AI SATURDAYS
COHORT 8

TEAM ANOMAH-NGU

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<u>INTRODUCTION</u>

Object recognition has become one of the most explored and fundamental fields in machine learning. It includes things like pest detection, facial identification and decoding of handwritten information.

Optical character recognition (OCR) is the use of technology to distinguish printed or handwritten text characters inside digital images of physical documents, such as a scanned paper document. (TechTarget, 2022).

For more than 10 years, in many applications and identification algorithms, digit recognition has been efficiently investigated in the area of OCR handwriting.

Handwritten digit recognition is a significant area within the field of computer vision and machine learning, focused on the task of accurately identifying and interpreting handwritten digits. This technology involves training a computer system to recognize and classify handwritten digits into their respective numerical representations (0-9). The primary goal is to automate the digit recognition process and facilitate various applications where digit identification is essential.

Handwritten digit recognition is a prevalent multiclass classification problem usually built into the software of mobile banking applications, as well as more traditional automated teller machines, to give users the ability to automatically deposit paper checks. Here, each class of data consists of several handwritten versions of a single digit in the range $0 - 9$, giving a total of ten classes. Handwriting character recognition has become a common area of research because of developments in technology such as handwriting recording tools and powerful mobile computers. Because handwriting is highly dependent on the writer, however, it is challenging to develop a highly reliable recognition system that recognizes every handwritten character input to an application.

IMPORTANCE OF HANDWRITTEN DIGIT RECOGNITION:

- Data Digitization: Handwritten digit recognition helps in converting analog data, such as handwritten forms, surveys, or historical documents, into digital format for easier storage, analysis, and processing.
- Automation and Efficiency: Automation of digit recognition in forms, checks, or other documents leads to increased efficiency by reducing manual labor and potential errors associated with human transcription.
- Human-Computer Interaction: Handwritten digit recognition is crucial for developing intuitive interfaces where users can input numerical data using stylus or touchscreens, enhancing user experience in devices like tablets and smartphones.

- Information Retrieval: Handwritten digit recognition supports efficient information retrieval in libraries, archives, and databases containing handwritten material, making historical or rare documents more accessible and searchable.

APPLICATIONS OF HANDWRITTEN DIGIT RECOGNITION:

- Optical Character Recognition (OCR): Handwritten digit recognition is a fundamental component of OCR systems used to convert handwritten documents, receipts, or forms into editable and searchable text.
- Automated Banking and Finance: Automatic recognition of handwritten digits in checks, forms, or financial documents speeds up processing in the banking sector, improving accuracy and reducing manual effort.
- Postal Services and Address Recognition: Handwritten digit recognition assists in automated sorting and routing of mail by reading handwritten zip codes, addresses, and postal codes.
- Digitization of Historical Documents: Handwritten digit recognition plays a vital role in digitizing historical documents, manuscripts, and old records, preserving them in digital form and enabling wider access.
- Digital Note-Taking and Education: In educational settings, handwritten digit recognition can be used to convert handwritten notes, equations, or mathematical solutions into digital formats for easy sharing and collaboration.
- Medical Record Keeping and Analysis: Digitizing handwritten medical records and prescriptions aids in efficient record-keeping, data analysis, and automated prescription filling systems.

POTENTIAL IMPACT IN VARIOUS FIELDS:

- Healthcare: Improved accuracy and efficiency in medical record-keeping and prescription management, leading to enhanced patient care and safety.
- Finance and Banking: Faster processing of financial documents and checks, reducing processing times and improving customer satisfaction.
- Education: Enhanced learning experiences by digitizing handwritten notes and facilitating interactive educational platforms for students and educators. recognition can be applied in educational settings for grading, evaluation, and analysis of handwritten assignments and exams. This can save educators valuable time and provide students with quicker feedback on their work. It could help reduce bias in grading.
- Archives and Libraries: Preservation and accessibility of historical and cultural documents, allow researchers and historians to study and learn from the past.
- Logistics and Postal Services: Streamlined sorting and delivery processes, improving the efficiency and accuracy of mail handling and package deliveries.

The impact of handwritten digit recognition extends to various domains, from improving operational efficiency and customer service to preserving historical records and promoting accessibility. Handwritten digit recognition continues to evolve with advancements in machine learning, neural networks, and deep learning, further enhancing its accuracy, speed, and versatility in real-world applications across multiple domains.

PROBLEM DESCRIPTION

Handwritten digit recognition is a challenging and significant problem in the fields of machine learning and artificial intelligence. The core objective of this project is to develop a system capable of accurately identifying and classifying handwritten digits (ranging from 0 to 9) into their respective numeric representations. This problem involves several key aspects and challenges. Here are some of the likely problems and potential solutions:

Complexity of Handwriting -Styles and Quality:
Problem: Handwriting is highly variable from person to person, even for the same digit, due to differences in writing styles, sizes, slant, and spacing. The system needs to be robust and smart enough to handle this variability and still produce accurate results.
Solution: Incorporating diverse training data from various sources to expose the model to a wide range of handwriting styles, or utilizing models that can adapt to different writing styles.

Ambiguities and Similar-looking Digits:
Problem: Digits like '1' and '7' or '9' and '4' can look similar, leading to confusion in recognition.
Solution: Enhancing the model's ability to distinguish similar-looking digits by incorporating contextual information and leveraging more advanced algorithms such as recurrent neural networks (RNNs) or convolutional neural networks (CNNs).

Noisy Data and Irregular Shapes:
Problem: Noise, smudging, or irregular shapes in the handwritten digits can introduce inaccuracies during recognition.
Solution: Preprocessing techniques like image denoising, edge detection, and contour analysis can help in cleaning and preparing the input data for better recognition performance.

Overfitting and Generalization:
Problem: Overfitting occurs when the model becomes overly specialized to the training data and performs poorly on unseen data.
Solution: Implementing techniques such as regularization, cross-validation, and early stopping to prevent overfitting and ensure the model generalizes well to unseen data.

Limited Training Data:

Problem: Insufficient training data can hinder the model's ability to generalize effectively, especially when dealing with rare or specific handwriting styles.

Solution: Acquiring or generating additional diverse training data, employing data augmentation techniques, or using transfer learning from related tasks to improve model performance.

Computation and Speed:

Problem: Real-time applications may require fast recognition, posing challenges in achieving low-latency predictions.

Solution: Optimizing the model architecture, leveraging hardware acceleration (e.g., GPUs, TPUs), and implementing efficient algorithms to speed up the recognition process.

PROPOSED METHOD

The proposed strategy is intended to follow the Data Science/Machine Learning (DS/ML) pipeline, covering the stages of data sourcing, data cleaning and preparation, machine learning model development, and model deployment.

Data Sourcing
MNIST Dataset:

Utilize the MNIST dataset, a standard benchmark dataset for handwritten digit recognition.. The dataset will be sourced from reliable sources such as Kaggle or directly from the MNIST dataset provider.

Data source 1: containing 60,000 training images and 10,000 testing images
https://www.kaggle.com/datasets/avnishnish/mnist-original

Data source 2: containing 42,000 training images and 28,000 testing images
https://www.kaggle.com/competitions/digit-recognizer/data

Data Cleaning and Preparation
Data Preprocessing:

Conduct preprocessing tasks including normalization, reshaping, and feature extraction to enhance the quality of the dataset and prepare it for model training. This ensures that the input data is consistent, relevant, and optimal for the machine learning model.

Feature extraction strategies such as direction feature, chaincode feature, gradient feature, etc., would be considered.

Handling Imbalanced Data (if applicable):

Address any imbalances in the dataset to ensure that the model is not biased towards the majority class, thus improving its ability to accurately predict all digits.

Machine Learning Model

Convolutional Neural Network (CNN):

Implement a CNN architecture, a proven and efficient approach for image recognition tasks. The model will be designed with appropriate layers, activation functions, and optimization techniques to effectively learn features from the preprocessed images.

Hyperparameter Tuning:

Conduct hyperparameter tuning using techniques like grid search or random search to optimize the model's performance and find the best set of hyperparameters.

Model Evaluation and Validation:

Evaluate the model's performance using metrics such as accuracy, precision, recall, and F1-score. Utilize techniques like cross-validation to validate the model's robustness.

Model Deployment

Web Application Interface:

Develop a user-friendly web application where users can draw digits and the trained CNN model will predict the handwritten digit in real-time.

Integration with Backend: Integrate the trained CNN model into the web application's backend using appropriate frameworks and libraries, allowing seamless prediction of handwritten digits.

User Guide and Documentation:

Provide comprehensive documentation and a user guide for the web application, explaining how to use it and interpret the results.

What Sets Our Approach Apart?

Our project differentiates itself by adhering to the DS/ML pipeline while focusing on the MNIST dataset, a gold standard in handwritten digit recognition. We plan to leverage the proven efficiency of CNNs, implementing hyperparameter tuning to achieve the best model performance. The integration of the model into a web application ensures accessibility and real-world applicability, allowing users to experience the utility of our solution interactively.

Through this comprehensive approach, we aim to demonstrate proficiency in handling the complete data science lifecycle, from data sourcing and cleaning to machine learning model development and deployment. Our emphasis on robustness, accuracy, and usability sets us apart, making our Handwritten Digit Recognition solution a valuable asset.

PROPOSED SPLIT

Data Sourcing Sub team: Mofiyinfoluwa Aladesuyi

Data Cleaning and Preparation sub team: Taiwo Olorunnishola, Mofiyinfoluwa Aladesuyi

Model Sub team: Victor Bassey, Mukhtar Abdulquadir

Model Deployment sub team: Taiwo Olorunnishola, Mukhtar Abdulquadri, Victor Bassey, Mofiyinfoluwa Aladesuyi

CONCLUSION

This project represents a joint endeavor with large potential to improve the operations of various industries as well as cause a shift forward for Machine Learning and Artificial Intelligence as a whole. Recognizing handwritten digits is not only a problem for academic settings but a challenge present in many practical applications of our daily lives.

It is quite essential to recognize that the challenges associated with carrying out this project are worthy of note, from the data preprocessing and model training to the deployment requirements. However, with the assured assistance of our mentor, we are committed to overcoming these challenges while garnering knowledge and skills, and seeing through this project as one step further for technology.

References

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