

# Neural Network Models for Object Recognition using MNIST

A Comprehensive Approach for Handwritten Digit  
Recognition

Roshni Kasturi

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# Introduction

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- AI in object detection
- Objective

# Significance of the MNIST Dataset

(Modified National Institute of Standards and Technology database)

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- Commonly used for benchmarking machine learning algorithms in computer vision.
- Regarded as a "Hello World" dataset for introducing image classification tasks (Deng, 2012).

# Data Overview and Preparation

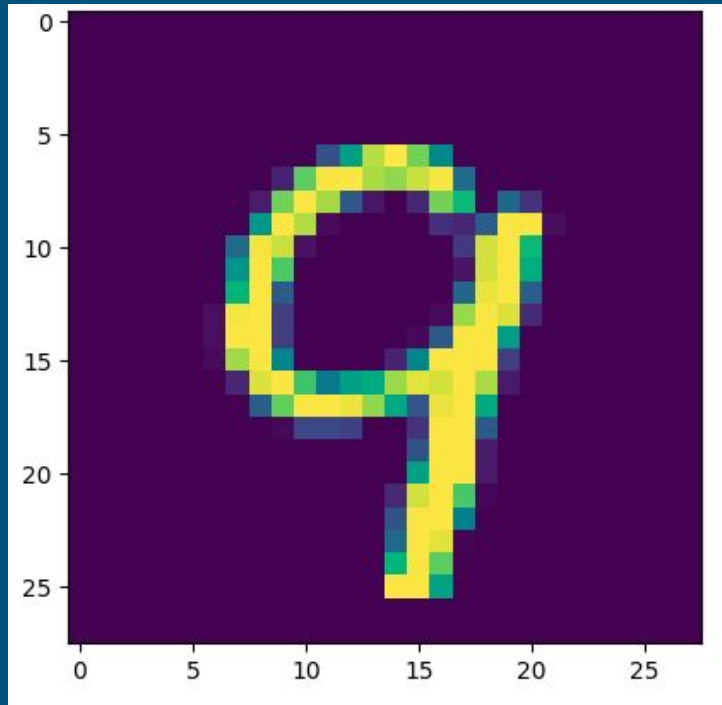
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- Data Split / Partition
  - Random split of the training set into:
    - training (80%) - 48,000 images
    - validation (20%) datasets - 12,000 images
  - While the test set has 10,000 images
- Image dimensions
  - 28x28 pixels, 1 channel
- 10 object categories (digits 0-9)

# Data Preparation

## Importance of a Separate Validation Set

- Unbiased performance monitoring
- Hyperparameter tuning
- Detection of overfitting



# Neural Network Architecture

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- Input Layer
  - Consists of 784 neurons ( $28 \text{ pixels} \times 28 \text{ pixels}$ )
- Hidden Layer (Dense Layer)
  - Features 128 neurons utilizing the ReLU activation function
- Output Layer (Dense Layer)
  - Contains 10 neurons representing the digits 0-9
  - Employs the Softmax activation function to produce a probability distribution

# Activation Functions

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- ReLU (Rectified Linear Unit)
  - Equation
  - Hidden layers
- Softmax
  - Output layer

$$f(x) = \max(0, x)$$

# Loss Function

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Function used: Categorical Crossentropy

- Ideal for multi-class classification tasks (Bishop, 2006)
- Assesses the difference between actual labels and predicted probabilities

$$L(y, \hat{y}) = -y \ln(\hat{y}) - (1 - y) \ln(1 - \hat{y})$$

Image Source: (Derivation for Log Loss Function in Classification, 2023)



# Training the Model

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- Epochs: 20
  - Balanced Training Duration
  - Empirical Success
  - Validation Monitoring
- Batch size: 32
- Learning rate: 0.001 (default):
  - Proven Effectiveness of Defaults
  - Simplifies Model Development
  - Baseline Performance
  - Rapid Prototyping

# Design Strategy

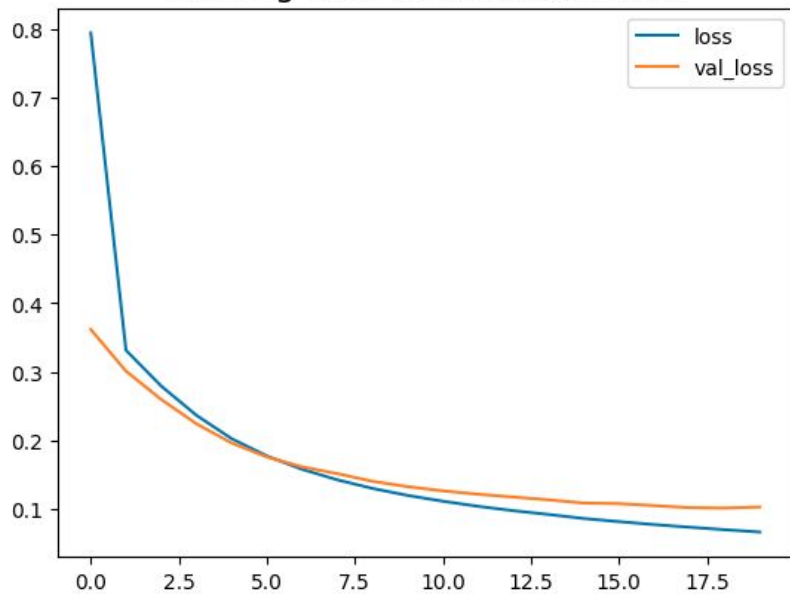
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- Layer combinations for Feature Extraction
  - Conv2D
  - Pooling Layer
  - Flattening Layer
- Regularization to prevent overfitting
  - EarlyStopping
- Optimization Techniques
  - Loss Function (categorical\_crossentropy)
  - Optimizer (adam)
  - Metrics (accuracy)

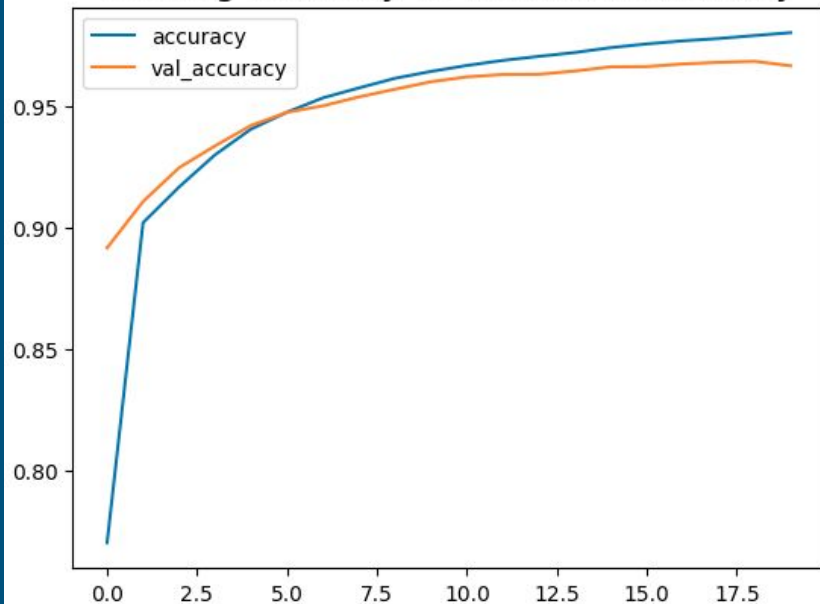
# Model Evaluation

## Training vs Validation Performance Metrics

Training Loss Vs Validation Loss



Training Accuracy Vs Validation Accuracy



# Model Evaluation

## Classification Report

	precision	recall	f1-score	support
0	0.97	0.99	0.98	980
1	0.98	0.99	0.99	1135
2	0.95	0.97	0.96	1032
3	0.97	0.96	0.96	1010
4	0.97	0.97	0.97	982
5	0.96	0.98	0.97	892
6	0.98	0.97	0.98	958
7	0.99	0.93	0.96	1028
8	0.96	0.95	0.96	974
9	0.94	0.97	0.96	1009
accuracy			0.97	10000
macro avg	0.97	0.97	0.97	10000
weighted avg	0.97	0.97	0.97	10000

# Model Evaluation

## Confusion Matrix

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```
array([[ 970,    1,    0,    0,    2,    1,    2,    0,    2,    2],
       [   0, 1120,    5,    1,    0,    1,    2,    0,    6,    0],
       [   6,    0, 1006,    2,    3,    1,    2,    2,    9,    1],
       [   1,    0,   13,  969,    1,   12,    0,    3,    6,    5],
       [   1,    0,    3,    0,  949,    1,    4,    1,    2,   21],
       [   2,    1,    0,    7,    0,  871,    3,    1,    3,    4],
       [   7,    3,    1,    0,    4,    9,  929,    1,    4,    0],
       [   0,    8,   22,   11,    2,    1,    0,  956,    2,   26],
       [   9,    1,    7,    7,    6,    6,    4,    2,  928,    4],
       [   1,    5,    0,    2,   10,    7,    1,    1,    0,  982]])
```

# Summary

## Project Overview

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- Neural network model created for object recognition
  - Specifically, handwritten numerical digits
- Focus:
  - Architecture
  - Training
  - Evaluation
- Importance of a separate validation set

# Summary

Potential Improvements

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Experimentation with:

- Different CNN architectures / variations
  - ResNet
  - DenseNet
- With hyperparameter tuning

....for optimized model performance

# Summary

## Reflections on Learning

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- Data preprocessing and preparation is key!
- Model evaluation can also help eliminate errors
- Visualization of performance metrics provided greater understanding
  - Compared to numerical performance metrics alone





Thank you!

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