L07\_ CNN\_ Chihuahua vs Muffin

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**CNN Architecture vs Traditional Neural Network:**

Convolutional Neural Network and Traditional Neural network both are same thing that are used to train the deep learning but in traditional neural networks, when image is converted in vector form or flatten, its losses it’s spatial. Also, traditional neural network is best for small images with pixel size of 28 by 28 or less because once the image pixels increase, the number of weighted parameters will be out of control. In convolutional neural networks, the spatial features are not loss. Each convolutional layer detects and extract features from the input image and make feature map. Image dimensions shrink in the convolutional layer, but the layer’s depth increase with each layer. Then, all the feature maps are flattened to be fed to fully connected layers like traditional neural networks to generate the output.

**Model Performance:**

Both neural networks performed well, but to detect the edges and feature of image and dealing with large numbers of images and pixel of images, CNN performed well. Whereas MLP is beneficial for tabular data or sequential data or dealing with smaller images like CIFAR-10. CNN had 95% accuracy where MLP accuracy was 65%.

A screenshot of a computer program

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A screenshot of a graph

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**Comparison:**

When the model was training through CNN, the changes in accuracy and training loss was evident and better than traditional neural network. After running the epochs for the tenth time the training loss decrease from 0.59053 to 0.1981 and the accuracy increased from 0.4500 to 0.9583. While when did the same lab ran through traditional neural networks the training loss decrease from 0.6685 to 0.3394 and the accuracy increased from 0.6333 to 0.9750. The output where both models were tested on 17 pictures to detect chihuahua and muffin, the MLP failed in 6 pictures while CNN only failed in 1 picture. Also, the coding was also less for CNN as compared to MLP. As you can see from the training of both models when ten iterations were run.

**A collage of a dog

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**CNN Data:**

A screenshot of a computer

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**MLP Data:**

A screenshot of a computer error

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**Challenges Faced:**

In this lab, there were not many challenges to overcome, it was a straightforward lab with mostly all the parameters present.

**Modification to the lab:**

I changed the learning rate from 0.001 to 0.01 and it affected the accuracy of the model. Initially it was getting only one picture wrong but now it got 7 pictures wrong. It’s validation accuracy got to 0.7667.

A collage of a dog

Description automatically generated

**Real-World Application:**

CNN have changed the way we have used the technology in past. With equipping every phone with visual search engine, everyone can look up the things they see in their environment. CNN has helped customer to find products in online shopping by simply taking pictures. For Tesla to make self-driving car, CNN is playing a big role by detecting road conditions and interpreting camera data to make driving decisions. From law enforcement to healthcare, CNN is making its mark in recognizing criminal from the crowd to benign skin lesion in scans.

**Ethical Delima:**

To train CNN, large dataset is required, and it is not always easy to gather that much information without jeopardizing individual privacy. Therefore, strict protocol and informed consent should be used while collecting the data and making sure that the personal information is anonymize as much as possible. CNN technology is also a leading threat in making powerful drone and other weapons, that can do target identification automatically. Also, in training if bias data is fed to CNN, then the model prediction will also be biased.

**References**

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