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HANDWRITTEN DIGIT RECOGNITION USING MACHINE LEARNING

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ABSTRACT

The handwritten digit recognition system is a popular research topic, and much research has been done throughout the years. The implementation of this system will be beneficial for many sectors in today's world. Various types of algorithms can be used to develop a solution for this system. However, the accuracy of the results plays an important role in determining the best solution for the handwritten digit recognition system. In this project, selected machine learning and deep learning algorithms were used to build models to find the most suitable model with the best possible accuracy. According to the results, the CNN model performed better than the other models with an accuracy of 99.25% and 0.99 for each Precision, Recall and F1 Score compared to all the other models.

Keywords: *Digit Recognition, Handwritten, Recognition Model; Machine Learning; Deep Learning*

1. INTRODUCTION

Handwritten recognition of characters has been around since the 1980s. According to the Collins dictionary, a digit refers to a written symbol of any number between 0-9. Digits play a vital role in the daily routine of life. Industries such as banks, healthcare, and insurance have a high dependency on digits. In a bank, starting from creating an account to cash withdrawal needs the right digits or numbers. Every bank process starts with clients filling up a form by writing on it. As an important detail, their account number, identification number, or even phone number are requested. Digits in those forms are then identified by the bank officers manually or scanned by computers. Whereas in healthcare industries; patients' details in forms, doctor's notes on patient's diseases, and even medicine-consuming guidelines need correct interpretation of the digits. Forms that are filled up using handwriting like tax forms have their focus on numerical entries too. Not just that, online handwriting recognition on tablets and zip code recognition for postal mail sorting uses digit [1].

Handwritten digit recognition system is a popular research topic among technologists. This system is used to recognize characters, especially digits written by humans. This topic involves various data analytics algorithms and techniques. Machine learning is a subset of Artificial Intelligence AI and computer science. Algorithms are used to improve the accuracy of the results extracted from data that has been collected. A handwritten digit recognition system requires high-accuracy results and reliability. This is important as the system converts handwritten digits into machine-readable format. There are many challenges in handwritten digit recognition as there are various styles of handwriting of humans. Additionally, there are different symbols for digits in different languages. However, it's not simple to find the right algorithm to build the system. Selectively several machine learning algorithms must be researched and trained to find the most accurate method. Poor quality of human handwritten digits compared to printed copies or typed digits becomes a hurdle for machines to recognize the digits accurately.

This is a huge issue in many industries like healthcare, insurance and banking, especially where one wrongly interpreted digit from a customer's handwriting results in a big problem. For example, due to poor handwriting, a zero and eight may look similar or even digit nine. In this case, a computer system may interpret it as a different digit instead of the correct digit which ends up wrong. Thus, a handwritten recognition system requires a more accurate, intelligent and reliable algorithm solution.

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There is much research that has been done previously but achieving 100% accuracy seems to be almost impossible. The problem context behind this challenge is that even 1% inaccuracy can lead to many wrong interpretations in recognizing the digits. Therefore, this paper aims to study and analyse the various methods present in building the models and developing the handwritten digit recognition system.

2. LITERATURE REVIEW

The research about recognition started with optical character recognition (OCR) as physicist Emanuel Goldberg invented a machine that could convert characters into telegraph code and in the 1920's he went a step further by creating the first electronic document retrieval system. Later, OCR technology proliferated, and businesses started to rely on it to convert data from paper documents [2]. Since then, the research on recognition has become in-depth and the understanding of algorithms has become better. The most suitable research papers are reviewed in this section as data analytics methods have technologically improved a lot. These research papers cover the latest information and results that can be helpful for this project.

Reference [3] studied the effectiveness of some machine learning algorithms in handwritten digit recognition systems. The paper presented Multilayer Perceptron (MLP), SVM, Naïve Bayes, Bayes Net, Random Forest, J48 and Random Tree as the approaches used for offline handwritten digit recognition. Simulations were done based on accuracy, time consumption and different errors. Based on these parameters, MLP has been found to have the highest accuracy with 90.37% overall compared to other machine learning algorithms. However, this **RESEARCH WAS DONE AS AN INITIAL ATTEMPT WITHOUT USING ANY** standard classification techniques. This research focused only on machine learning algorithms and did not attempt to analyse algorithms from other domains of data analytics.

Reference [4] proposed an automatic handwritten digit recognition on document images using SVM, Artificial Neural Network (ANN) and CNN. It resulted that, CNN achieved the highest accuracy with 71% performance compared to ANN and SVM models.

Unlike the other research works, the K-Nearest Neighbour (KNN) algorithm was analysed along with SVM, and CNN was analysed to study the accuracy of handwritten digit recognition. The two authors have used the MNIST dataset for a comprehensive data analysis on the topic. The results were tabulated by parameters of the confusion matrix and precision, Recall and F1 score were calculated using that table for all three models built using the algorithms. As for the observations, KNN relatively had less accuracy compared to SVM and CNN. Whereas CNN was crowned as the algorithm with the highest accuracy of 99.4% for the training data and 98.4% for the test data. It was also discussed that; the number of epochs has impacted the accuracy of CNN where more the number of epochs the higher the accuracy achieved.

In 2020, research on handwritten digit recognition was done by Savita Ahlawat and Amit Choudhary suggested that a combination of convolutional neural network (CNN) and support vector machine (SVM) achieved a higher accuracy of 99.28% for the training data compared to SVM alone. The proposal stated that handwritten digit recognition involves automatic feature generation using CNN and the SVM is implemented in predicting the output. Various parameters such as gamma and degree and decision function are altered and go through several stages of testing. Finally, the maximum accuracy was achieved when the gamma is 0.1, degree 5 and the decision function with one-on-one [5]. Implementation of hybrid algorithms is new for the handwritten digit recognition field and still in the early stages.

The research was conducted on handwritten digit recognition, particularly for baking systems using the CNN method. The research is about using CNN to develop an automatic banking deposit number recognition system for the cash deposit process at the bank counter. The authors stated that CNN is the best algorithm to implement for their proposed idea as it has the highest accuracy of all the algorithms present [6]. Similarly, another research was done using the CNN approach to analyze the deep learning algorithm in proving the effectiveness of for handwritten digit recognition system. As shown in Table 1, CNN achieved its maximum accuracy of 99.87% in the MNIST dataset hence it is proved that CNN is a great approach from deep learning algorithm for handwritten digit recognition system by the authors [7].

Feature extraction and classification are machine learning technology's two primary functions. The CNN design does away with the necessity for a separate feature extraction method by

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combining classification and feature extraction techniques into a single model [12]. SVM [13] is a sophisticated classification method with strong generalization capabilities that are based on the principles of structural risk reduction and statistical learning theory through manual feature extraction.

Table 1: Comparison of models

Algorithms	CNN	MLP	SVM
Accuracy (%)	71.00 [4] 99.87 [7]	90.37 [3]	98.35 [5] 39.00 [4] 97.83 [14]
Parameters	GPU: CPU = 30:1 15000 iterations Lr = 0.01, Decay = 1e-6, Momentum = 0.9	Execution time = 2:32 min Number of epochs = 30	Gamma = 0.1 Degree = 5 C = 1.0, Penalty = 12, max_iter = 1000, tol = 1e-4

The review has shown various methods and approaches. Each approach has different results in different environments of testing. The application of machine learning and deep learning shows great potential for developing a handwritten digit recognition system with a high level of accuracy.

Traditional handwritten digit recognition system includes two stages: feature extraction and classification. Most of them use shallow structures to deal with computing units and limited kinds of samples, such as Support Vector Machines (SVM) [14]. Faced with complex classification problems, the generalization ability and performance of SVM are insufficient when the samples have rich meanings. Recently, Convolutional Neural Network (CNN) [15] has been widely used in the field of computer vision because of its excellent performance and has made outstanding achievements in the accuracy of various machine learning tasks.

3. METHODOLOGY

The study employed the CRISP-DM data mining methodology, starting with business understanding to identify crucial factors for optimal handwritten digit recognition. The MNIST dataset, consisting of 60,000 grayscale images of single digits, underwent data understanding, cleaning, and exploration. Noise reduction techniques were applied to enhance image quality. Selected algorithms were trained and tested with appropriate parameters. Evaluation criteria included accuracy percentage and precision score. The models' deployment was emphasized for practical use, with a focus on organizing and presenting knowledge gained for production purposes. The data analysis process involved collecting, modelling, and analyzing data for decision-making. Data exploration examined the MNIST dataset's structure, revealing 10 rows of digits (0-9) and 785 columns in both training and test sets. Data cleaning confirmed the absence of missing values or outliers. Normalization was performed to scale pixel values (0-255) to a range of 0 to 1 and reshape transformed pixel arrays into a (28,28,1) matrix for improved deep learning model implementation.

3.1 Data Visualization

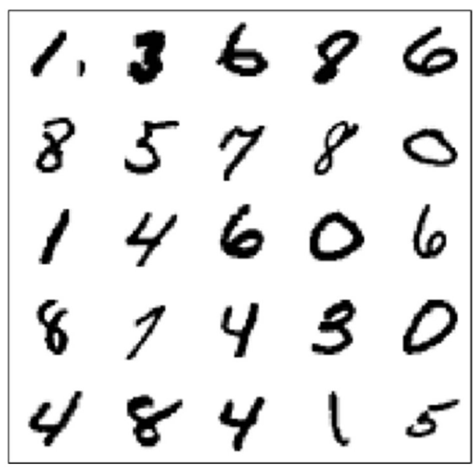

Figure 1: Sample of digits

Figure 1 shows that there are different types of writing styles for each digit. For example, number 8 has five different styles within this sample number and there could be more styles in the dataset and the real world.

3.2 Data Preparation

The 'label' column (numbers) is encoded into a hot vector for each class and there are 10 classes (0-9). The training data is segmented into two exclusives which are a train and validation sets. Train data is used for the model training whereas validation data is used for cross-validation of the model's accuracy and to see how well the model is generalized for the data other than training data.

4. MODELLING & ANALYSIS

4.1 Convolutional Neural Network (CNN)

A CNN model was constructed using the LeNet-5 architecture. The model featured two Conv2D layers with 32 and 64 filters, respectively. The kernel size was set to 5x5 for the first layer and reduced to 3x3 for the second layer. Rectified linear unit (ReLU) activation, same padding, and MaxPool2D with a (2,2) pool size and strides were applied. A Dropout layer with a 25% dropout rate was included. The dense layer had a value of 255, representing the maximum pixel value in the training dataset. The final layer was a softmax classifier related to cross-entropy loss. The RMSProp optimizer with default values for learning rate, rho, epsilon, and decay was employed for effective and faster model convergence. Learning rate annealing was implemented using ReduceLROnPlateau to monitor and adjust the learning rate during training epochs, contributing to achieving high accuracy. The training utilized CUDA to enhance speed, with 15 epochs and a batch size of 112. The training process took approximately 40 minutes, revealing that the training accuracy consistently surpassed the validation accuracy. The training and validation losses exhibited minimal differences. The model achieved the highest validation accuracy of 99.32% and a training accuracy of 99.5%.

4.2 Multilayer Perceptron (MLP)

The Multilayer Perceptron (MLP) model has a simple architecture with four sequential layers in the Keras model. The first layer is a flattened layer that converts a 2D image matrix into a 1D vector to suit MLP's requirement for 1D input. The second layer is a dense layer with 128 neurons and ReLU activation, facilitating quick convergence. The third hidden layer mirrors the second in terms of units and activation. The fourth layer is the output layer with softmax activation, representing the network's guess for each digit. To control underfitting or overfitting, a kernel_regularizer parameter of 0.002 is applied, like dropout in the CNN model, with 10 units in this layer.

The model summary provides an overview of the layers, their order, output shapes, parameters per layer, and the total model parameters. The optimizer used is the same as in the CNN model. The MLP model is compiled with defined parameters, including a TensorBoard callback for metric visualization. It is fitted with 15 epochs and a batch size of 112, completing training in 20 seconds due to its simple architecture. The highest training accuracy achieved is 97.55%, and validation accuracy is 97.17%. Training loss gradually decreases, while validation loss varies across epochs.

4.3 Support Vector Machine (SVM)

The SVM model-building process began with both linear and non-linear models using default hyperparameters for comparison. The linear SVM model yielded an accuracy of approximately 90.56%, as shown in the confusion matrix. The non-linear SVM model, employing the 'rbf' kernel with default gamma and C values, demonstrated an increased accuracy of 94.39%.

Considering the higher accuracy of the non-linear model, hyperparameter tuning was performed specifically for it. The optimization focused on finding the optimal C and gamma values. C controls error, while gamma influences the curvature in the non-linear SVM model. A 5-fold cross-validation with grid search was employed for this purpose, taking nearly 40-50 minutes. The results indicated that at higher gamma values (0.01), the model exhibited overfitting, with 100% training accuracy but less than 80% test accuracy. The analysis revealed that a gamma value of 0.001, combined with C=15, provided the highest test accuracy around 94% while avoiding overfitting.

The final hyperparameters selected were C = 10 and gamma = 0.001, and the SVM model was fitted accordingly.

5. RESULTS AND DISCUSSION

A model's performance is evaluated based on different metrics such as accuracy, loss, error value and precision score. The different evaluation metrics will allow data analysts to understand a model's performance based on its strengths and weaknesses. For this project, three models, CNN, MLP and SVM will be evaluated based on certain metrics and a decision will be made to choose the best algorithm for handwritten digit recognition.

5.1 CNN

The Convolutional Neural Network (CNN) model achieved an accuracy of approximately 99.31% with a loss of 0.0326 in the validation test. This high accuracy indicates the model's strong predictive capabilities.

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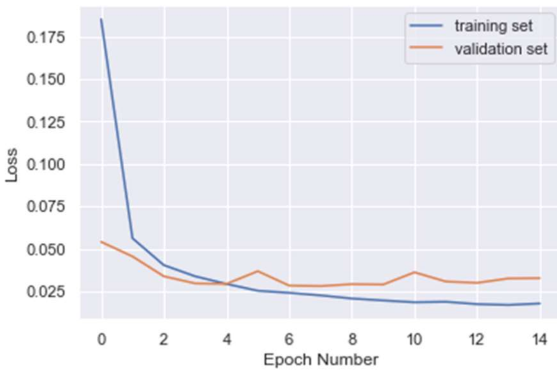

Figure 2: Loss graph - CNN

Figure 2 illustrates the loss for the training and validation sets over epochs, showing an initial disparity that converges as epochs progress, with a slight difference at the end where the validation set loss is slightly higher. Despite this, the model exhibits a good fit, as the loss consistently decreases with each epoch.

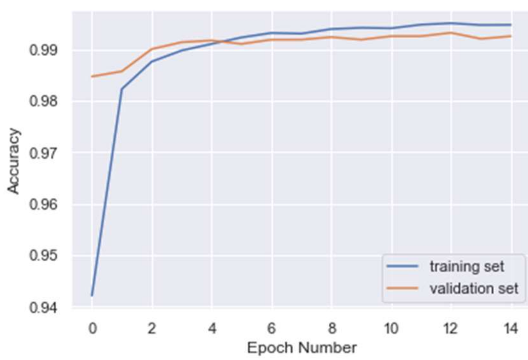

Figure 3: Accuracy graph - CNN

Figure 3 displays the accuracy for both sets, indicating that training accuracy surpasses validation accuracy due to the model's familiarity with the training data.

Metrics such as recall and F1 score further validate the model's positive performance. Despite not achieving 100% accuracy, the CNN model is effective in predicting most images as per the classification report shown in Figure 4.

Classification Report

	precision	recall	f1-score	support
0	1.00	0.99	0.99	624
1	1.00	0.99	0.99	654
2	0.99	0.99	0.99	572
3	0.98	1.00	0.99	589
4	0.99	0.99	0.99	580
5	0.99	0.99	0.99	551
6	0.99	0.99	0.99	580
7	0.98	0.99	0.99	633
8	0.99	0.98	0.99	585
9	0.99	0.99	0.99	632
accuracy			0.99	6000
macro avg	0.99	0.99	0.99	6000
weighted avg	0.99	0.99	0.99	6000

Figure 4: Classification Report - CNN

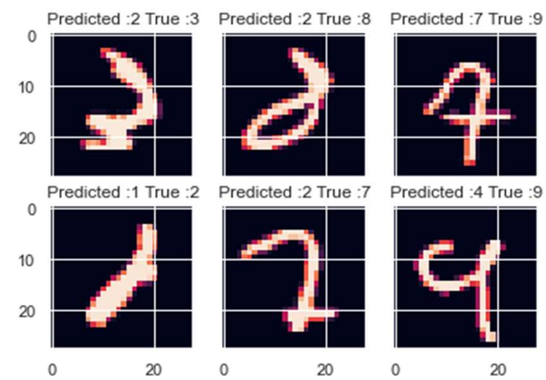

Figure 5: Prediction - CNN

The predictions are illustrated in Figure 5, which reveals instances where predicted values deviate from true values. A specific example with index number 2853 from the test data is highlighted, showcasing an accurate prediction by the CNN model.

5.2 MLP

The provided text discusses the performance evaluation of a Multilayer Perceptron (MLP) model based on certain figures. The model achieved an accuracy of approximately 97% and a loss of 0.1767 on the validation test. The text emphasizes the importance of validation accuracy in assessing the model's predictive capability and suggests that hyperparameters can be optimized for better results.

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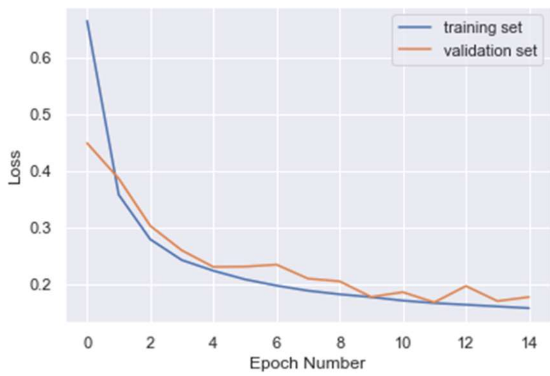

Figure 6: Loss graph - MLP

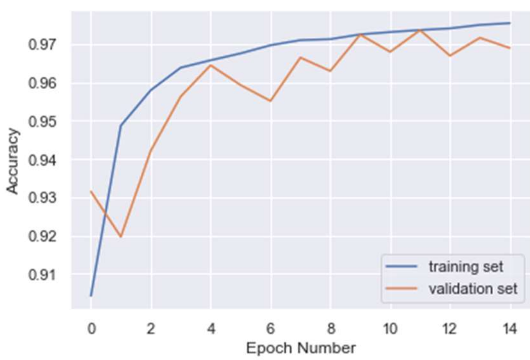

Figure 7: Accuracy graph - MLP

Figure 6 and Figure 7 illustrate the model's loss and accuracy for both training and validation sets across epochs respectively. The text notes an initial disparity in loss scores between the sets, which converges as epochs progress, with a slight divergence towards the end. Despite this, the model is deemed to have a good fit, given the consistent decrease in loss scores.

Figure 8 demonstrates accurate predictions for all classes, indicating good model performance. The classification report further assesses precision, recall, and F1-score, highlighting high scores across most classes, with minor errors in precision for one class (class 7) as shown in Fig. 9.

Classification Report

	precision	recall	f1-score	support
0	0.98	0.99	0.98	624
1	0.98	0.99	0.98	654
2	0.95	0.98	0.96	572
3	0.97	0.96	0.97	589
4	0.98	0.95	0.97	580
5	0.97	0.96	0.97	551
6	0.99	0.98	0.99	580
7	0.92	0.99	0.95	633
8	0.99	0.96	0.97	585
9	0.96	0.94	0.95	632
accuracy			0.97	6000
macro avg	0.97	0.97	0.97	6000
weighted avg	0.97	0.97	0.97	6000

Figure 8: Classification report - MLP

While the MLP model exhibits high accuracy, the text acknowledges that no model achieves 100% accuracy. For practical purposes, important errors are examined, revealing instances where predicted values deviate from true values.

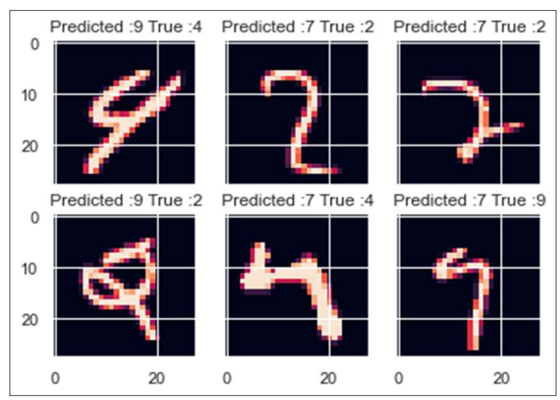

Figure 9: Prediction - MLP

Figure 9 specifically shows accurate predictions for test data using the MLP model. Overall, the model is considered to perform well, with detailed evaluations of accuracy, precision, recall, and important errors.

5.3 SVM

The Figure 10 presents a classification report depicting the accuracy results of an SVM model. This model was constructed using optimal hyperparameters, specifically C=10 and gamma=0.001, resulting in a maximum accuracy of 95.31%. Diagram 56 illustrates precision scores ranging from 0.92 to 0.98 for different classes, while recall scores fall within the range of 0.93 to 0.98. Additionally, the f1 scores span from 0.95 to 0.98.

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These scores collectively indicate a high level of performance for the model, with values considered to be quite good.

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Classification Report

              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1805
           1       0.97      0.98      0.98      1994
           2       0.93      0.94      0.94      1759
           3       0.95      0.93      0.94      1846
           4       0.95      0.96      0.95      1726
           5       0.95      0.95      0.95      1653
           6       0.97      0.97      0.97      1787
           7       0.92      0.96      0.94      1937
           8       0.96      0.93      0.94      1730
           9       0.96      0.93      0.95      1763

    accuracy                           0.95     18000
   macro avg       0.95      0.95      0.95     18000
weighted avg       0.95      0.95      0.95     18000
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Figure 10: Confusion matrix - SVM

5.4 Model Comparison

Table 2 reveals that the CNN model outperformed other models in terms of accuracy, achieving 99.31%. Despite taking 30 minutes for training, it demonstrated superior performance. In comparison, the MLP model completed training in just 20 seconds with 97% accuracy. The suggestion is that, with improved hyperparameter tuning, both CNN and MLP could potentially achieve even higher accuracies. On the other hand, the SVM model exhibited the lowest accuracy among the deep learning models and took 40 minutes for training. In conclusion, the CNN model is deemed the most suitable algorithm for a handwritten digit recognition system.

Table 2: Model comparison

Model / Metrics	Model Comparison Summary		
	CNN	*MLP*	*SVM*
Test Accuracy	99.31%	96.89%	95.31%
Precision (avg)	0.99	0.97	0.95
Recall (avg)	0.99	0.97	0.95
F1 score (avg)	0.99	0.97	0.95
Training time	30 min	20 sec	40 min

This excerpt discusses the performance of convolutional neural network (CNN) models in handwritten digit recognition tasks, comparing them to existing studies and highlighting the accuracy achieved in a current project. The excerpt mentions Table 3, which likely summarizes previous research on handwritten digit recognition using CNN models. The accuracies reported in these studies range from 98% to 99.87%. However, it notes that these studies may lack clear evaluation steps, implying that the methodologies used to assess model performance might not have been sufficiently rigorous or transparent. The CNN model developed in the current project achieves a notably higher accuracy. It comes close to the highest recorded accuracy of 99.31% with only a marginal difference of 0.06%. This implies that the model developed in this project performs exceptionally well in recognizing handwritten digits.

Importantly, the excerpt highlights that the current project's CNN model was evaluated using rigorous cross-validation steps to eliminate overfitting. Cross-validation is a technique used to assess how well a model will generalize to an independent dataset. By employing this technique, the project ensures that the reported accuracy is reliable and not inflated due to overfitting. The comparison suggests that the CNN model developed in the current project outperforms other existing models in handwritten digit recognition. Despite the marginal difference in accuracy, the rigorous evaluation process enhances confidence in the performance of the current model. This indicates that the project's model may represent a significant advancement in the field of handwritten digit recognition.

Overall, the excerpt provides insights into the performance of CNN models in handwritten digit recognition tasks, emphasizing the importance of rigorous evaluation methods and highlighting the superior performance of the CNN model developed in the current project.

Table 3: Comparison of CNN results with existing studies

Research Paper	Test Accuracy (%)
Hybrid CNN-SVM Classifier for Handwritten Digit Recognition (CNN-SVM) [5]	99.28
Handwritten Digit Recognition Using Deep Learning (CNN) [7]	99.87
Handwritten Digit Recognition System using Convolutional Neural Network (CNN) [8]	98.00
Implementation of Handwritten Digit Recognizer using CNN [9]	99.15

Research Paper	Test Accuracy (%)
Recognition of Handwritten Digit using Convolutional Neural Network (CNN) [10]	99.15
Handwritten Digit Recognition using Machine and Deep Learning Algorithms (CNN) [11]	99.31
Hand Written Digit Recognition Using Machine Learning (CNN) [16]	95.00
Hand Written Digit Recognition Using Machine Learning (CNN) [17]	98.40
This study (CNN) with proper validation	99.31

6. CONCLUSION

The conclusion drawn from the project is that Convolutional Neural Networks (CNNs) have proven to be the most efficient and accurate model for the task of recognizing handwritten digits. Through rigorous cross-validation procedures, a suitable architecture for the CNN model was identified, resulting in an impressive accuracy rate of 99.25%. This accuracy rate signifies the effectiveness of the CNN model in accurately identifying and classifying handwritten digits, showcasing its potential for various applications in fields such as character recognition, optical character recognition (OCR), and digitized document processing. The thoroughness of the cross-validation steps ensures that the chosen model architecture is robust and reliable, offering confidence in its performance across different datasets and real-world scenarios. Therefore, the project's findings highlight the superiority of CNNs for handwritten digit recognition tasks and emphasize their significance in advancing machine learning technologies for image classification tasks.

The project embarked on an exploration of Multilayer Perceptron (MLP) and Support Vector Machine (SVM) algorithms, recognizing their potential but also acknowledging the necessity for refinement. This recognition underscores the importance of comprehending the nuanced capabilities and limitations inherent in each algorithm. It underscores the significance of crafting bespoke solutions that align with the unique attributes of the problem at hand. In the pursuit of refining these algorithms, the project leaned heavily on a foundation of extensive research. This research encompassed a wide array of sources, including scholarly journal articles, authoritative books, and pertinent online resources. This comprehensive approach to gathering insights played a pivotal role in shaping the process of model construction. By delving into a diverse range of literature, the project was able to extract valuable insights and best practices. These insights likely informed decisions regarding parameter tuning, feature selection, model architecture, and other crucial aspects of the model-building process. Ultimately, the project's approach underscores the importance of marrying theoretical understanding with empirical evidence to iteratively refine and enhance machine learning models.

The accuracy of the models significantly impacts the speed of digit recognition in the era of electronic data. Despite the commendable achievements, there is still room for enhancement, particularly through fine-tuning hyperparameters such as learning rate, optimizers, model depth, and epochs. Future research, especially focused on CNN, holds the potential for achieving nearly 100% accuracy, with a specific emphasis on model and pixel depth tuning for further development.

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