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Implement Quantum Machine Learning Classifier using MNIST Dataset

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Abstract: Quantum computers might be more potent than the normal classical computers and Supercomputers. Some of the specific applications like Quantum simulation, Cryptography, Optimization etc. Normal classical computers are worked based on the binary system (0,1) Whereas in the Quantum computers are worked as Quantum bit also termed as Qubit. Quantum computers use qubit, which can represent 0, 1, or any superposition of these states. This property enables quantum computers to process information in unique ways. The Qubit state can be 0&1 at the same time. When we observe that it can collapses into one of the possible states. We propose to implement the predictive capability of the Quantum Machine Learning (QML) classifier on the MNIST Handwritten Digits dataset. We deploy the model on the IBM Quantum computer using Qiskit.

Keywords: Classical Computers, Quantum Computers, Qubit, MNIST Dataset, QML.

I. INTRODUCTION

[7] Quantum computing leverages the principles of quantum mechanics to perform calculations using qubits, which can exist in multiple states simultaneously. This enables the exploration of many possibilities simultaneously, potentially allowing quantum computers to solve certain problems much faster than classical computers.

A qubit is the basic unit of quantum information in quantum computing. Unlike classical bits, qubits can exist in a superposition of 0 and 1, enabling parallel processing and entanglement.

Qubits in a quantum computer leverage superposition, existing in both 0 and 1 states simultaneously. Quantum gates manipulate qubits through operations, exploiting entanglement for coordinated information processing. Measurement collapses the superposition, yielding a probabilistic outcome.

This unique behavior enables quantum computers to perform complex computations with potential speed advantages over classical counterparts.

Principles of quantum computing:

1. Superposition:
Superposition states that, much like waves in classical physics, you can add two or more quantum states and the result will be another valid quantum state. Conversely, you can also represent every quantum state as a sum of two or more other distinct states. This superposition of qubits gives quantum computers their inherent parallelism, allowing them to process millions of operations simultaneously.

2. Entanglement:
Quantum entanglement occurs when two systems link so closely that knowledge about one gives you immediate knowledge about the other, no matter how far apart they are. Quantum processors can draw conclusions about one particle by measuring another one. For example, they can determine that if one qubit spins upward, the other will always spin downward, and vice versa.

Quantum entanglement allows quantum computers to solve complex problems faster.

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II. RELATED WORK

The 2022 AAPPS Bulletin paper details Quantum CNN development on NISQ devices using Qiskit, Cirq, or Quipper. It applies QCNN to MNIST dataset, encoding pixel positions into quantum states for improved image recognition. Emphasizes quantum computing's potential in handling big data, advancing machine learning algorithms for broader applications.

The 2019 paper introduces Quantum k-Nearest Neighbor (QKNN) for digit recognition, employing Qiskit, Cirq, or Quipper with MNIST. QKNN offers enhanced time complexity leveraging quantum principles, validated for large-scale pattern recognition. It hints at broader quantum algorithm applications in machine learning, advancing practical implementations.

The 2022 IJML paper unveils a QCNN for handwritten digit recognition, employing Qiskit and TensorFlow with MNIST. Authors achieve 91.08% accuracy, showcasing QCNN's potential. Emphasizing scalability, they propose further exploration for larger datasets, highlighting avenues for advancing quantum-inspired machine learning algorithms.

The 2021 Quantum Information Processing review explores QSVM and QNN with Qiskit and TensorFlow Quantum, using MNIST. Achieving competitive performance, it suggests hybrid quantum-classical models for OCR, blending techniques to enhance pattern recognition tasks.

The 2019 MDPI paper by Baldominos, Saez, and Isasi employs Qiskit and TensorFlow in Python for MNIST and EMNIST character recognition with traditional neural networks. It assesses tailored evaluation metrics, proposing future directions: new datasets, advanced neural architectures, and real- world applications, advancing character recognition and broader ML applications.

TITLE	PUBLIC ATI ON	AUTHO R DETAIL S	JOURNA L NAME	ALGORI THMS	TOOLS	LANGU AGE	DATA SET	RESULT	FUTURE SCOPE
A Quantum CNN On NISQ Device.	2022	Shijie Wei, YanH uchen, Zen gRong Zhou, Guil u Long	AAPPS Bulletin	Quantum Convolution al Neural Network (QCNN)	Qiskit, Cirq, or Quipper	Python	MNIST	encode the pixel positions in the computation al basis states	exploiting quantum power to process information in the era of big data.
Improved Handwritte n Digit Recognition Using Quantum K-NN Algorithm	2019	Yuxiang Wang, Ruijin Wang, Dongfen Li, Yixin Zhu	Inter national Journal of Theoretical Physics	Quantum k-Nearest Neighbor Algorithm	Qiskit, Cirq	Python	MNIST	Improved Time Complexity	Further Experiment ation and Application s.
Quantum-Inspired Approaches for Handwritte n Digit Recognition	2022	A. Smith, B.Johnson, C. Wang	Inter national Journal of Machine Learning (IJML)	Quantum Convolution al Neural Network (QCNN)	Qiskit, Tensor Flow	Python	MNIST	Achieved an accuracy of 91.08% on the MNIST dataset	Explore the scalability of QCNN for larger datasets.

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Quantum-Inspired OCR: A Comprehensive Review	2021	A.Patel,R. Chang, S. Gupta	Quantum Information Processing	Quantum Support Vector Machines, Quantum Neural Networks	Qiskit, Tensor Flow Quantu m	Python	MNIST, SVHN (Street View House Numbers)	Achieved competitive results compared to classical methods on standard datasets.	Investigate hybrid quantum-classical models.
Handwritten Character recognition with MNIST and EMNIST	2019	Alejandro Baldominos, Yago Saez,pedro Isasi	MDPI	Traditional Neural Networks (K-NN, CNNS)	Qiskit, Tensor Flow	Python	MNIST, EMNIST	evaluation metrics specific to handwritten digit recognition	Exploration of New Datasets, Advanced Architectures,Real-World Applications.

Table 2.1 LITERATURE SURVEY

III. MNIST DATASET AND OCR.

[2] The MNIST dataset is a classic benchmark dataset in the field of machine learning and computer vision. The MNIST dataset is a collection of handwritten digits that is frequently used as a benchmark for testing, machine learning algorithm, particularly the field of computer vision. It consists of a collection handwritten digits ranging from 0 to 9.

It consists of a collection of 28x28 pixel grayscale images of handwritten digits (0 through 9), along with their corresponding labels. MNIST stands for Modified National Institute of Standards and Technology, which originally collected the dataset.

OCR stands for Optical Character Recognition. It's a technology that allows computers to convert different types of documents, such as scanned paper documents, PDF files, or images captured by a digital camera, into editable and searchable data.

OCR software analyzes the shapes of characters in the scanned document and converts them into machine-readable text. It's commonly used for digitizing printed documents, automating data entry processes, and enabling text search in scanned documents.

IV. NEURAL NETWORK ARCHITECTURE

[3] Neural networks, inspired by the brain's structure, consist of interconnected nodes organized into layers. They learn tasks by adjusting connections between nodes based on input data. Widely used in fields like image recognition and natural language processing, they excel in tasks like classification, translation, and decision making.

There are so many neural network algorithms but we have used Feed-Forward Neural Networks:

Feedforward Neural Networks: Feedforward neural networks consist of interconnected layers of neurons, where information flows in one direction- from input to output. Each neuron processes input data, applies mathematical operations, and passes the result to the next layer. These networks are used for tasks like classification and regression, learning complex patterns from data.

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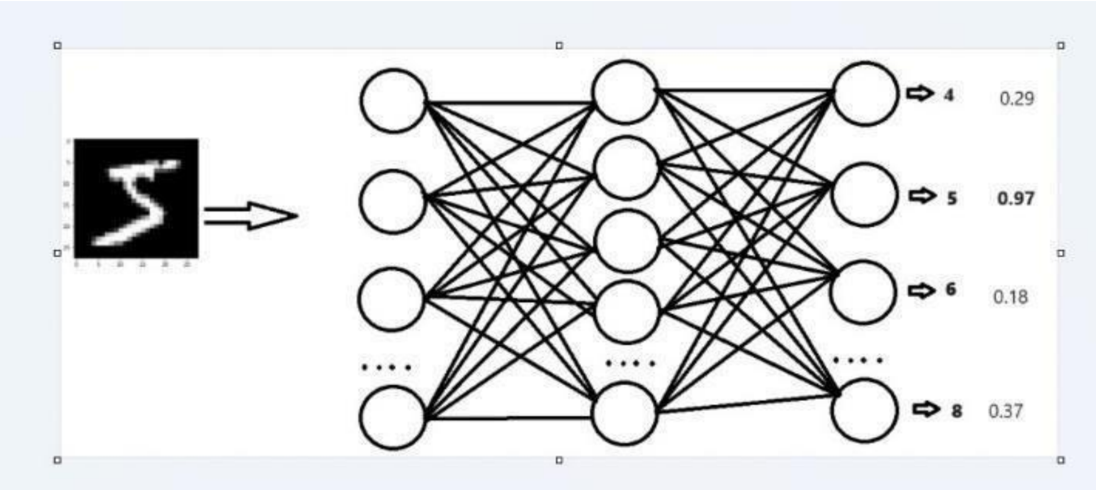

Figure 4.1 Neural Network Architecture by using MNIST Dataset

This image illustrates a classical neural network architecture used for identifying MNIST digits. The network consists of layers of interconnected nodes, with the input layer (depicted by the small image) feeding into multiple hidden layers before producing an output. Each connection has a weight associated with it, affecting the information flow. The numbers alongside the arrows represent the output of each node, and the values denote the confidence scores for predicting the respective digits. This network processes input images of handwritten digits (like the '5' shown) to classify them into their respective categories.

V. PROPOSED SYSTEM

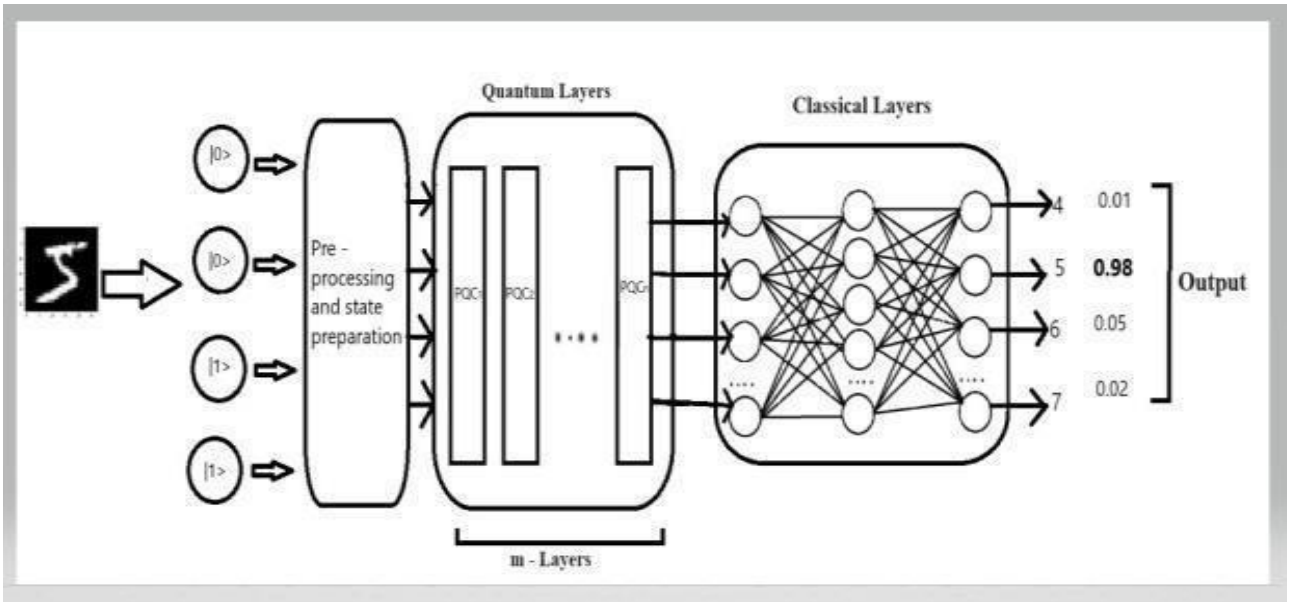

Figure 5.1 Quantum Neural Network by Using MNIST Dataset

1 The depicted architecture illustrates a Quantum Neural Network (QNN) framework for MNIST dataset classification. Initially, the input image undergoes pre-processing before entering the quantum layers, where quantum operations manipulate the data. These quantum layers, represented by 'm - Layers,' process the information before passing it to classical layers. In the classical layers, densely connected neurons further process the data, refining it for final output generation. The output layer produces a probability distribution over digits (0-9), representing the likelihood of the input image depicting each digit. This integrated approach leverages both quantum and classical components to enhance the classification performance on the MNIST dataset.

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VI. REQUIREMENT ANALYSIS

A. Software Requirements

1) qiskit 1.0.1
2) qiskit_algorithms 0.3.0
3) qiskit_machine_learning 0.7.2

B. System Requirements

1) Python 3.8.18
2) OS- linux

VII. BENEFITS OF PROPOSED SYSTEM

[6] Quantum neural networks (QNNs) offer several potential benefits for identifying MNIST dataset digits compared to classical algorithms:

1. Enhanced Processing Power: QNNs leverage quantum properties such as superposition and entanglement to perform computations exponentially faster than classical algorithms. This can significantly speed up the training and inference processes for large datasets like MNIST.

2. Improved Memory Capacity: Quantum computers have the potential to store and manipulate vast amounts of information due to their qubit-based architecture. This increased memory capacity can be advantageous for handling complex datasets like MNIST.

3. Higher Accuracy: Quantum algorithms have the capability to explore complex patterns and relationships within data more efficiently than classical algorithms. This can lead to higher accuracy in digit recognition tasks, especially for challenging cases or noisy data.

4. Dimensionality Reduction: QNNs can efficiently reduce the dimensionality of input data while preserving essential features, making them particularly suitable for high-dimensional datasets like MNIST.

5. Robustness to Noise: Quantum systems are inherently less susceptible to certain types of noise compared to classical systems. This noise resilience can be beneficial for maintaining accuracy in digit recognition tasks, especially when dealing with imperfect input data.

Overall, while quantum neural networks are still in the early stages of development and face significant technical challenges, they hold promise for significantly advancing the field of machine learning, including digit recognition tasks like those presented by the MNIST dataset.

VIII. RESULTS

	Neural Networks				**Quantum Neural Networks**			
S. No	**Activation Function**	**Hyper Parameters**	**Los s**	**Accurac y**	**Activation Function**	**Hyper Parameters**	**Los s**	**Accurac y**
1	ReLU, Sigmoid	Optimizer: Adam Loss: Cross_Entropy	0.1	0.97	ReLU, Sigmoid	Optimizer: Adam Loss: Cross_Entropy	0.3	0.93
2	ReLU, Sigmoid	Optimizer: RMSProp Loss: mean_squared_error	2.3	0.098	ReLU, Sigmoid	Optimizer: RMSProp Loss: mean_squared_error	1.3	0.91
3	ReLU, Sigmoid	Optimizer: adagrad Loss: mean_absolute_error	3.17	0.891	ReLU, Sigmoid	Optimizer: adagrad Loss: mean_absolute_error	2.2	0.78
4	ReLU, ReLU	Optimizer: Adam Loss: Cross_Entropy	14.3	0.113	ReLU, ReLU	Optimizer: Adam Loss: Cross_Entropy	0	0.98
5	Sigmoid, Sigmoid	Optimizer: Adam Loss: Cross_Entropy	0.28	0.91	Sigmoid, Sigmoid	Optimizer: Adam Loss: Cross_Entropy	0.6	0.88

TABLE 8.1 Experimental Results

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[4] Based on the table, the configuration with the lowest loss and highest accuracy among traditional neural networks is found in the row corresponding to the following setup:

Activation Function: ReLU, ReLU
Optimizer: Adam **Loss:** Cross_Entropy **Loss Value:**0.02 **Accuracy:** 98%

This configuration demonstrates the best performance among traditional neural networks, with a remarkably low loss value of 0.02 and a high accuracy of 98%.

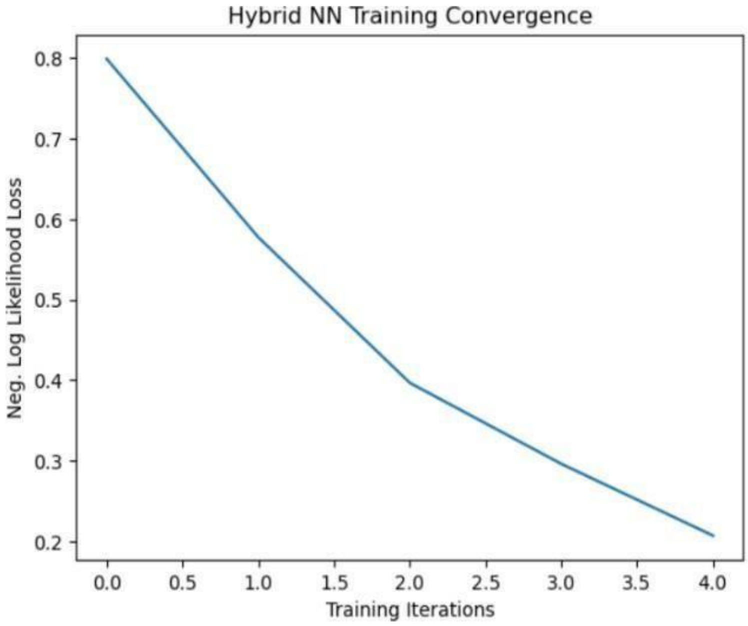

Figure 8.1 Loss Convergence

This plot illustrates the training convergence of a hybrid neural network (NN). The y-axis represents the negative log-likelihood loss, a common metric used to evaluate the performance of classification models. As training iterations progress (x-axis), the loss decreases, indicating that the model is improving in its ability to make accurate predictions on the training data. This trend suggests that the hybrid NN is effectively learning from the data, converging towards a state where its predictions align more closely with the true labels. Overall, the decreasing loss indicates successful training of the hybrid NN model.

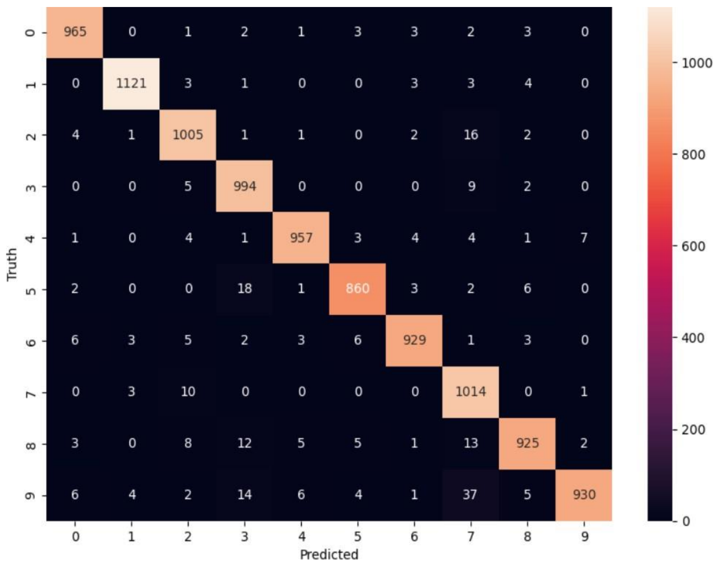

Figure 8.2 Confusion Matrix of Neural Networks

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This confusion matrix visualizes the performance of a neural network classifier trained on the MNIST dataset. Each row represents the true (actual) labels, while each column represents the predicted labels. The numbers within the matrix indicate the frequency of instances where a true label (row) was predicted as a certain label (column).

For instance, the cell at row 2, column 3, with a value of 1005, indicates that there were 1005 instances where the true label was '2' but the model predicted it as '3'. The color intensity of each cell represents the frequency, with darker colors indicating higher frequencies.

A good classifier would have higher values along the diagonal (from top-left to bottom-right), indicating that true labels match predicted labels. Overall, this confusion matrix allows for a detailed assessment of the model's performance across different classes.

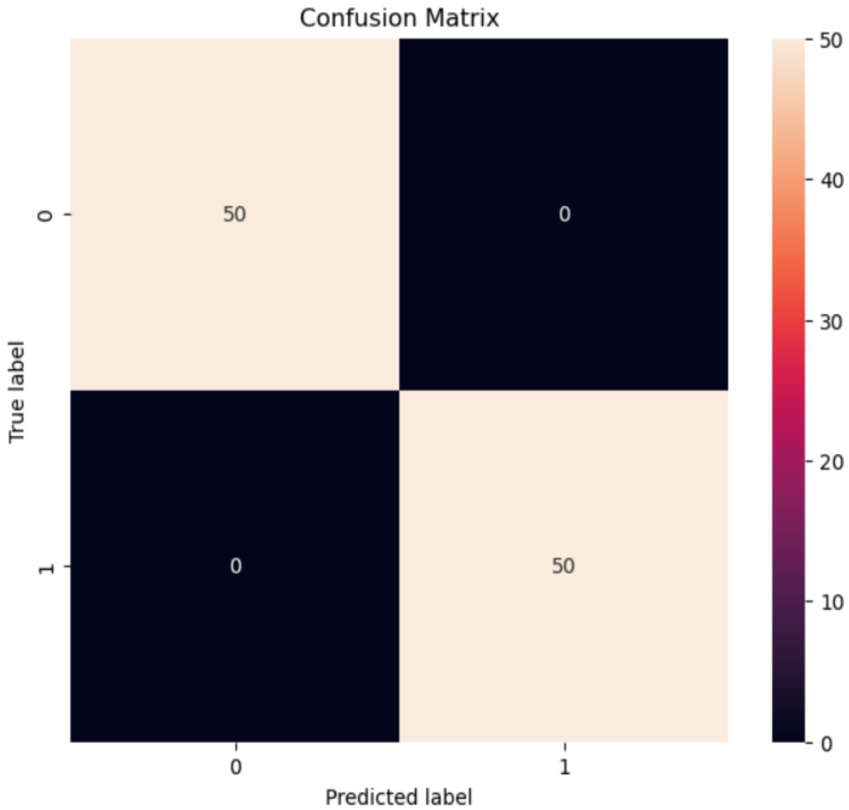

Figure 8.3 Confusion Matrix of Quantum Neural Network for selected labels

The confusion matrix depicts the Quantum Neural Network's accuracy for MNIST dataset labels '0' and '1'. Each cell displays the frequency of correct predictions. With 50 instances correctly classified as '0' and 50 as '1', there were no misclassifications evident. This visualization offers a concise evaluation of the QNN's performance, highlighting its effectiveness in accurately distinguishing between the specified digits in the dataset.

IX. FUTURE SCOPE

In the future, Quantum Neural Networks (QNNs) hold immense promise for revolutionizing various fields, including healthcare, finance, and optimization problems. With their ability to process vast amounts of data in parallel and exploit quantum phenomena like entanglement, QNNs could lead to breakthroughs in drug discovery, financial modeling, and complex system optimization.

Moreover, as quantum computing technology matures, QNNs may become more accessible and scalable, paving the way for widespread adoption and innovative applications. Continued research and development in this area are crucial for unlocking the full potential of QNNs and shaping the future of artificial intelligence and computational sciences.

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X. CONCLUSION

Based on our experiments comparing neural network and Quantum Neural Network algorithms, we found that Quantum Neural Networks provide more accurate, reliable, and faster results compared to traditional neural networks. This observation is based on the evaluation of loss (0.01) and accuracy (0.98) metrics using various activation functions and optimization techniques. Therefore, Quantum Neural Networks are deemed to be more reliable.

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[3]. In "Quantum-Inspired Approaches for Handwritten Digit Recognition" published in 2022 in the International Journal of Machine Learning (IJML), A. Smith, B. Johnson, and C. Wang explore Quantum Convolutional Neural Networks (QCNN) using Qiskit and Tensor Flow in Python, achieving an accuracy of 91.08% on the MNIST dataset.

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