Unit 9

Convolutional Neural Networks (CNN)

This activity involved me following along with a demonstration of a convolutional neural network (CNN) where the model was trained using CIFAR-10, a well-established computer vision dataset.

It was my first time using TensorFlow in a practical example, which made it interesting to see how it's applied outside of theoretical concepts. The first step involved converting the dataset into tuples and creating a list called Label_names, which contained labels like "cat," "deer," and "airplane." The dataset was then explored, starting with the first image, which turned out to be a picture of a frog. To make the data easier to feed into the neural network, both the training and testing datasets were scaled, and categorical encoding was applied to the target labels (y data).

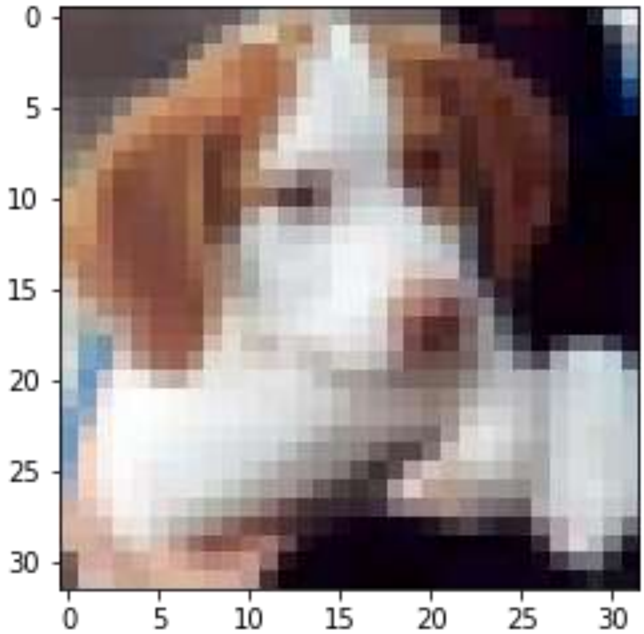
I learned that as the dataset size increases and the number of classes to classify grows, the model requires more filters to capture the necessary features.

Next, the model was built. I hadn't seen a model constructed in this way before, as it was more complex, incorporating components like filters and kernel sizes. The model was structured in layers: the convolutional layer, followed by a second set of layers, and another convolutional layer. After that, the images were flattened before being passed through the final layers, which included neurons in the dense hidden layer and the classifier.

```
## ************* FIRST SET OF LAYERS *************************

# CONVOLUTIONAL LAYER
model.add(Conv2D(filters=32, kernel_size=(4,4),input_shape=(32, 32, 3), activation='relu',))
# POOLING LAYER
model.add(MaxPool2D(pool_size=(2, 2)))

## *************** SECOND SET OF LAYERS ***********************
#Since the shape of the data is 32 x 32 x 3 =3072 ...
#We need to deal with this more complex structure by adding yet another convolutional layer

# *************CONVOLUTIONAL LAYER
model.add(Conv2D(filters=32, kernel_size=(4,4),input_shape=(32, 32, 3), activation='relu',))
# POOLING LAYER
model.add(MaxPool2D(pool_size=(2, 2)))

# FLATTEN IMAGES FROM 32 x 32 x 3 =3072 BEFORE FINAL LAYER
model.add(Flatten())

# 256 NEURONS IN DENSE HIDDEN LAYER (YOU CAN CHANGE THIS NUMBER OF NEURONS)
model.add(Dense(256, activation='relu'))

# LAST LAYER IS THE CLASSIFIER, THUS 10 POSSIBLE CLASSES
model.add(Dense(10, activation='softmax'))


model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

They also introduced an element from TensorFlow called EarlyStopping, which I wasn't entirely familiar with.

I also followed along with the classification report and confusion matrix. The classification report showed average values: precision = 0.68, recall = 0.67, and F1-score = 0.67. Finally, the model predicted the label for a single image of a dog, correctly identifying it as "dog."



To answer the question from the Wall (2019) article, I reflected on the ethical and social implications of CNN technology, particularly in terms of its potential impact on privacy, bias, and accessibility.

Article reflection:

The article on facial recognition technology raised several important ethical and social concerns, particularly regarding its inherent biases and potential for misuse. One of the key issues highlighted was the reduced accuracy of facial recognition systems when applied to individuals with darker skin tones. This discrepancy is largely due to the predominance of white and male datasets used in training these systems, which results in a higher error rate for people of color. This bias undermines the claim of objectivity that is often associated with such technologies, demonstrating that they can perpetuate existing societal inequalities.

The article also addressed the risks of deploying facial recognition in law enforcement and surveillance, particularly its potential to infringe on individual rights. For example, the London Metropolitan Police’s trial of facial recognition technology resulted in an alarming 80% false match rate, which raises significant concerns about the possibility of wrongful accusations and miscarriages of justice. This suggests that, when used in high-stakes contexts such as policing, the consequences of false identifications could be severe.

Additionally, the article explored how facial recognition technology could reinforce systemic biases in society. If algorithms are trained on biased data, they are likely to perpetuate those biases, especially in areas like predictive policing. This could disproportionately affect marginalized communities, exacerbating existing inequalities rather than mitigating them.

In conclusion, the article emphasized the need for greater scrutiny, transparency, and regulation of facial recognition technology. It is crucial that these systems are developed and implemented in a responsible manner, with attention to their social and ethical implications, to ensure that they do not cause harm or exacerbate existing injustices.