CAPSTONE PROJECT

Handwritten Digit Recognition

PRESENTED BY

STUDENT NAME: VARMA POLKONDA SAIRAM

COLLEGE NAME: AVANTHI INSTITUTE OF ENG. & TECHNOLOGY

DEPARTMENT: COMPUTER SCIENCE ENG.

EMAIL ID:SAIRAMVARMA395@GMAIL.COM

AICTE STUDENT ID: STU67f564c6529611744135366

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PROBLEM STATEMENT

The goal of this project is to develop a deep learning model for the classification of handwritten digits (ranging from 0 to 9) using the MNIST dataset. The MNIST dataset consists of 70,000 labeled grayscale images of handwritten digits, which will be used to train and evaluate the model. The objective is to preprocess the data, design an effective neural network architecture, and evaluate the model's performance in terms of accuracy. This project addresses challenges such as feature extraction from pixel data and the prevention of overfitting.

PROPOSED SOLUTION

The proposed solution for handwritten digit recognition involves the following steps:

1. **Data Preprocessing**:
    - Load the MNIST dataset in CSV format and normalize the pixel values to a range of 0 to 1 by dividing by 255.0.
    - Convert the labels into one-hot encoded format to facilitate multi-class classification.
2. **Model Architecture**:
    - Design a **feed-forward neural network** using **Keras** with the following layers:
        - An **input layer** that accepts a 784-dimensional vector (flattened 28x28 image).
        - One or more **hidden layers** with ReLU activation to introduce non-linearity.
    - An **output layer** with 10 neurons (representing digits 0-9) and a **softmax activation** function to classify the digits into one of the 10 classes.

3.Model Training:

- •Compile the model using the **Adam optimizer** and **categorical cross-entropy loss** function, which is suitable for multi-class classification.
- •Train the model using the training data and validate it on a portion of the dataset to prevent overfitting.

4.Model Evaluation:

- •After training, evaluate the model on the test dataset to assess its accuracy.
- •Visualize the results by comparing predicted labels with true labels for some test images.

5.Optimizations:

- •Experiment with different architectures, learning rates, and batch sizes to improve model performance.
- •Use techniques like **dropout** or **early stopping** to prevent overfitting and enhance generalization.

This solution will build an effective and efficient model for handwritten digit classification based on the MNIST dataset.

SYSTEM APPROACH

1. System Requirements:

- **Hardware**: 4GB RAM (8GB recommended), modern CPU, 1GB disk space, GPU (optional).
- **Software**: Python 3.x, TensorFlow/Keras, Pandas, NumPy, Matplotlib/Seaborn, Scikit-learn, Jupyter Notebook.

2. Libraries Required:

- **TensorFlow/Keras**: For deep learning model (CNN).
- **Pandas**: For data manipulation.
- **NumPy**: For numerical computations.
- **Matplotlib/Seaborn**: For visualization.
- **Scikit-learn**: For data preprocessing and evaluation.

3. Methodology:

1. **Data Collection**: Use MNIST dataset (70,000 images of digits 0–9).
2. **Preprocessing**: Normalize pixel values, one-hot encode labels, split data into training and testing sets.
3. **Model Design**: Build a CNN with convolutional layers, pooling, and fully connected layers, with softmax for classification.
4. **Training**: Use categorical cross-entropy loss, Adam optimizer, and early stopping.
5. **Evaluation**: Measure accuracy, precision, recall, and confusion matrix.
6. **Optimization**: Tune hyperparameters and improve model performance with regularization techniques (e.g., dropout).
7. **Deployment**: Deploy the trained model for real-time digit recognition.

Expected Outcome:

- High accuracy (98–99%) in recognizing handwritten digits.
- Real-time deployment for OCR applications.

ALGORITHM & DEPLOYMENT

- **Load Dataset**: Load MNIST dataset (60,000 training, 10,000 testing images).
- **Preprocess Data**:
- Normalize pixel values to [0, 1].
- One-hot encode labels (0-9).
- **Build CNN Model**:
- Convolutional layers to extract features.
- Max-pooling layers to reduce dimensionality.
- Flatten and fully connected layers for final classification.
- Softmax output layer for digit prediction.
- **Compile Model**: Use **categorical cross-entropy** loss and **Adam** optimizer.
- **Train Model**: Train with epochs (10–20) and batch size (32–64).
- **Evaluate**: Test model accuracy, precision, recall on the test set.
- **Prediction**: Input new handwritten digit and predict using the model.

DEPLOYEMENT

- **Save Model**: Save trained model
- **Web Application**: Use **Flask** or **Django** to create a web interface.
- **Image Upload**: Users upload images, which are processed and fed into the model for prediction.
- **Host**: Deploy the web app on **Heroku**, **AWS**, or **Google Cloud**.
- **Mobile App (Optional)**: Use **TensorFlow Lite** for mobile deployment.
- **Monitor**: Continuously monitor performance and retrain as needed.

RESULT

Expected Result for Handwritten Digit Recognition

The expected result of the handwritten digit recognition model can be broken down into several key metrics and outcomes:

1.Model Accuracy:

- The CNN model, when trained on the MNIST dataset, should achieve an accuracy of around **98%–99%** on the test set. This means the model is correctly predicting the digit in 98 to 99 out of 100 cases.

2.Performance Metrics:

- **Precision, Recall, F1-Score**: These metrics can be computed to evaluate how well the model is performing for each class (digit 0–9).
- **Confusion Matrix**: Provides a detailed view of how well the model classifies each digit. A high number of diagonal elements indicates that the model is correctly identifying the digits.

3.Predictions:

- When fed a new image of a handwritten digit, the model should output the correct digit (0–9).
- For example, given the image of a "5", the model will correctly predict **5**.

4.Real-time Inference:

- **Web Application**: The trained model should predict digits in real time through a web interface. Users can upload a handwritten digit image, and the model will return the predicted digit.
- **Mobile Deployment (if done)**: If the model is deployed on a mobile app (using TensorFlow Lite), the app should accurately predict handwritten digits from real-time captures.

5.Generalization:

- The model should generalize well to unseen handwritten digits, including slightly different writing styles or noise in the image, with minimal drop in accuracy.

CONCLUSION

Summarize the findings and discuss the effectiveness of the proposed solution. Highlight any challenges encountered during the implementation and potential improvements. Emphasize the importance of accurate bike count predictions for ensuring a stable supply of rental bikes in urban areas.

FUTURE SCOPE

Future Scope of Handwritten Digit Recognition

The handwritten digit recognition system, while highly effective on datasets like MNIST, can be extended and enhanced in several directions for broader real-world impact:

1.Recognition of Alphabets and Words

- Extend the system to recognize **handwritten letters (A–Z)** and **complete words or sentences** using datasets like EMNIST or IAM.
- Useful in applications like **form processing**, **note transcription**, and **educational tools**.

2.Multilingual Handwriting Recognition

- Adapt the model to support recognition of handwritten characters in **other languages** such as Hindi, Telugu, Arabic, Chinese, etc.

3.Real-Time Writing and Drawing Interfaces

- Integrate with **stylus-based or touch-screen applications** to recognize and convert handwritten input in real time.

4.Banking and Postal Automation

- Use in **cheque processing**, **automated postal code reading**, or **form digitization**.

5.Integration with OCR Systems

- Combine with OCR (Optical Character Recognition) to create a complete handwritten document recognition system, converting **entire handwritten pages to editable text**.

6.Improving Accuracy with Advanced Models

- Explore advanced architectures like **Capsule Networks**, **ResNet**, or **transformers** for improved accuracy and robustness.

7.Edge Deployment

- Optimize and deploy models on **embedded systems**, **mobile phones**, or **IoT devices** for **offline handwriting recognition**.

8.Personalized Handwriting Recognition

- Train models to adapt to **individual users' handwriting styles** for personalized recognition systems.

These future enhancements can make the system more versatile, accurate, and applicable to a wide range of industries.

REFERENCES

List and cite relevant sources, research papers, and articles that were instrumental in developing the proposed solution. This could include academic papers on bike demand prediction, machine learning algorithms, and best practices in data preprocessing and model evaluation.

GitHub Link: https://github.com/SAI000000/HDR

SCREENSHOT

```
    plt.title(f"True: {true_labels[i]}\nPred: {predicted_labels[i]}")
    plt.axis('off')
plt.tight_layout()
plt.show()
```

```
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
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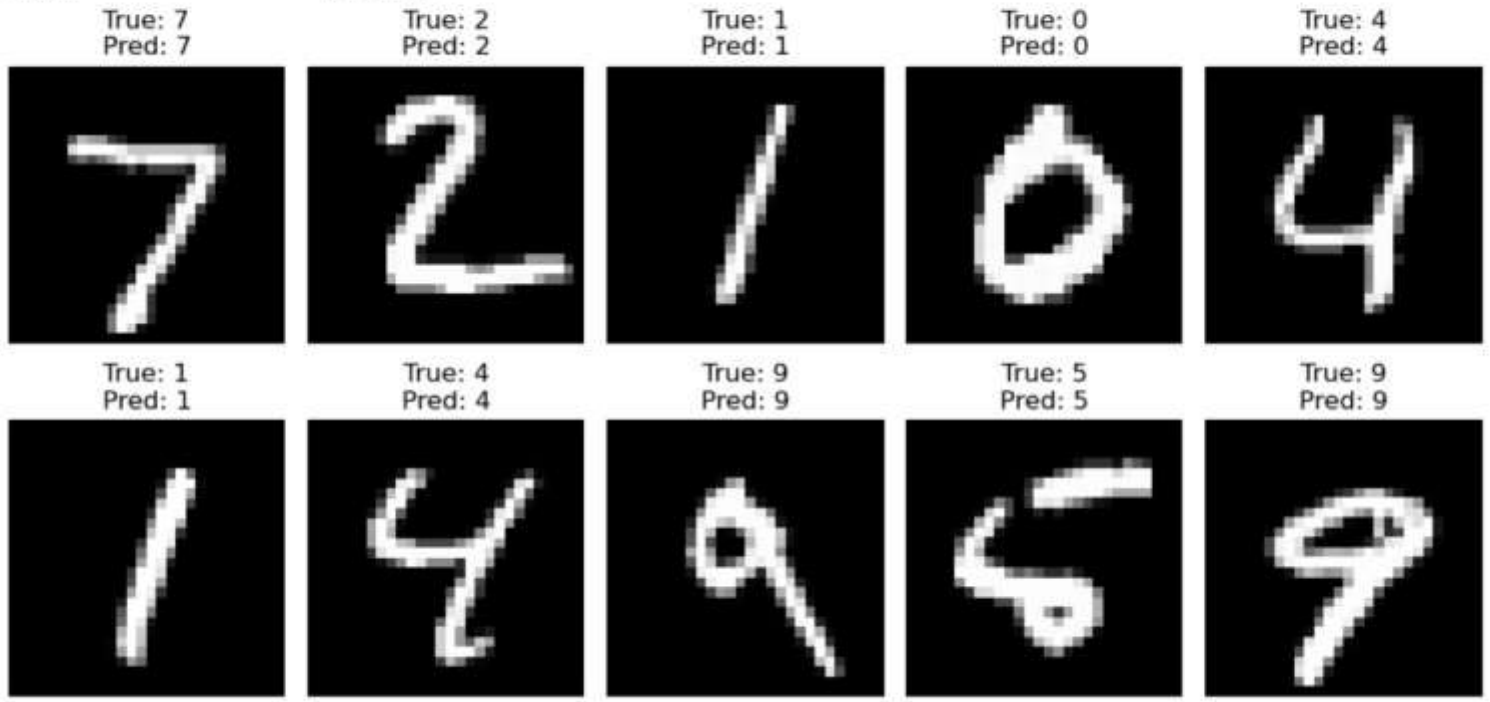

Thank you