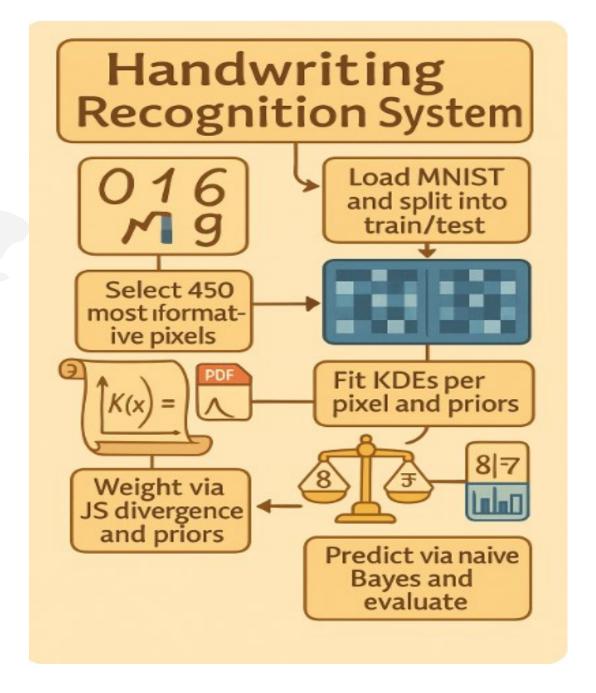
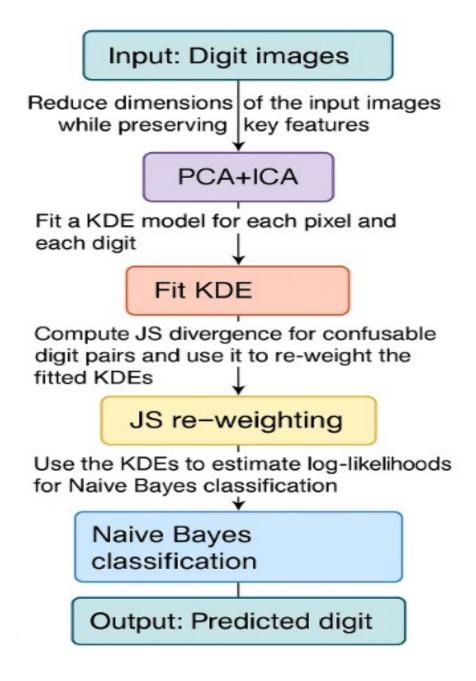
#### KDE-Based Digit Classifier



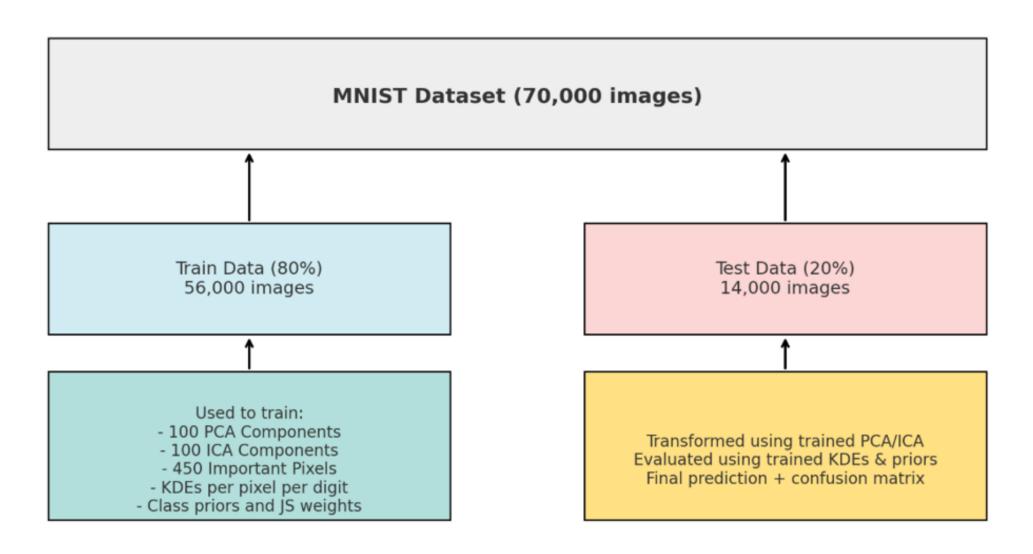
## Theory Foundation

- Naive Bayes is a **probabilistic classification algorithm** based on **Bayes' theorem**, which assumes that features are **conditionally independent** given the class.
- We apply this principle to our image classification system:
  - Each **pixel position** is treated as an independent feature.
  - We assume that pixel values at different positions do not influence each other.
- This allows us to model the likelihood of each digit by estimating per-pixel probability densities using Kernel Density Estimation (KDE).
- Classification then becomes a product of per-pixel probabilities.

### System Overview



#### Data Usage Flow in KDE-Based Prediction System



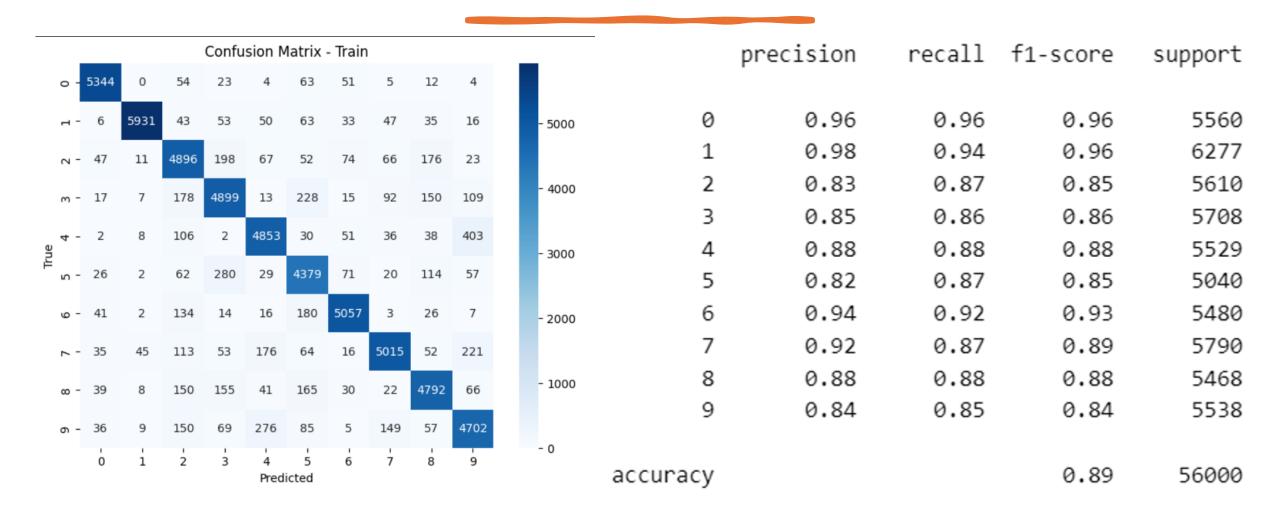
# System Performance and Runtime Summary

• Train Accuracy: 0.8905

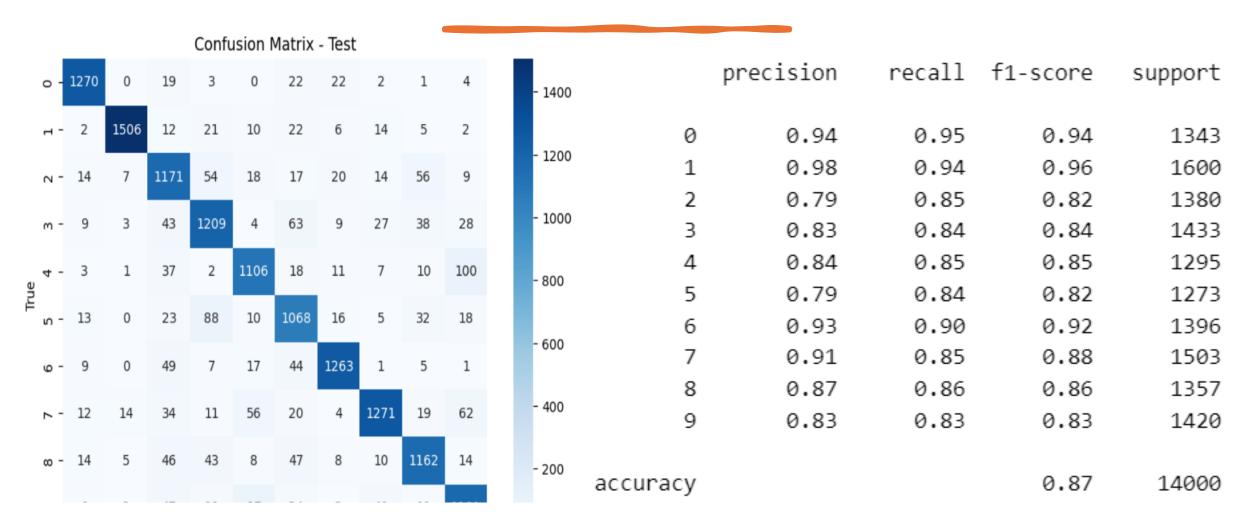
• Test Accuracy: 0.8719

Phase	Sub-step	Time (s)	Description
Data Prep	Load & Split	9.46	Load MNIST from OpenML, normalize pixel values, and split into train/test sets
	Variance Filtering	0.88	Remove pixels with variance below 0.005 to reduce noise
	PCA + ICA	88.07	Apply PCA and ICA to reduce dimensionality while preserving key features
	Mutual Info Selection	271.84	Select 450 pixels with highest mutual information relative to class labels
Model Fitting	KDE Fitting	149.69	Fit a PDF per digit (0–9) for each selected pixel using kernel density estimate
Evaluation	Train Prediction	402.79	Predict and evaluate 56,000 training images using log- likelihood summation
	Test Prediction	100.70	Predict and evaluate 14,000 test images
TOTAL	_	1023.43	Complete end-to-end runtime: ~17 minutes

## Classification Report (Train Set)

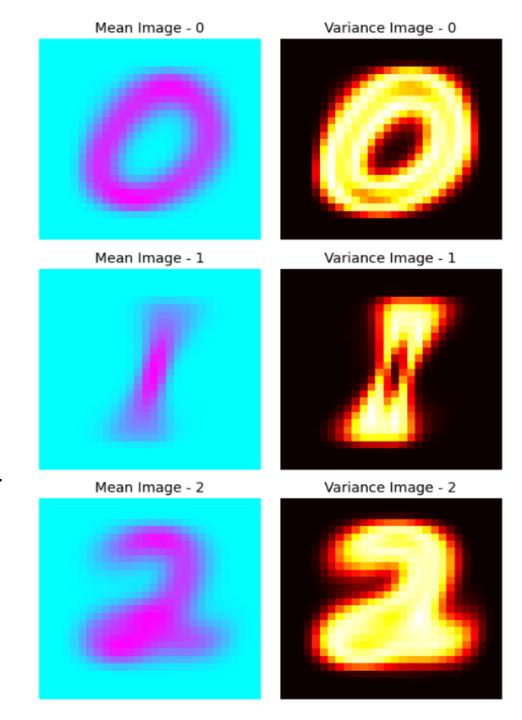


## Classification Report (Test Set)

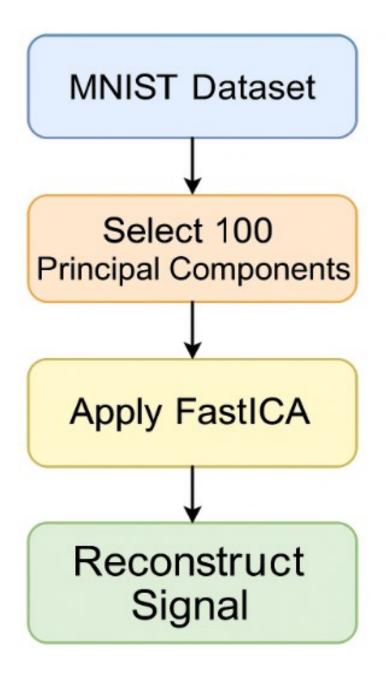


## Digit Mean and Variance Heatmaps

- **Mean images** show the typical shape and structure of each digit.
- Variance images highlight unstable pixel regions where people write differently.
- Heatmaps help identify **informative pixels** for KDE fitting and enhance **digit separability** in classification.

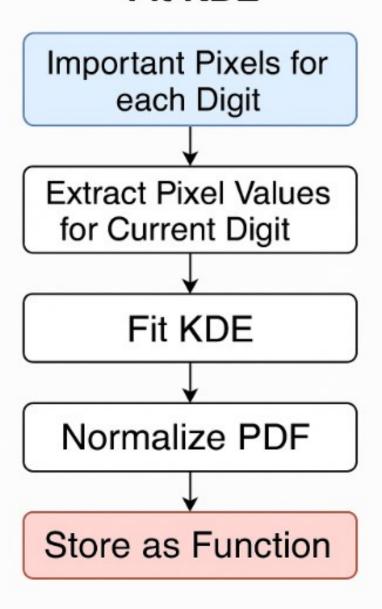


#### Preprocessing: Dimensionality Reduction

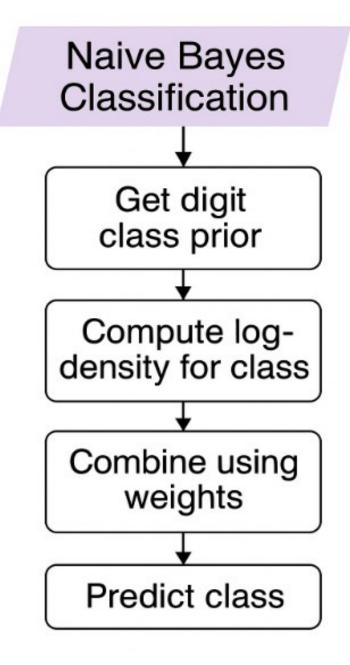


# Fitting KDE Models per Digit and Pixel

#### Fit KDE



#### Naive Bayes Classification Process



## Understanding the KDE Curve

#### What is the KDE Curve?

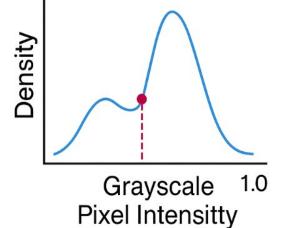
The X-axis is the grayscale pixel intensity, from black (0) to white (1).

The Y-axis shows **probability density**, indicating how common each pixel value is for the class.

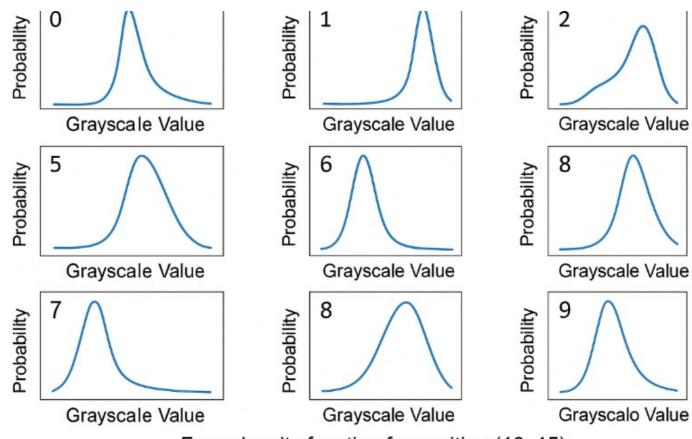
#### In simple terms:

The curve represents how the pixel typically looks for the class.

Interpolate KDE for Value

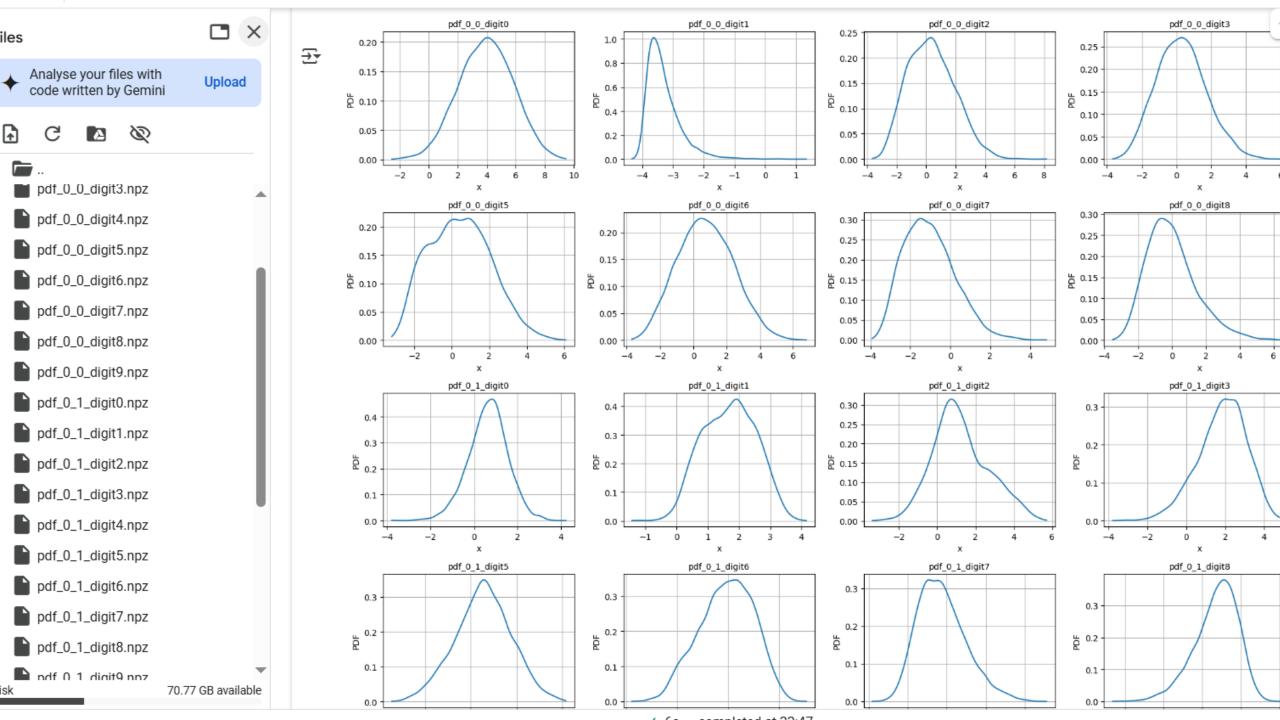


# PDF Distributions at Pixel Position (10, 15)



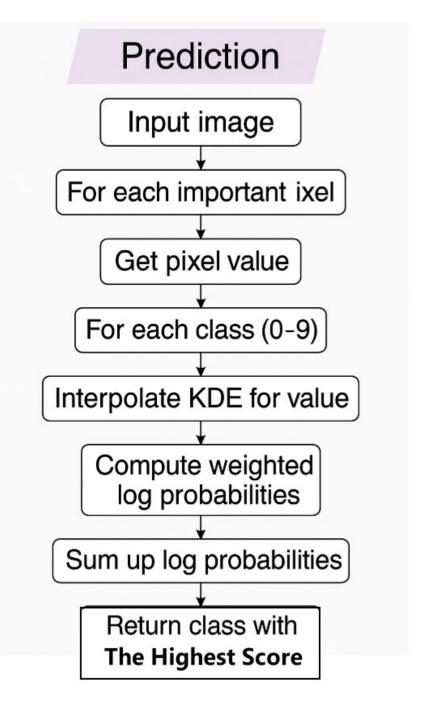
From density function for position (10, 15)

**Grayscale value: Pixel insensity** 



# Get Pixel Value Interpolate KDE for Value Density Value

### Prediction



### **Evaluation** Loop over images Accesss PDFs per pixel Compute accuracy Generate report

#### Evaluation

Sum up Log Probabilities and Return Class with Highest score

#### Log probabilities

$$0 = -10.9$$

$$1 = -33.3$$

$$2 = -20.8$$

$$3 = -39.1$$

$$4 = -27.3$$

$$5 = -15.7$$

$$6 = -25.3$$

$$7 = -35.2$$

$$8 = -27.8$$

$$9 = -19.6$$

Return class with highest score