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DIGITDETECT: A CNN-BASED SYSTEM FOR MANUAL HANDWRITING RECOGNITION

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ABSTRACT
The project "DigitDetect: A Handwritten Digit Recognition Using CNN" focuses on developing an advanced system for recognizing handwritten digits with high accuracy. Leveraging Convolutional Neural Networks (CNNs), the system overcomes the challenges faced by traditional methods like K-Nearest Neighbors (KNN), such as variations in handwriting styles, sizes, and orientations. By using the MNIST dataset comprising 28x28 grayscale images, the model undergoes data preprocessing and augmentation, ensuring robust generalization. This approach highlights the efficiency of CNNs in automatically extracting meaningful features, making them ideal for improving performance and reliability in handwritten digit recognition tasks.

Keywords
Handwritten Digit Recognition, Convolutional Neural Network (CNN), Modified National Institute of Standards and Technology (MNIST) Dataset, Feature Extraction, Classification, Deep Learning, Image Recognition, Data Augmentation.

1. INTRODUCTION
Handwritten digit recognition involves identifying and converting handwritten numbers into a digital format. This technology is widely used in applications such as banking systems, automated data entry, and postal address recognition. The process requires analyzing shapes, patterns, and orientations to mimic human recognition, which is challenging due to the diverse styles and variations in handwriting. Addressing these variations demands advanced techniques capable of handling such complexities effectively.

Traditional methods for handwritten digit recognition, such as K-Nearest Neighbors (KNN), rely on manually extracted features and pixel-based comparisons. While effective to some extent, these approaches struggle with noisy data, varying sizes, and unseen handwriting styles. To overcome these limitations, this project utilizes Convolutional Neural Networks (CNNs), which excel at automatically extracting features and learning complex patterns. This approach ensures improved adaptability and accuracy, making the system reliable for real-world scenarios.

2. LITERATURE SURVEY
a) Handwritten Digit Recognition using Machine and Deep Learning Algorithms:
https://www.researchgate.net/publication/343054680_Handwritten_Digit_Recognition_using_Machine_and_Deep_Learning_Algorithms
With the advent of deep learning and machine learning algorithms, humans have never been more reliant on technology; these systems can now add sound to silent movies and identify objects in images. Research and development into handwritten text recognition is another significant and promising area. One way computers may interpret handwritten data is by handwriting recognition (HWR), which is

also called handwritten text recognition (HTR) [1]. In order to identify handwritten numbers in MNIST datasets, I think this research employs SVM, MLP, and CNN models. In order to determine the best digit recognition model, this study evaluates the aforementioned models' accuracy and execution time.
b) Automatic prediction of age, gender, and nationality in offline handwriting:
https://www.researchgate.net/publication/265592404_Automatic_prediction_of_age_gender_and_nationality_in_offline_handwriting
The classification of handwriting based on gender, age, and country of origin serves several purposes. Handwriting classification helps forensics investigators zero down on certain writers. There has been a dearth of research on this subject. The process of handwriting demographic categorisation includes extracting features and then classifying them. Because feature extraction influences system performance, characterisation of features allows authors to be recognised. In this study, we present a plethora of geometric criteria for the purpose of characterising and categorising handwritings according to age, gender, and country. Kernel discriminant analysis and random forests both use feature fusion. When all writers use the same handwritten text, the QUWI dataset reveals a gender classification rate of 74.05%, an age range classification rate of 55.76%, and a nationality classification rate of 53.66%. However, when writers use various styles, the rates drop to 73.59%, 60.62%, and 47-98%, respectively.
c) Handwritten Recognition Using SVM, KNN and Neural Network:
https://www.researchgate.net/publication/313247443_Handwritten_Recognition_Using_SVM_KNN_and_Neural_Network
With the use of handwriting recognition (HWR), computers can decipher handwritten text from a variety of media, including paper, photographs, and touch displays. In this piece, we will learn how to identify handwriting using SVM, KNN, and a Neural Network.
d) The Recognition of Handwritten Digits Based on BP Neural Network and the Implementation on Android:
https://ieeexplore.ieee.org/document/6455316
A hot subject in the fields of pattern recognition and image processing is offline handwriting recognition. Its many uses include cheque recognition, mail sorting, assistive reading devices for the visually impaired, and more. To identify handwritten numbers, this research employs feature extraction from Back Propagation (BP) neural networks. In order to train and test the neural network, the MNIST handwritten digit database is utilised. For feature extraction, we also suggest Principal Component Analysis (PCA), which speeds up training time for neural networks and increases their performance. On the other hand, we evaluate Fisher discriminant analysis, a neural network, and a set of thirteen attributes to see which one achieves the highest recognition rate. These algorithms will be ported to Android in due time.
e) Backpropagation Applied to Handwritten Zip Code Recognition:
https://ieeexplore.ieee.org/document/6795724
Learning networks are able to generalise better when given specific tasks to complete. This research demonstrates, via the use of network design, how to include such constraints into a backpropagation network. This approach has been used by the USPS to recognise handwritten zip code digits. From character normalisation to classification, a single network learns the whole recognition process.

3. METHODOLOGY

3.1 Proposed Work

The proposed system addresses the limitations of traditional methods like KNN by using CNNs for handwritten digit recognition. Artificial neural networks (CNNs) automatically extract visual data, assisting the model in comprehending intricate patterns and structures. This deep learning approach enhances accuracy by handling diverse handwriting styles, sizes, orientations, and distortions, ensuring better adaptability and performance in real-world scenarios.

3.2 System Architecture

The architecture of the "DigitDetect" system is based on Convolutional Neural Networks (CNNs), which are designed to process and analyze image data effectively. Three types of layers are used in deep learning: convolutional, pooling, and fully connected. The former two minimise spatial dimensions while keeping vital information, while the latter two categorise. These layers automatically detect shapes, curves, and edges after converting pictures from the MNIST collection to greyscale (28x28 pixels). Dropout layers are used to prevent overfitting, and an activation function like ReLU enhances non-linear learning. Finally, the softmax function is applied to output the probabilities of each digit, enabling precise classification.

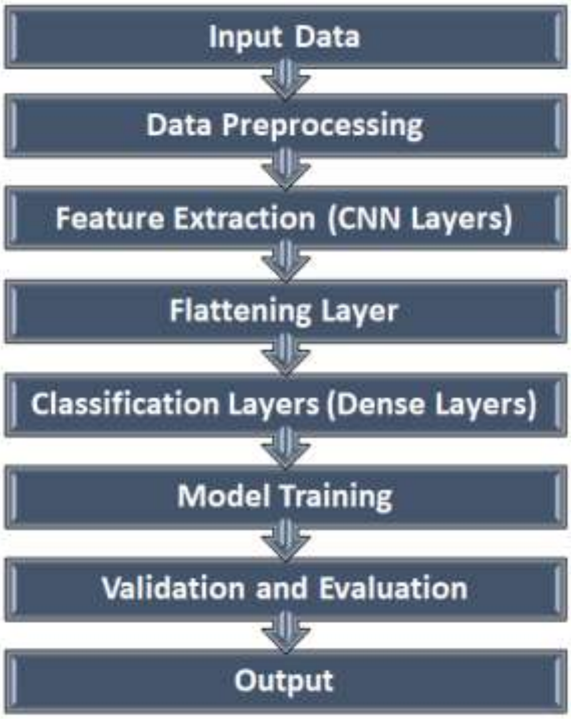

Figure 1: Proposed architecture

3.3 Modules & WorkFlow

3.3.1 Input Layer

- The input to the model consists of grayscale images of handwritten digits from the MNIST dataset, each resized to 28x28 pixels.

3.3.2 Data Pre-processing

- Normalization: In order to improve the performance of the model, the pixel values are adjusted to 0-1 by dividing them by 255.
- Reshaping: The images are reshaped from a 1D vector to a 28x28x1 format to make them suitable for processing by CNN.

3.3.3 Data Augmentation

- Rotation: Random rotations within ±15° are applied to simulate various angles of handwriting.
- Zooming: A zoom range of 0.01 is used to enhance the model's robustness against varying image sizes.
- Shifting: The images are shifted horizontally and vertically within 10% of their width and height to simulate minor shifts in writing.

3.3.4 Feature Extraction (CNN Layers):

- Conv2D: Through the use of convolutional layers, hierarchical features such as shapes, textures, and edges may be retrieved from images.
- MaxPooling2D: In order to reduce computational effort without sacrificing key qualities, Max Pooling layers decrease the size of the feature map.
- Batch Normalization: Batch normalization is applied to normalize activations, speeding up training and improving model stability.

3.3.5 Flattening Layer

- The 2D feature maps generated by the convolutional layers are flattened into a 1D vector, preparing the data for fully connected layers.

3.3.6 Classification (Dense Layers)

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- Following the collection of features by the convolutional layers, the fully linked layers conduct analysis.
- Incoming photos are sorted into 10-digit groups (0-9). This is done via a Softmax output layer.

3.3.7 Model Training

- Optimizer: As training progresses, the Adam optimiser modifies the model's weights.
- Loss Function: Categorical cross-entropy is the loss function for multi-class classification.
- Epochs: If the validation accuracy stops improving, training might finish early after 50 epochs.
- Batch Size: During training, 128 batches are utilised for maximum learning.

3.3.8 Validation and Evaluation

- The performance of the handwritten digit recognition model is evaluated on the MNIST test set to assess its performance.
- Performance Metrics: Using confusion, loss, and accuracy matrices, we measure how well the model performs.
- Final Accuracy: Through extensive training and testing, the model consistently achieves an accuracy exceeding 99% on the test set.

3.4 Algorithms

3.4.1 K-Nearest Neighbour

Traditional handwritten digit recognition systems often rely on algorithms like K-Nearest Neighbors (KNN). This algorithm classifies input images by comparing their features with a predefined training set. The classification is based on pixel-based features or basic image processing techniques, where the algorithm identifies the closest matches from the training data. However, KNN struggles with variations in handwriting styles, orientations, and noisy or unseen data, which limits its real-world applicability and accuracy.

3.4.2 Convolutional Neural Network

The proposed system leverages CNNs to overcome the limitations of traditional algorithms like KNN. CNNs automatically extract meaningful features from input images, eliminating the need for manual feature extraction. CNNs use deep learning techniques like pooling and fully connected layers to understand complex patterns and structures in data. This deep learning approach enables the system to handle diverse handwriting styles, distortions, and orientations, ensuring improved adaptability and accuracy in recognizing handwritten digits.

4. EXPERIMENTAL RESULTS

Figure 2: MNIST Dataset

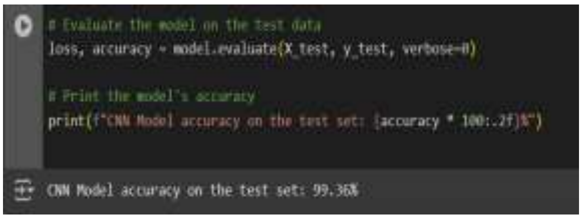

Figure 3: CNN Accuracy

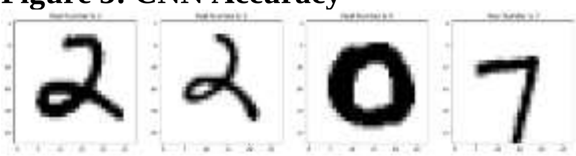

Figure 4: Sample Handwritten Input

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Figure 5: Accuracy Graph

5. CONCLUSION

Lastly, the results of the handwritten digit identification experiment demonstrate that the MNIST digits may be successfully categorised using Convolutional Neural Networks. This model demonstrates the remarkable accuracy with which deep learning can resolve practical problems. Banks, automated data extraction, invoice processing, and postal code recognition can all benefit from this system's enhanced efficiency and decreased need for human interaction. The results of this research demonstrate the potential automation of processes and broader uses of machine learning.

6. FUTURE SCOPE

The "DigitDetect" system has significant potential for expansion and enhancement. Future developments could involve training the CNN model on larger and more diverse datasets to improve its ability to recognize digits in various languages and scripts. Integrating the system with real-time applications, such as mobile devices and automated banking systems, could enhance its practical utility. Furthermore, optimizing the architecture for faster processing and reduced computational cost would make it more suitable for edge devices. Exploring transfer learning and advanced deep learning techniques can further boost accuracy and adaptability, enabling the system to perform effectively in challenging scenarios with complex handwriting styles or noisy inputs.

7. REFERENCES

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