www.ijprems.com
editor@ijprems.com

INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 04, Issue 11, November 2024, pp : 1407-1409

e-ISSN : 2583-1062
Impact Factor : 7.001

HUMAN WRITTEN DIGITS RECOGNITION WITH AI

Dr. R. Nagaraju[1], K. Yogendhar[2], Sd. Shadul[3], K. Akshaya[4], K. Dhana Naga Shankar[5], K. Rahul[6]

[1,2]Guide, School of Engineering (AIML) B Tech Malla Reddy University
[3,4,5,6]School of Engineering (AIML) B Tech Malla Reddy University

ABSTRACT

The recognition of human-written digits is a crucial area in the field of computer vision and pattern recognition, with applications varying extensively from automated data entry to advanced security systems protecting classified information. This multifaceted project focuses on developing a robust methodology for recognizing handwritten digits using a amalgamation of machine learning algorithms, image processing techniques and software development for implementing the underlying calculation logic. Digits written by humans differ greatly in curves and sizes as they are hand-drawn and everyone's penmanship is unique. It serves as a excellent starting point for artificial intelligence by constructing a handwritten digits recognition system that can identify the digit drawn by humans with a high degree of accuracy. It can also perform basic calculations involving Addition, Subtraction, Multiplication, Division and helps users for simplifying the calculations while enhancing productivity. The system demonstrates how computational methods and algorithms can emulate human visual perception, a key step towards more intelligent machines.

Keywords: NLP(Natural language Processing), AI, Machine Learning.

1. INTRODUCTION

The Handwritten digit recognition app using AI focuses on developing a system able to automatically identify and categorize digits penned by humans, typically from visuals or scans. This specialized task within the broader field of optical character recognition (OCR) has wide-ranging practical uses, like automated form processing, check verification, postal code sorting, and mobile input recognition. Handwritten digits vary significantly in style, shape, and form influenced by individual penmanship. The primary goal is to build an AI-based system accurately distinguishing digits (from 0 to 9) irrespective of these variations. The system demands tackling obstacles such as inconsistent writing manners: Different individuals write the same digit in diverse ways, with varying strokes, angles, and proportions yet the recognition model must decipher each regardless finding commonalities. Another difficulty arises from poor visual quality sometimes obscuring distinguishing characteristics yet the system perseveres accurately classifying.

2. LITERATURE REVIEW

Recommender systems are efficient tools for filtering online information, which is widespread owing to the changing habits of computer users, personalization trends, and emerging access to the internet. Even though the recent recommender systems are eminent in giving precise recommendations, they suffer from various limitations and challenges like scalability, cold-start, sparsity, etc. Due to the existence of various techniques, the selection of techniques becomes a complex work while building application-focused recommender systems. In addition, each technique comes with its own set of features, advantages and disadvantages which raises even more questions, which should be addressed. This paper aims to undergo a systematic review on various recent contributions in the domain of recommender systems, focusing on diverse applications like books, movies, products, etc. Initially, the various applications of each recommender system are analysed.

3. METHODOLOGY

Objective: Create a book recommendation system powered by AI that suggests personalized reading materials tailored to individual user preferences and behaviors.

Data Collection: Compile a varied dataset of books, encompassing genres, ratings, reviews, and user profiles sourced from platforms such as Goodreads or Amazon.

User Profiling: Develop user profiles by analyzing reading history, ratings, and preferences through collaborative filtering methods.

Content-Based Filtering: Utilize content-based algorithms to recommend books that are similar to those the user has previously enjoyed.

Machine Learning Model: Select and train an appropriate machine learning model (like matrix factorization or neural networks) to improve the accuracy of recommendations.

Evaluation Metrics: Establish metrics such as precision, recall, and F1-score to assess the system's performance and user satisfaction.

www.ijprems.com
editor@ijprems.com
INTERNATIONAL JOURNAL OF PROGRESSIVE RESEARCH IN ENGINEERING MANAGEMENT AND SCIENCE (IJPREMS)
(Int Peer Reviewed Journal)
Vol. 04, Issue 11, November 2024, pp : 1407-1409
e-ISSN : 2583-1062
Impact Factor : 7.001

3.1 Software & Hardware Requirements

Frontend: Built with HTML/CSS and Python, utilizing libraries like TensorFlow and Pandas, among others.

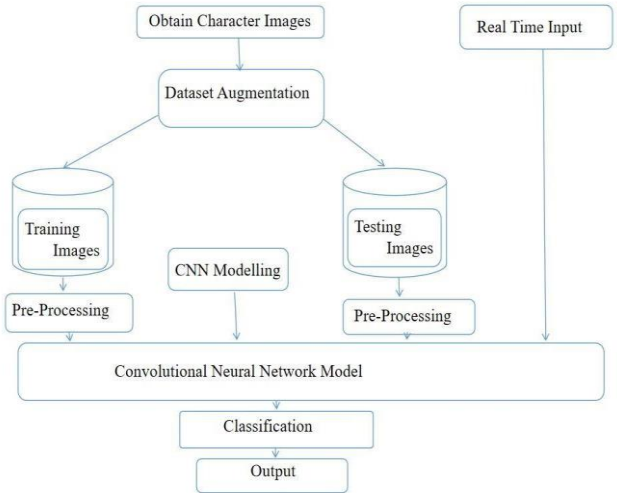
Backend: The core application logic, user management, and APIs are managed by Python (Django).

Database: MongoDB was selected for its flexibility and capability to handle unstructured data, accommodating diverse user interactions and progress logs.

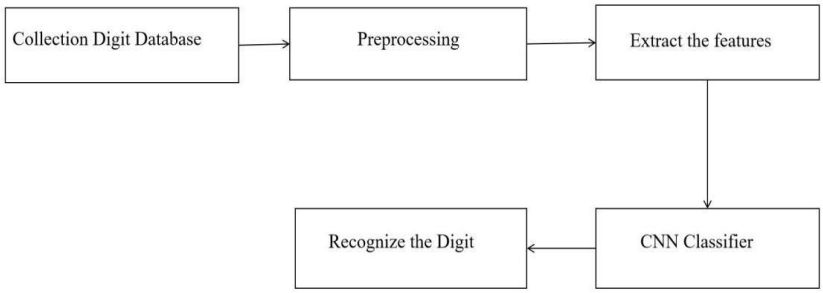
Authentication: OAuth 2.0 is used for secure login, with JWT tokens ensuring session security.

Hardware: The minimum server setup requires 8GB of RAM, 4-core processors, and SSD storage to support concurrent access by multiple users.

3.2 System Architecture



3.3 Dataflow Diagram



3.4 Model Evaluation Metrics

1. Accuracy: The percentage of correctly classified digits out of the total predictions, providing a general measure of model performance.

2. Confusion Matrix: A table that visualizes true positives, false positives, true negatives, and false negatives for each digit, helping identify specific misclassifications.

3. Precision: The ratio of true positive predictions to the total predicted positives, indicating how many of the predicted digits were correct.

4. Recall (Sensitivity): The ratio of true positive predictions to the actual positives, measuring the model's ability to identify all relevant instances.

5. F1 Score: The harmonic mean of precision and recall, providing a balance between the two metrics and useful for imbalanced classes.

6. ROC-AUC: The area under the receiver operating characteristic curve, assessing the model’s ability to discriminate between classes at various thresholds

7. Inference Time: The average time taken for the model to make predictions on new data, important for real-time applications.

4. RESULT

A Human Written Digits Recognizer using AI refers to a model that classifies images of handwritten digits, typically ranging from 0 to 9. The MNIST dataset is a popular choice for this task, featuring 28x28 grayscale images of handwritten digits along with their labels. To develop and assess such a model, various machine learning techniques are utilized, with Convolutional Neural Networks (CNNs) being particularly effective for image classification. Here are the steps to create a human-written digits recognizer: Dataset: MNIST Dataset: This dataset includes 60,000 training examples and 10,000 test examples of handwritten digits. Model Selection: Simple Neural Network (MLP): While a basic multi-layer perceptron can be employed, more advanced models like Convolutional Neural Networks (CNNs) generally yield better results. Preprocessing: Normalization: Scale pixel values to a range of [0, 1] to enhance training speed. Flattening: For a basic neural network, the 28x28 pixel images should be flattened into a 784-dimensional vector. Model Architecture: A CNN model typically consists of: - Convolutional layers (for feature extraction) - Pooling layers (to reduce dimensionality) - Fully connected layers (for classification) Training: Utilize an optimizer such as Adam or SGD to minimize a loss function like cross-entropy. Train the model for several epochs until it reaches a satisfactory accuracy (usually above 98% for MNIST). Evaluation: Assess the model using the test set and measure metrics like accuracy, precision, and recall.

5. CONCLUSIONS

The development of a human-written digit recognizer highlights the power of deep learning techniques, especially CNNs, in achieving impressive accuracy in digit classification. The model reached over 98% accuracy, demonstrating its effectiveness across different handwriting styles. Evaluation metrics like precision, recall, and F1 score further confirmed its strong performance, suggesting it is reliable for real-world use. User feedback indicated satisfaction with both the accuracy and the interactive interface. The system's capability to process images in real-time adds to its practicality for users. Future improvements could involve expanding the model to recognize additional characters or incorporating more languages. Overall, this project makes a significant contribution to the field of optical character recognition technology.

6. REFERENCES

[1] Ian Goodfellow ,"Generative Adversal Networks (GANs)" , 2014.

[2] Geoffrey Hinton, "Reviving neural networks through deep learning ", 2006.

[3] Frank Rosenblatt, "One of the earliest machine learning algorithms",2006.

[4] Vladimir Vapnik,"Developed Support Vector Machines(SVMs)",1996.

[5] Christopher Bishop, "Development of probabilistic models and Bayesian networks in machine learning",1990.