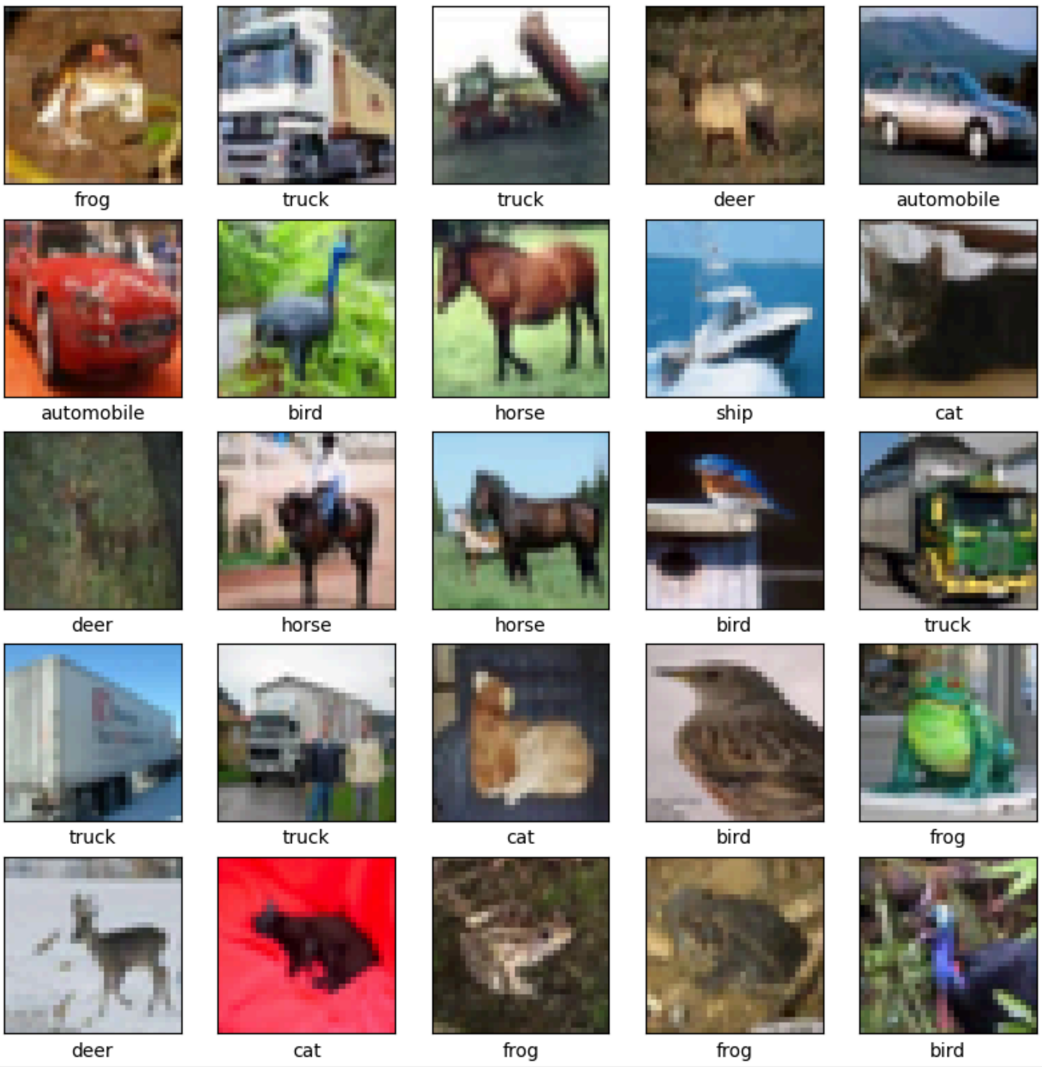
```
# Step 5: Defining the class names for CIFAR-10 images

class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'tr
```

```
# Step 6: Visualizing a few training images from the CIFAR-10 dataset.

plt.figure(figsize=(10, 10))
for i in range(25):
  plt.subplot(5, 5, i + 1)
  plt.xticks([])
  plt.yticks([])
  plt.grid(False)
  plt.imshow(train_images[i])
  plt.xlabel(class_names[train_labels[i].argmax()]) # Using argmax to get the label index

plt.show()
```




```
# Step 7: Building the CNN model (LeNet-5 CNN Architecture)

model = models.Sequential([
    layers.Conv2D(6, (5, 5), activation='tanh', input_shape=(32, 32, 3)),
    layers.AveragePooling2D((2, 2)),
    layers.Conv2D(16, (5, 5), activation='tanh'),
    layers.AveragePooling2D((2, 2)),
    layers.Conv2D(120, (5, 5), activation='tanh'),
    layers.Flatten(),
    layers.Dense(84, activation='tanh'),
    layers.Dense(10, activation='softmax')
])
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
# Step 8: Printing the model summary

model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 28, 28, 6)	456

```
# Step 9: Compiling the CNN model

model.compile(optimizer='adam', # Adam uses a default learning rate of 0.001
loss='categorical_crossentropy',
metrics=['accuracy'])
```

```
# Step 10: Training the CNN model.
trained_model = model.fit(train_images, train_labels, epochs=10, batch_size=32, validation_data=(tes
```

```
Epoch 1/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 43s 27ms/step - accuracy: 0.3185 - loss: 1.8989 - val_accuracy: 0.4045 - val_loss: 1.6714
Epoch 2/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 79s 25ms/step - accuracy: 0.4276 - loss: 1.6227 - val_accuracy: 0.4657 - val_loss: 1.4975
Epoch 3/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 41s 25ms/step - accuracy: 0.4845 - loss: 1.4483 - val_accuracy: 0.4910 - val_loss: 1.4253
Epoch 4/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 40s 24ms/step - accuracy: 0.5204 - loss: 1.3544 - val_accuracy: 0.5173 - val_loss: 1.3641
Epoch 5/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 38s 25ms/step - accuracy: 0.5399 - loss: 1.2963 - val_accuracy: 0.5255 - val_loss: 1.3505
Epoch 6/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 41s 25ms/step - accuracy: 0.5633 - loss: 1.2382 - val_accuracy: 0.5232 - val_loss: 1.3531
Epoch 7/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 41s 25ms/step - accuracy: 0.5741 - loss: 1.1992 - val_accuracy: 0.5288 - val_loss: 1.3335
Epoch 8/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 41s 25ms/step - accuracy: 0.5936 - loss: 1.1511 - val_accuracy: 0.5311 - val_loss: 1.3363
Epoch 9/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 40s 26ms/step - accuracy: 0.6034 - loss: 1.1187 - val_accuracy: 0.5293 - val_loss: 1.3479
Epoch 10/10
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 40s 25ms/step - accuracy: 0.6174 - loss: 1.0918 - val_accuracy: 0.5461 - val_loss: 1.3261
```

```
# Step 11: Evaluating the performance of the CNN model

test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
print(f'\nTest accuracy is: {test_acc}')
```

```
313/313 - 3s - 9ms/step - accuracy: 0.5461 - loss: 1.3261

Test accuracy is: 0.5461000204086304
```

```
# Plotting training and validation accuracy
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(trained_model.history['accuracy'], label='Training Accuracy')
plt.plot(trained_model.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.ylim([0, 1])
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.grid(True)

# Plotting training and validation loss
plt.subplot(1, 2, 2)
plt.plot(trained_model.history['loss'], label='Training Loss')
plt.plot(trained_model.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.ylim([0, 2])
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.grid(True)
plt.show()
```