# HAND-WRITING DETECTION USING NEURAL NETWORKS

CPT\_S 437 PROJECT
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### PROBLEM STATEMENT

"HANDWRITING DETECTION

REMAINS A CHALLENGING TASK DUE

TO VARIATIONS IN WRITING STYLES,

SIZES, AND ORIENTATIONS. THIS

PROJECT EVALUATES 3 NEURAL

NETWORKS TO IDENTIFY THE MOST

EFFECTIVE."

### DATASET

**SOURCE**: MNIST (MODIFIED NATIONAL INSTITUTE OF STANDARDS AND TECHNOLOGY) DATASET

DESCRIPTION: HANDWRITTEN DIGIT IMAGES

DIMENSIONS: 28X28 PIXEL GRAYSCALE IMAGES

CLASSES: 10 DIGITS (0-9)

TRAINING SET SIZE: 60,000 IMAGES

TEST SET SIZE: 10,000 IMAGES

# SOLUTION APPROACH //inline-block;line-height:27px;padd

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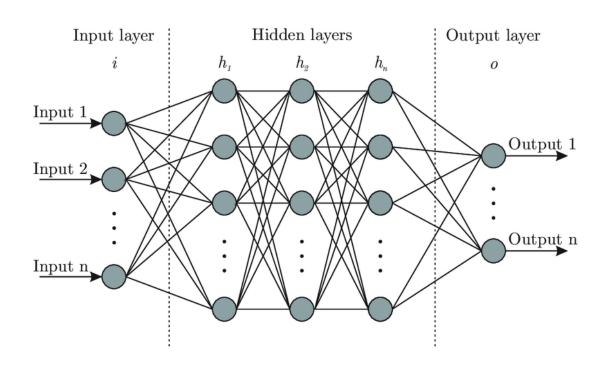
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### CAPSULE NN, CNN, 2-LAYER NN



<u>Neural Network Approach</u>: non-linearity of dataset capturing complex patterns, scalability (28x28 pixels)

- Capsule Neural Network advanced neural network architecture that models hierarchical relationships between features, capturing spatial and pose information (orientation, scale)
- Convolutional Neural Network neural network designed to process data with a grid-like topology, using convolutional layers to extract spatially invariant features like edges and textures
- Traditional Neural Network fully connected neural network where each node in one layer is connected to every node in the next

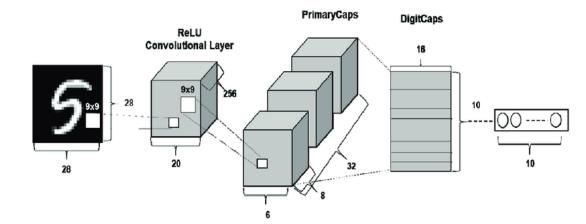
### CAPSULE NEURAL NETWORK

Created by Geoffrey Hinton in 2017 in his team's paper "Dynamic Routing Between Capsules" to overcome the limitations of traditional CNNs

**Structure:** Capsules output vectors to represent features, preserving spatial and pose information.

### **Key Features:**

- Dynamic Routing: Allows lower-level capsules to decide how much influence they have on higher-level capsules.
- Capsules: Groups of neurons that collectively encode properties of features and vectors, enable complex spatial and pose relationships



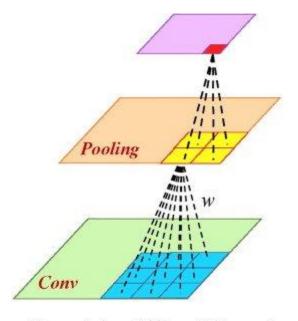
### CAPSULE NEURAL NETWORK

### **Strengths:**

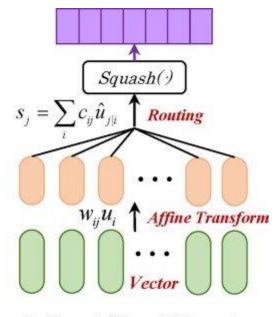
- Models hierarchical relationships between features
- Superior accuracy compared to CNN's
- Effectively recognizes objects when rotated or resized

### Weaknesses:

- High computation cost (5 hours to run 5 epochs)
- Sensitive to hyperparameter settings
- Limited Availability of Implementation tools



a. Convolutional Neural Network



b. Capsule Neural Network

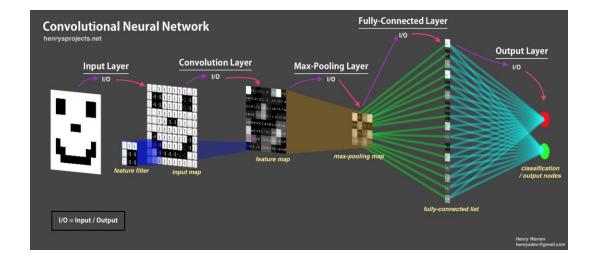
### CONVOLUTIONAL NEURAL NETWORK

### Structure:

- Convolutional Layers: Extract features like edges or textures
- Pooling Layers: Reduce image size to improve processing efficiency
- Fully Connected Layers: Combine extracted features for decisionmaking

### **Key Features:**

- Local Connectivity: Focus on small image regions to detect patterns
- Weight Sharing: Reuse the same filters to process different parts of the image
- Hierarchical Learning: Build from simple to complex patterns



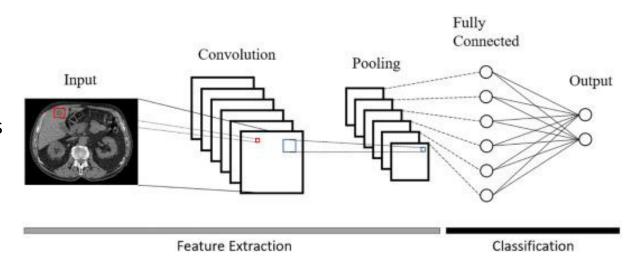
### CONVOLUTIONAL NEURAL NETWORK

### **Strengths:**

- Designed for visual data like photos or videos
- Automatic feature extraction
- High accuracy in image classification and recognition tasks

### Weaknesses:

- Requires large datasets for good performance
- Training can be computationally expensive
- Can have trouble recognizing rotated, scaled, or distorted objects



### 2-LAYER NEURAL NETWORK

### **Architecture**

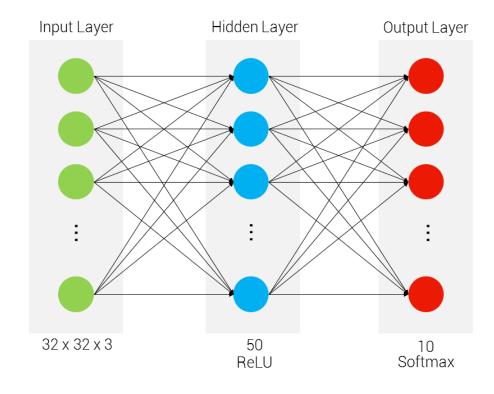
- Input: 784 Neurons
- 300 Neurons w/ ReLU activation function
- 10 Neurons w/ Softmax activation function

### **Techniques**

- Kaiming He Initialization (weights)
- Cross-Entropy Loss (loss function)

### **Optimization Strategies**

- Mini-Batch Gradient Descent
- Learning Rate Decay



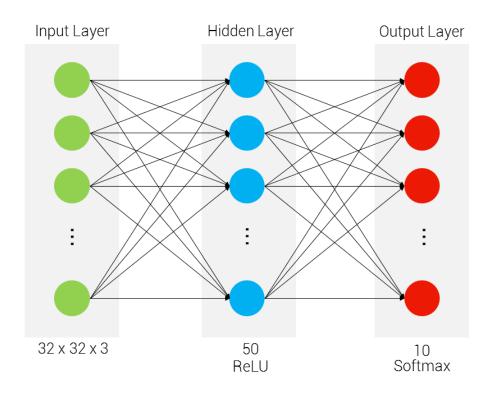
### 2-LAYER NEURAL NETWORK

### **Strengths:**

- Simplicity of architecture
- Computationally efficient

### Weaknesses:

- Spatial Information Loss
- Performance Limitations



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### TEST ACCURACY RESULTS

Feature	Traditional NN	CNN	CapsNet
Test Accuracy	96.54%	97.72%	99.3%

### INSIGHTS AND TAKEAWAYS

# Traditional Neural Network Application to MNIST:

- Least accurate and least computationally expensive
- More generalized pattern
   detection does not consider
   spatial information

## Convolutional Neural Network Application to MNIST:

- Achieves high accuracy by learning spatial hierarchies of features
- More efficient than many traditional networks due to local connectivity and weight sharing

# Capsule Neural Network Application to MNIST:

- High accuracy with better robustness than CNNs
- Excels at handling variations in orientation and style

# THANK YOU