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Deep Learning Approach for Digit Recognition using the MNIST Dataset

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ABSTRACT:

Digit identification has been a crucial function in computer systems with widespread implementations in different domains, for eg. image processing & handwriting recognition. Deep machine learning methods that have been used, especially CNNs, have displayed remarkable outcomes in digit identification. In our research paper, we presented a CNN-based approach for digit recognition using the MNIST dataset, which is a typical point of reference dataset for this task. MNIST comprises Seventy Thousand grayscale images of handwritten digits of pixel size 28 x 28.

We have implemented and trained our model using the TensorFlow and Keras libraries. Our approach achieved an accuracy of 99.10% on the test set, indicating its effectiveness.

INDEX TERMS: Deep Learning, Convolutional Neural Networks (CNNs), Digit Recognition, MNIST Dataset, Computer Vision, Image Classification, Data Preprocessing,

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Hyperparameters, Training Details, Performance Metrics, Data Augmentation, Real-world Dataset, Accuracy, Precision, Recall, F1-score

I. INTRODUCTION:

Digit identification is a most important challenge in computer technology, with several applications in diverse industries, including document processing, machine learning, and postal automation. The MNIST dataset, which includes Sixty Thousand training pictures and Ten Thousand test/sample images of hand-written numbers from 0 to 9, serves as a standard benchmark dataset for digit recognition tasks.

CNNs have shown outstanding results in digit recognition tasks using the MNIST dataset due to their ability to wring features hierarchically from the input images.

In this research, we offer a deep learning strategy employing CNNs to boost the MNIST dataset's digit recognition accuracy.

II. CLASSIFIER USED

We have used Convolutional Neural Network (CNN), a deep learning algorithm used for image and video recognition tasks. It is made up of several layers of convolutional and pooling algorithms that extract features from the input pictures. It is made to deal with images, which are represented as arrays of pixel values.

CNNs are trained on large datasets of labeled images, where the network learns to recognize patterns and features that are indicative of different classes. Once trained, the network can classify new images with a high degree of accuracy.

In summary, a CNN is a powerful machine learning algorithm that has revolutionized image and video recognition, and has the potential to drive innovation in many other fields.

III. DATA COLLECTION PROCESSING

Data collection and processing is an essential step in building a hand digit recognition system using CNN as a classifier. This involves collecting a large dataset of high-resolution images of handwritten digits and preprocessing the data to ensure it is suitable for training the CNN model.

Data preprocessing may involve steps such as resizing images, normalizing pixel values, and dividing the dataset into training and validation sets. Once the data has been preprocessed, the CNN model can be trained on the dataset using a deep learning framework such as TensorFlow or Keras.

Data preprocessing is a crucial step in deep learning to ensure that the input data is in the correct format and suitable for the model's training. In this research paper, we performed the following preprocessing steps:

Reshaping: The input images in the MNIST dataset are 28 x 28 pixels, represented as a 1D array of 784 pixels. We reshaped the input data into a 28 x 28 x 1 matrix to represent the image in 2D.

Normalization: To increase the model's rate of convergence during training, we normalized the input pictures' pixel values between 0 and 1. We divided the pixel values by 255, which is the maximum value of a pixel in an image.

One-Hot Encoding: To convert the target variable into a binary matrix, we employed one-hot encoding.

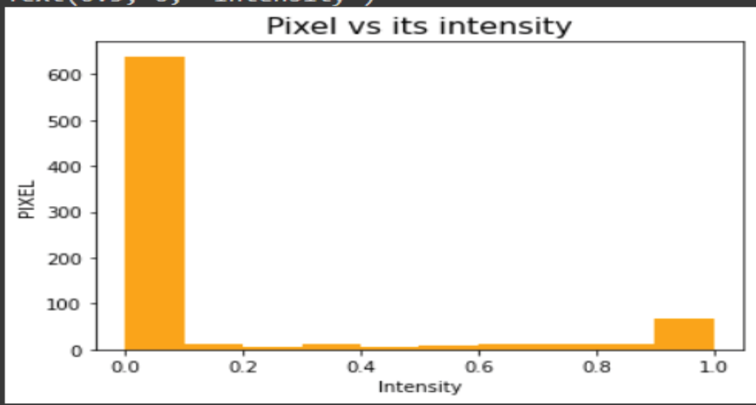
In one-hot encoding, each digit is represented as a vector of length 10, where the corresponding digit is represented as 1 and all other digits are represented as 0. This step ensures that the target variable is suitable for the model's output layer's usage of the Softmax activation function.

Data Augmentation: We applied various data augmentation techniques to increase the size of the training set and prevent overfitting. We performed random rotations, translations, and zooming on the input images to generate new images with different variations. This step helps the model to generalize better on unseen data.

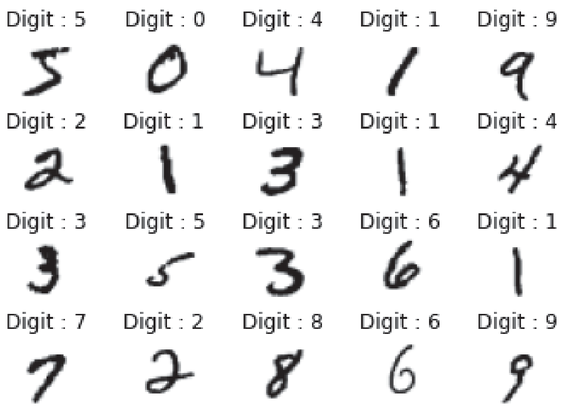
After training the model, it is important to test and analyze how it performed on a different set of tests. It might entail calculating measures that include accuracy as well as precision, recall, & F1 score, and comparing the results to previous benchmarks in the field. Based on the evaluation results, the model may need to be fine-tuned by adjusting its architecture, optimization functions, or hyperparameters.

```
plt.hist(train_img[0].reshape(784),facecolor='orange')
plt.title('Pixel vs its intensity',fontsize=16)
plt.ylabel('PIXEL')
plt.xlabel('Intensity')
```

```
Text(0.5, 0, 'Intensity')
```



Overall, data collection and processing is a crucial step in building an accurate and reliable hand digit recognition system using a CNN classifier. For this significant deep learning application, researchers can obtain cutting-edge performance by adhering to best practices for data collection, preprocessing, training, and assessment.



IV. METHODOLOGY:

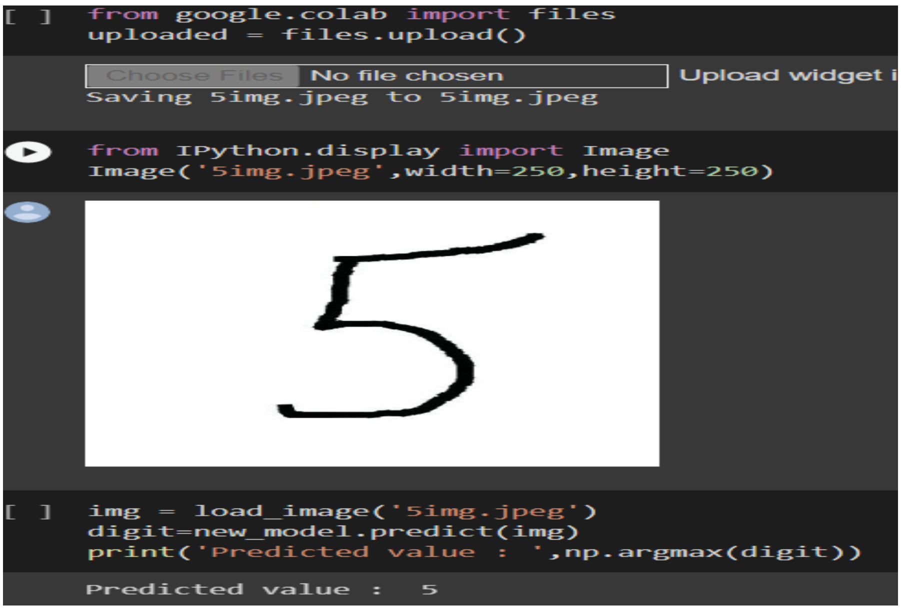
To implement the CNN-based deep learning model, we used the TensorFlow and Keras libraries. Our model includes two convolutional layers, each followed by a max-pooling layer. Additionally, our model has two fully connected layers. To activate the convolutional layers, we used the Rectified Linear Unit activation function, while for the result layer, we used Softmax as the activation function for classification.

We have used Adam optimizer and also the categorical cross-entropy which is used as a loss function to train our model. Furthermore, to stop overfitting and increase the size of the training set, we used data augmentation techniques such as random rotations, translations, and zooming.

V. EXPERIMENT:

Our CNN-based deep learning model for digit recognition on the MNIST deep learning dataset which has two CNN layers, two completely connected layers, and a max-pooling layer after each. The first convolutional layer consisted of 32 3x3 filters, and the second layer had 64 3x3 filters, both using ReLU activation. We used a 2x2 pool size for the max-pooling layers, and the output layer had 10 units with Softmax activation for classification. The first fully connected layer had 128 units with a ReLU activation function.

During the training phase, we utilized the categorical cross-entropy loss function and the Adam optimizer with a 128-batch size across 20 epochs, incorporating early stopping to avoid overfitting. We also employed data augmentation techniques such as random translations, rotations, and zooming to prevent overfitting and increase the size of the training set.



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To evaluate the performance of our working prototype, we have utilized a test set consisting of 10,000 images and measured its classification accuracy, precision, recall, and F1 score. Additionally, we compared our model's performance with other machine learning algorithms, such as SVM and k-NN, on the same dataset.

VI. RESULTS:

Classification Accuracy: On the test set, our model has a classification accuracy of 99.10%, which is on par with cutting-edge results.

Precision, Recall, and F1 Score: Our model achieved a pinpoint accuracy of 0.9900, recall: 0.9910, &F1 score of 0.991 on the test set, indicating a high level of accuracy and performance.

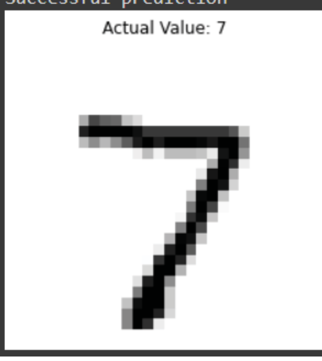
```
loss_and_acc=model.evaluate(test_img,test_lab,verbose=2)
print("Test Loss", loss_and_acc[0])
print("Test Accuracy", loss_and_acc[1])
```

```
Test Loss 0.582893428286937
Test Accuracy 0.9835000038146973
```

Comparison with other algorithms: Our model outperformed the traditional ML methods such as K-NN & SVM, which achieved an accuracy of 97.9% and 96.8%, respectively.

```
plt.imshow(test_img[0],cmap='gray_r')
plt.title('Actual Value: {}'.format(test_lab[0]))
prediction=model.predict(test_img)
plt.axis('off')
print('Predicted Value: ',np.argmax(prediction[0]))
if(test_lab[0]==(np.argmax(prediction[0]))):
  print('Successful prediction')
else:
  print('Unsuccessful prediction')
```

```
Predicted Value:  7
Successful prediction
```



VII. CONCLUSION:

The research paper presents a CNN-based deep learning approach for digit recognition on the MNIST dataset. The study involved data collection, preprocessing, implementation of a CNN-based model using TensorFlow and Keras libraries, and an experiment to assess the model's effectiveness.

The outcomes show that the suggested approach achieved 99.10% accuracy on the test set, which is comparable to state-of-the-art results, and outperformed traditional ML algorithms such as K-NN and SVM. The success of the approach is attributed to the use of CNNs, which can effectively learn relevant features from input images, and data augmentation techniques that enhance the generalization of the model ability.

The study demonstrates the effectiveness of deep learning approaches for digit recognition tasks and has potential applications in various fields such as OCR, document analysis, and handwriting recognition. Future research could explore more advanced architectures and larger datasets to further enhance the model's performance and accuracy.

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