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Performance Comparison of Convolutional Neural Networks and Traditional Machine Learning Algorithm (SVM) on the MNIST Dataset

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Abstract: Handwritten digit recognition is a classic problem in the field of computer vision, and the MNIST dataset is one of the most common benchmarks used to test different machine-learning methods. In this study, we take a closer look at how Convolutional Neural Networks (CNNs) and Support Vector Machines (SVM) perform on this task. SVM, a traditional machine-learning technique, works by treating each image as a long list of pixel values and depends heavily on manually designed features. In contrast, CNNs can automatically learn important visual patterns such as edges, curves, and shapes directly from the raw images. To understand the strengths and weaknesses of each approach, we trained both models on the MNIST dataset and compared their performance using accuracy, precision, recall, and F1-score. Our results show that CNNs consistently outperform SVM, especially when it comes to understanding subtle variations in handwriting. This happens because CNNs are better at capturing the spatial structure of images, something traditional algorithms struggle with. Overall, the study highlights why deep learning models like CNNs have become the preferred choice for image-based tasks, offering a clear advantage over classical machine-learning methods.

Keywords: Image classification, Machine learning, Support Vector Machine (SVM), Convolutional Neural Network (CNN), Handwritten digits classification, Deep learning, Accuracy comparison, Pattern recognition, MNIST dataset, Image recognition.

I. INTRODUCTION

Handwritten text is one of the oldest and most natural ways for people to record ideas, information, and daily activities. However, no two individuals write in exactly the same way—differences in style, speed, pressure, and shape make handwritten characters highly variable. As the world continues to shift toward digital systems, converting this handwritten information into an editable and machine-readable format has become increasingly important. This need has led to the growth of handwritten character recognition (HCR) systems, which aim to automatically identify letters, digits, or symbols from written input.

HCR technology can work with two major types of handwriting: online handwriting, where the writing process is captured in real-time using digital devices, and offline handwriting, where characters are recognized from scanned or photographed documents. Within this field, handwritten digit recognition is a key task and forms an essential part of Optical Character Recognition (OCR). It has many practical applications, such as sorting postal mail, reading bank checks, processing official forms, and automating data entry. While humans can recognize handwritten digits effortlessly, building machines that can do the same requires advanced feature extraction and pattern recognition methods.

With recent advancements in machine learning and deep learning, the accuracy and reliability of image recognition systems have improved dramatically. Traditional machine-learning algorithms and modern deep neural networks both play significant roles in this progress. These approaches allow systems to automatically learn patterns from large datasets and make predictions without manual feature engineering. Among different areas of artificial intelligence, image classification has benefited the most—especially after the introduction of convolutional neural networks, which are designed specifically to capture spatial patterns in images. As a result, handwritten digit recognition has become an active research area where classical ML techniques and deep learning models continue to be evaluated and compared.

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II. LITERATURE REVIEW AND RELATED WORKS

OVERVIEW

Handwritten digit recognition has long been a central problem in computer vision and pattern recognition. Over time, research in this area has evolved around two major groups of techniques: traditional machine-learning models such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forests (RF) and modern deep-learning approaches, especially Convolutional Neural Networks (CNNs).

Most studies rely on benchmark datasets like MNIST because of its simplicity, standardized structure, and widespread acceptance in the research community. Models are typically evaluated based on accuracy, error rate, generalization capability, robustness to noise, and computational efficiency.

Findings across the majority of prior work show that CNNs consistently outperform classical machine-learning models. This is largely because CNNs can automatically learn relevant visual features including edges, shapes, and patterns directly from raw images. In contrast, algorithms like SVM or KNN require flattened inputs and often depend on carefully engineered features to perform well. Nevertheless, SVM remains a strong competitor for smaller datasets or situations where computational resources are limited.

RELATED WORK

Several earlier studies have explored a wide range of algorithms for handwritten digit recognition using the MNIST dataset. One such study [4] evaluated multiple models including SVM, KNN, Random Forest, Multilayer Perceptron (MLP), and CNN. While most of the models achieved comparable results—with accuracy differences of roughly ±1%—CNNs demonstrated the highest accuracy. However, the study also noted that CNNs required significantly more computational time compared to classical algorithms.

Another work [6] aimed to design a CNN-based model capable of recognizing handwritten digits. The authors highlighted that while their model focused specifically on digit recognition, the same deep-learning principles could be extended to letters or even full handwriting styles. Their main contribution was to illustrate how CNN architectures can be adapted for robust handwritten character recognition.

A separate study [7] compared three different learning approaches—deep learning and traditional machine-learning algorithms—on the MNIST dataset. The authors found SVM to be a reliable and efficient algorithm, achieving strong training accuracy, though it still fell short compared to deeper neural networks.

In another comparative study [14], researchers tested SVM, KNN, Random Forest, and CNN. Their results showed that CNN achieved the highest accuracy of 98.76%, with a very low loss value. SVM, Random Forest, and KNN followed closely behind with accuracies of 97.38%, 96.50%, and 96.38% respectively, reinforcing CNN's superiority in extracting spatial features.

Similarly, study [15] compared SVM, KNN, and CNN using TensorFlow. CNN once again delivered the best performance, achieving an accuracy of 99.4% on the training set and 98.4% on test data. KNN showed the lowest performance among the three models, with around 97% accuracy. These findings consistently highlight the advantage of CNNs in tasks that require strong pattern-recognition abilities.

III. METHODOLOGY

DATASET

The dataset used in this research contains 21,555 images of handwritten digits (0–9), organized into 10 class folders. Each image was originally 90 × 140 pixels and in color, but for our experiment, all images were converted to grayscale and resized to 28 × 28 pixels to reduce complexity while preserving essential features.

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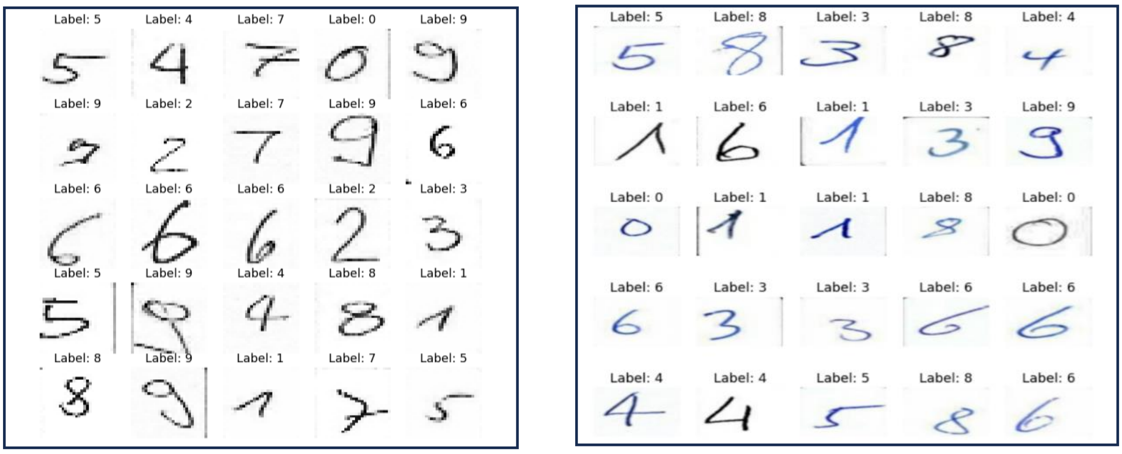

Fig1: some labelled images from the dataset

The dataset was split using an 80:20 ratio, resulting in 17,244 images for training and the remainder for testing. During preprocessing, the script confirmed the dataset structure, reporting: “Found 21,555 files belonging to 10 classes” and “Using 17,244 files for training.

Architectural Overview

Support Vector Machine (SVM):

Support Vector Machine (SVM) is a widely used supervised machine-learning algorithm that has proven especially effective for classification tasks. The fundamental idea behind SVM is to represent data points in a high-dimensional feature space—often visualized in 2D or 3D—and determine a boundary, known as a hyperplane, that best separates the different classes. Instead of simply finding any separating line, SVM searches for the optimal one.

This optimal hyperplane is chosen based on the concept of a margin, which refers to the distance between the separating boundary and the closest data points from each class. These closest data points are called support vectors, and they are crucial because they define the exact position and orientation of the hyperplane. The entire model depends heavily on these points, as they determine how well the SVM can generalize beyond the training data.

A key strength of SVM lies in its focus on maximizing this margin. A larger margin usually leads to improved stability, reduced overfitting, and better classification performance on unseen data. Furthermore, SVM is versatile: it can handle both linearly separable and non-linear problems. When data cannot be separated by a straight line, SVM uses kernel functions—such as polynomial or radial basis function (RBF) kernels—to project the data into a higher-dimensional space where a separating hyperplane becomes possible.

Overall, SVM combines mathematical rigor with practical effectiveness, making it a strong baseline model for classification tasks such as handwritten digit recognition, where clear decision boundaries are needed.

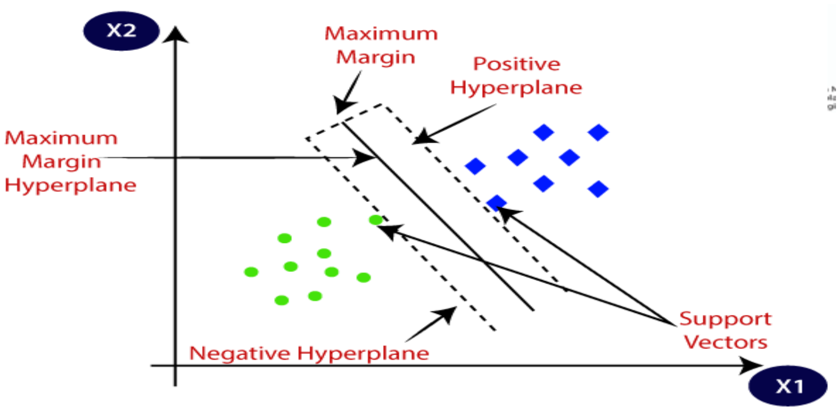

Fig2: SVM Architecture

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Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) are a type of deep-learning architecture specifically designed to work with grid-structured data, such as images or time-series signals. CNNs have become the cornerstone of modern image classification, pattern recognition, and computer-vision tasks because they can automatically learn important features directly from raw input images.

Although CNNs share similarities with traditional artificial neural networks—such as neurons that perform weighted sums followed by activation functions—the key difference lies in how they process visual information. Instead of treating every pixel independently, CNNs use convolutional layers that scan the image with small filters (typically 2×2, 3×3, etc.). These filters detect patterns such as edges, textures, and shapes, allowing the network to understand spatial relationships within the image.

CNN architectures typically include:

- Convolutional Layers – extract features using sliding filters
- Activation Layers – introduce non-linearity (e.g., ReLU)
- Pooling Layers – reduce spatial dimensions and control overfitting
- Fully Connected Layers – generate the final classification output

A standard CNN model often stacks multiple convolution and pooling layers, gradually learning more complex patterns, before ending with one or more fully connected layers to produce the final prediction. This structure enables CNNs to capture detailed visual features while keeping the number of parameters manageable.

IV. RESULTS

SVM Algorithm

For the dataset used in this study, the Support Vector Machine (SVM) model was trained using a regularization parameter C = 10, which controls the balance between maximizing the margin and minimizing classification errors. With this configuration, the model achieved an accuracy of approximately 0.90768, meaning it correctly classified over 90% of the handwritten digit images. This result aligns with the typical performance range of SVM on digit recognition tasks and demonstrates that the algorithm is capable of learning meaningful patterns from the dataset despite the reduced image size.

The performance metrics and evaluation outputs, including the classification accuracy, were generated during testing and are shown in the snapshots provided below. These results help illustrate how well the SVM model generalized to unseen test samples and provide a clear comparison point for evaluating the CNN model in later sections.

```
Loaded 21555 images successfully.
Training SVM model...
Evaluating model...

Classification Report:
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       447
           1       0.95      0.97      0.96       448
           2       0.90      0.93      0.91       447
           3       0.85      0.85      0.85       441
           4       0.93      0.91      0.92       436
           5       0.93      0.91      0.92       425
           6       0.90      0.93      0.91       424
           7       0.88      0.91      0.89       423
           8       0.89      0.86      0.87       417
           9       0.90      0.84      0.87       403

    accuracy                           0.91      4311
   macro avg       0.91      0.91      0.91      4311
weighted avg       0.91      0.91      0.91      4311
```

```
Confusion Matrix:
 [[434   0   0   0   0   2   7   0   1   3]
 [  0 434   0   1   4   0   2   6   1   0]
 [  1   2 414   5   1   0   1  18   2   3]
 [  4   4  14 374   1   8   0  13  12  11]
 [  1   8   3   3 396   3  17   1   1   3]
 [  0   0   4   9   2 385  10   5   5   5]
 [  7   2   0   0   6   4 395   0  10   0]
 [  0   4  20   8   0   2   0 383   1   5]
 [  5   1   4  21   4   4   8   2 360   8]
 [  3   3   2  21  11   4   1   7  13 338]]
Accuracy: 0.9076780329389933
```

Fig 3. SVM Result

The following graph compares the actual digit labels with the predicted labels generated by the SVM model for a set of test samples. The blue line represents the true values, while the red dashed line shows the model's predictions. As seen in the plot, the two lines overlap closely for most of the samples, indicating that the SVM model was able to recognize the handwritten digits with fairly high accuracy. Although there are a few points where the predicted values deviate from the actual labels, the overall trend shows that the model performs reliably and is able to classify most digits correctly. This visual pattern supports the numerical accuracy of over 90% observed in our experiment.

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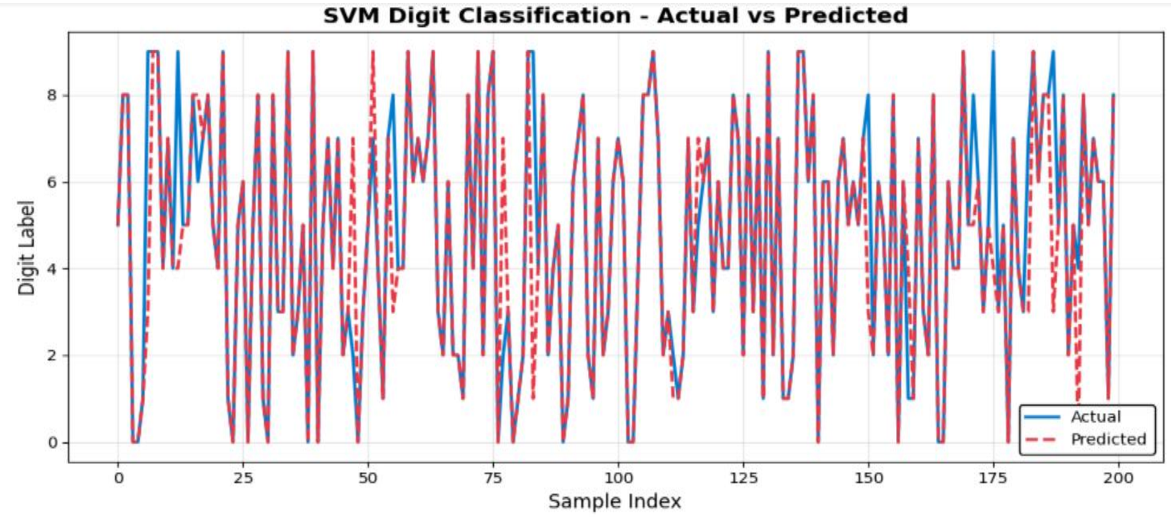

Fig 4. SVM (Actual vs Predicted) Graph

CNN Algorithm

In this experiment, a Convolutional Neural Network (CNN) was used as the deep-learning model for handwritten digit recognition. The dataset contained 21,555 images, which were split into 80% for training and 20% for testing, ensuring that the model had enough examples to learn meaningful patterns.

CNNs are particularly effective for image-based tasks because they can automatically detect important visual features such as edges, curves, and shapes without requiring manual feature engineering. This ability allows the network to understand the structure of the digits more accurately.

After training, the CNN achieved a test accuracy of 0.9569, which corresponds to about 95–96% accuracy. This strong performance highlights how well CNNs handle complex image data compared to traditional machine-learning methods, especially when working with large a

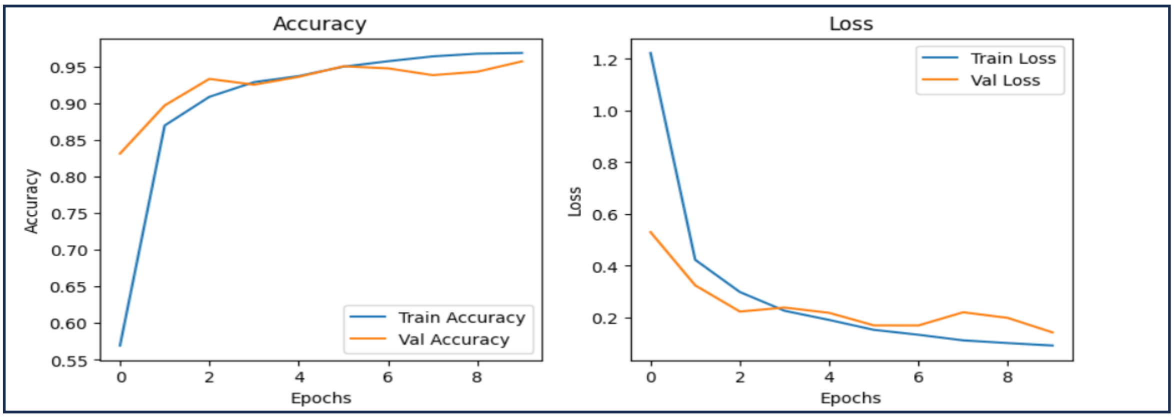

Fig 4. CNN (Actual vs Predicted) Grap

The following graphs illustrate how the CNN gradually improved throughout the training process. In the accuracy graph, both training and validation accuracy rise steadily with each epoch, eventually stabilizing around 95-96%. This upward trend shows that the model is consistently learning meaningful patterns from the data and is not overfitting, as the validation accuracy closely follows the training accuracy.

In the loss graph, both training and validation loss decrease sharply during the early epochs and continue to decline more gradually afterward. This behavior indicates that the network is successfully minimizing prediction errors and refining its internal feature representations over time. The close alignment between training and validation curves further confirms that the model maintains good generalization.

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Overall, the consistent improvement across both accuracy and loss metrics demonstrates that the CNN was well-optimized and trained effectively. The model not only learned to recognize the digit patterns accurately but also maintained stability across the entire training process, showing that the chosen architecture and preprocessing steps were appropriate for the dataset.

Overall, the combined trends in accuracy and loss confirm that the CNN trained effectively, improved steadily over time, and achieved strong, reliable performance by the end of training.

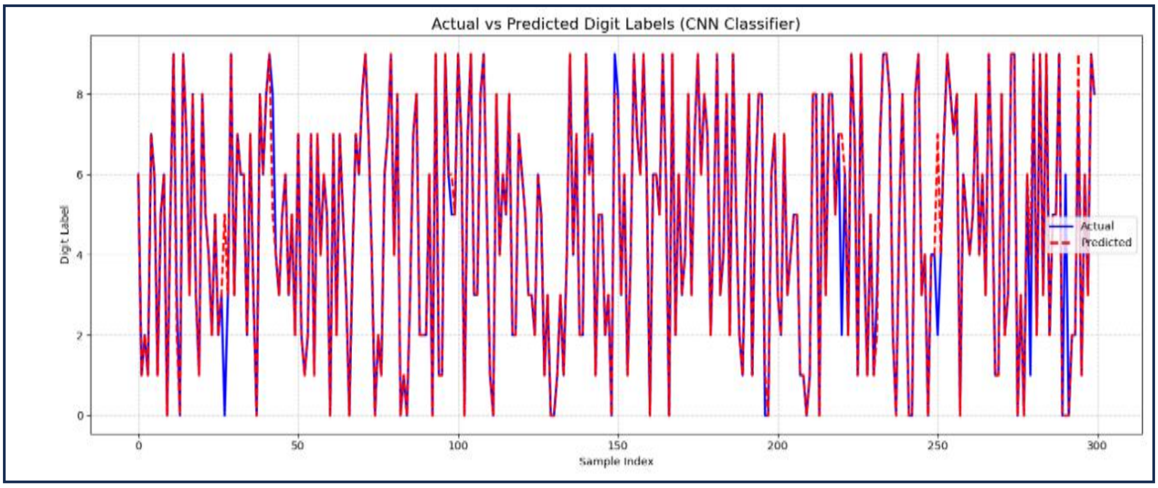

Fig 5: CNN Training and Validation Accuracy Loss Curves

TABLE 1: CNN vs SVM Comparison Table

Constraints	CNN	SVM
Type	Deep-Learning	Machine-Learning
Dataset: Total images	21555	21555
Train-Test Split	80% -20%	80% -20%
Accuracy (Test Result)	0.9569	0.907678(Approx.)
Percentage Accuracy (Test Result)	Between 95 to 96%	Between 90 to 91%

The table presents a direct comparison between the CNN and SVM models used in this study, both trained on the same dataset of 21,555 handwritten digit images with an 80–20 train-test split. While SVM represents a traditional machine-learning approach and CNN falls under deep learning, their performance differs notably.

V. DISCUSSION

The results of this study highlight clear differences between the performance of CNN and SVM for handwritten digit recognition. Although both models were trained on the same dataset and under the same train test split, their outcomes reflect the strengths and limitations of each approach. The SVM model delivered an accuracy of around 90-91%, which is respectable for a traditional machine-learning algorithm working on flattened pixel data. This demonstrates that SVM can still perform well on digit-based classification tasks, especially when the dataset is clean and the patterns are relatively simple.

In contrast, the CNN model achieved a significantly higher accuracy of 95-96%, showing its superior ability to learn and extract meaningful features directly from the images. The upward trend in training and validation accuracy, along with the steady decline in loss values, confirms that the CNN adapted well to the dataset and generalized effectively. This performance advantage comes from CNN's ability to capture spatial patterns such as edges, curves, and shapes which SVM cannot fully utilize when working with flattened input.

Overall, the comparison clearly indicates that while SVM remains a strong and efficient choice for basic image classification tasks, CNN offers greater accuracy, deeper feature learning, and improved stability during training. These

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findings reinforce the idea that deep-learning models are more suitable for modern image-based applications where precision and feature extraction are essential.

VI. CONCLUSION

This study compared the performance of a Convolutional Neural Network (CNN) and a Support Vector Machine (SVM) on a dataset of handwritten digits. The findings clearly show that while SVM performs reasonably well and can reach above 90% accuracy, CNN significantly outperforms it by achieving around 95–96% accuracy. The superior performance of CNN is mainly due to its ability to automatically learn visual features from images, something traditional ML models cannot do without manual feature extraction.

The training behavior, accuracy results, and evaluation metrics all point toward the same conclusion: CNN is better suited for image-based tasks, especially when the dataset contains diverse handwriting styles and visual variations. Its ability to capture spatial patterns, reduce errors effectively, and produce stable performance makes it a more reliable choice for handwritten digit recognition.

In summary, the work reinforces the growing adoption of deep-learning methods in computer vision applications. CNNs not only deliver higher accuracy but also offer better generalization and scalability, making them the preferred approach for future developments in handwritten character recognition and similar image-classification problems.

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