Handwriting Recognition Using Deep Learning Techniques

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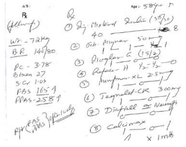
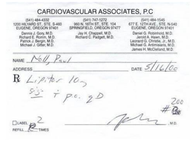
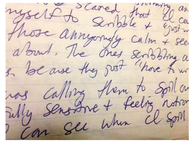
Overview:







- Medical records are an essential component of patient's care. Handwritten prescriptions can be difficult to read and understand, and misinterpretation of their contents might result in catastrophic medical errors. This project tries to address this problem by digitizing handwritten text and making it easily readable and understood. It entails extracting text from handwriting images and converting it to digital text using Computer Vision techniques and Deep Learning models.

Objective:

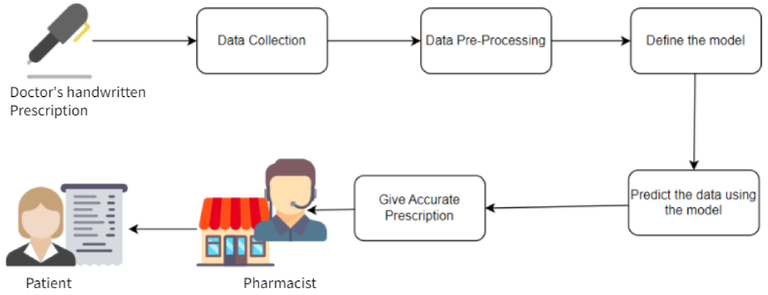
Can a handwritten text recognition system's accuracy be improved with the use of deep learning techniques and OpenCV?

Dataset:

- IAM Handwriting Database 3.0 served as the project's dataset. The IAM Handwriting Database is a publicly accessible dataset that includes handwritten words from 657 different authors. The dataset comprises 13,353 isolated and labeled handwritten words. It has a wide variety of handwriting styles, making it ideal for training and evaluating handwriting recognition models.

Implementation:

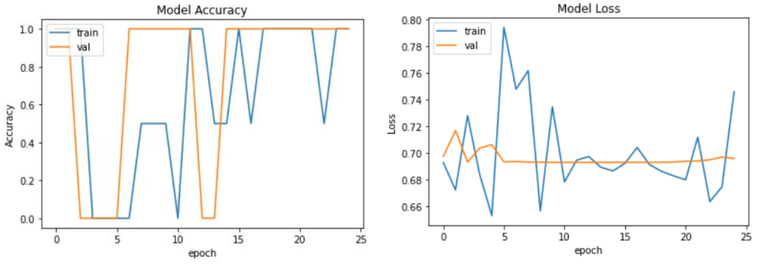
- Traditional OCR technologies fall short when it comes to comprehending handwritten text. I, therefore, suggested a model that makes use of TensorFlow's flexibility and deep learning capabilities. First, we preprocessed the dataset by resizing and turning the images to grayscale. Then, we utilized a combination of convolution layers, max-pooling layers, and fully connected layers to build a convolutional neural network (CNN) architecture that would recognize and digitize handwritten text, leading to an accurate prescription.



Results:

- Despite a few dataset input size concerns and not being able to achieve the desired accuracy, I was able to produce some impressive results. The algorithm was able to recognize and digitize a significant number of handwritten texts.
- The model was trained over a total of 25 epochs. It is clear that the test accuracy of the model after each epoch varied. Validation accuracy was always slightly more than training accuracy. By the end of the 25th epoch, the training accuracy had reached the validation accuracy.

```
Epoch 1/25
1/1 [==============================] - 28s 28s/step - loss: 0.6930 - accuracy: 1.0000 - val_loss: 0.6977 - val_accuracy: 1.0000
Epoch 2/25
1/1 [==============================] - 0s 289ms/step - loss: 0.6725 - accuracy: 1.0000 - val_loss: 0.7170 - val_accuracy: 1.000
0
Epoch 3/25
1/1 [==============================] - 0s 316ms/step - loss: 0.7281 - accuracy: 1.0000 - val_loss: 0.6933 - val_accuracy: 0.000
0e+00
Epoch 4/25
1/1 [==============================] - 0s 314ms/step - loss: 0.6841 - accuracy: 0.0000e+00 - val_loss: 0.7038 - val_accuracy:
0.0000e+00
Epoch 5/25
1/1 [==============================] - 0s 321ms/step - loss: 0.6533 - accuracy: 0.0000e+00 - val_loss: 0.7064 - val_accuracy:
0.0000e+00
Epoch 6/25
1/1 [==============================] - 0s 323ms/step - loss: 0.7942 - accuracy: 0.0000e+00 - val_loss: 0.6935 - val_accuracy:
0.0000e+00
Epoch 7/25
1/1 [==============================] - 0s 329ms/step - loss: 0.7479 - accuracy: 0.0000e+00 - val_loss: 0.6938 - val_accuracy:
1.0000
Epoch 8/25
1/1 [==============================] - 0s 312ms/step - loss: 0.7618 - accuracy: 0.5000 - val_loss: 0.6934 - val_accuracy: 1.000
0
```



- In addition, despite fluctuations in the training loss, the validation loss remained consistently low.

Conclusion:

- While the system's accuracy was not as great as we had planned, it was still a significant move forward in the field of handwritten text recognition.
- In the future, the model can be enhanced and made more accurate and efficient by additional experimentation.
- The project could have a substantial influence on patient care outcomes and assist healthcare organizations in better serving their patients.