Image Classification

Agenda

1. The Data
2. Modelling
3. The Final Test

π

pi

α alpha	β beta	γ gamma	δ delta	ϵ epsilon	ζ zeta	η eta	θ theta
ι iota	κ kappa	λ lambda	μ mu	ν nu	ξ xi	π pi	ρ rho
σ sigma	τ tau	ϕ phi	χ chi	ψ psi	ω omega	Γ Gamma	Δ Delta
Θ Theta	Λ Lambda	Ξ Xi	Π Pi	Σ Sigma	Φ Phi	Ψ Psi	Ω Omega
	ε varepsilon	$\varkappa$ varkappa	ϖ varpi	ϱ varrho	φ varphi	ϑ vartheta	

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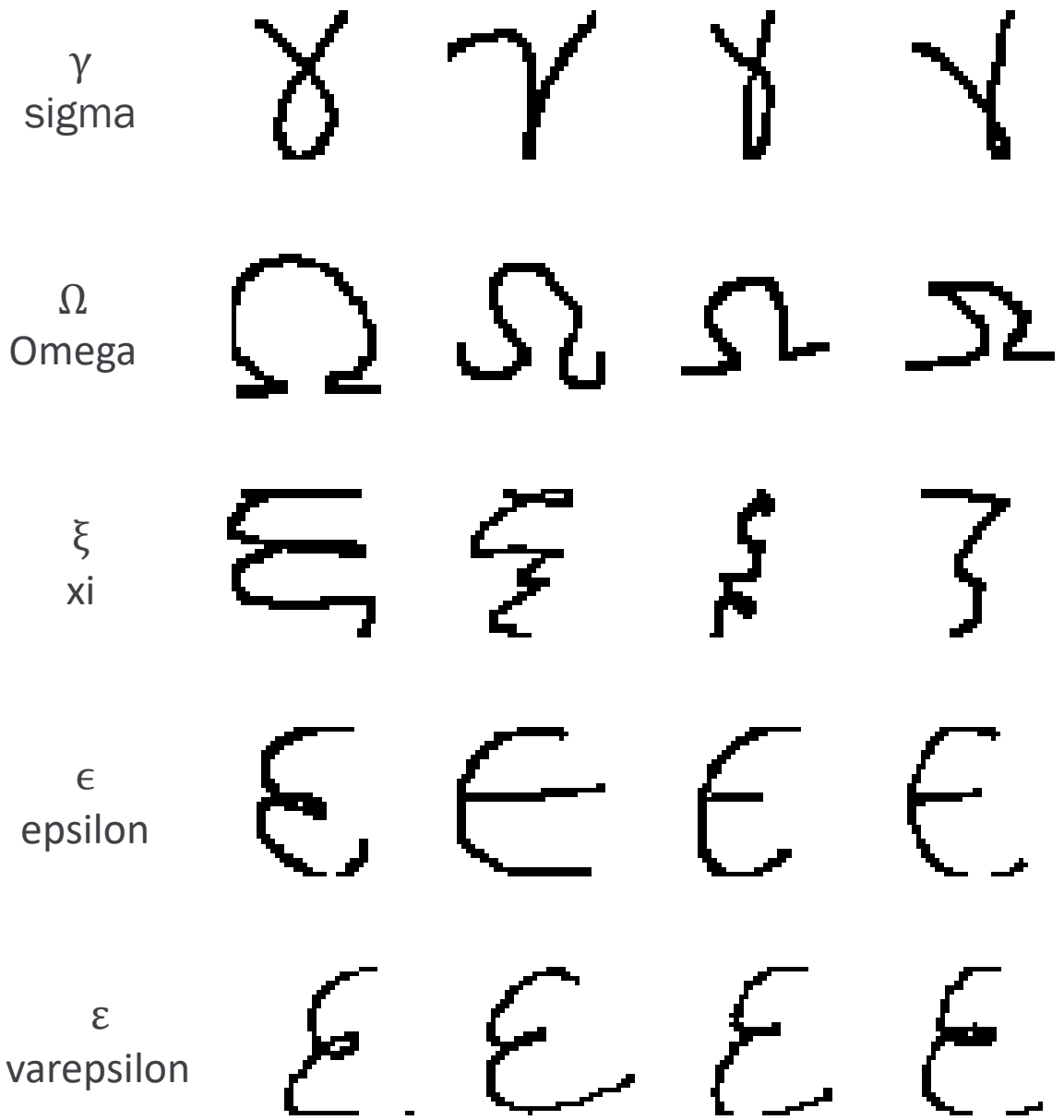
The Data

Known as HASYv2(1) and contains roughly 170,000 32x32 black and white images of various characters and mathematical symbols.

(1)Thoma, Martin. "The hasyv2 dataset." *arXiv preprint arXiv:1701.08380* (2017).



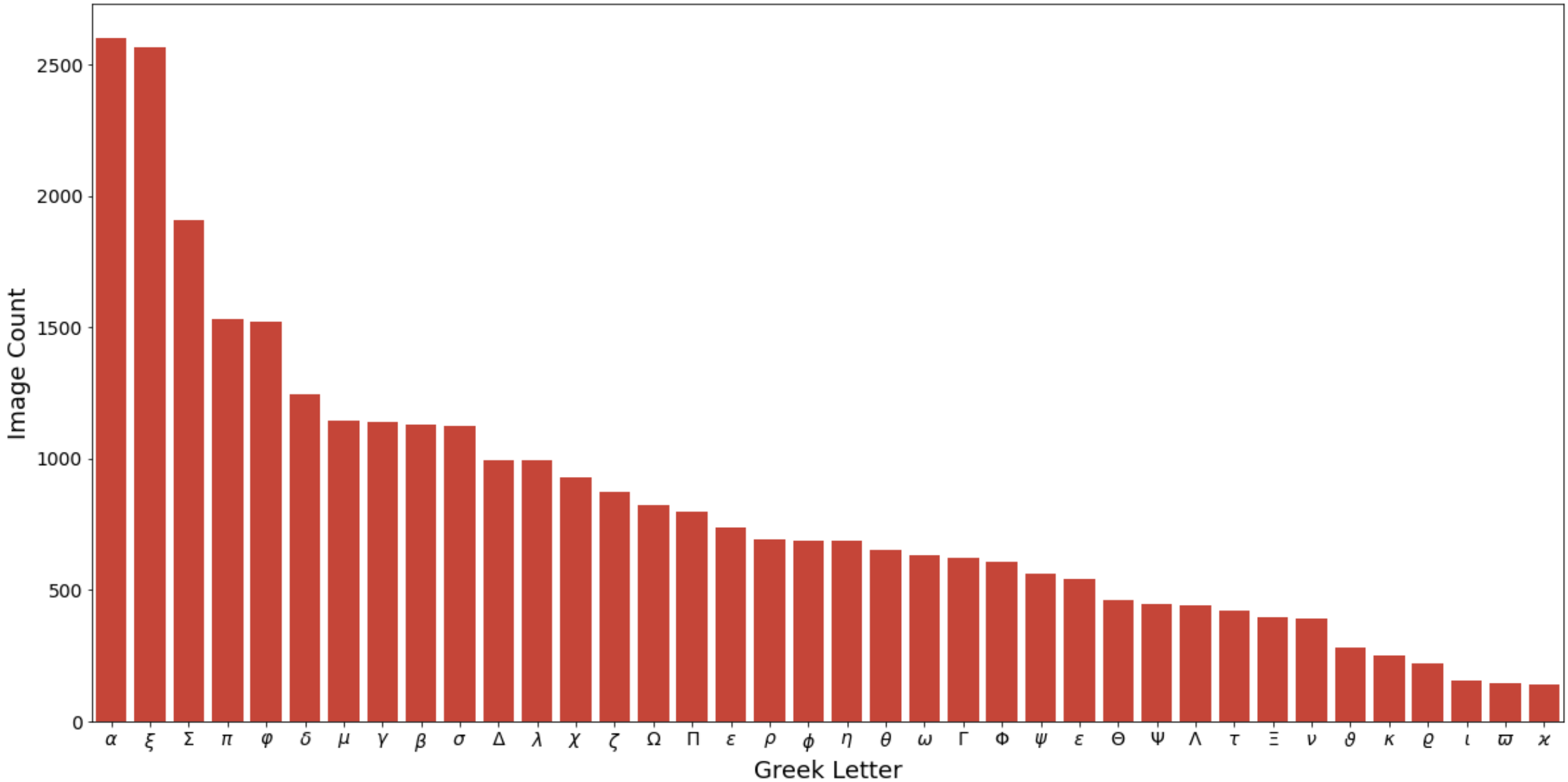

Greek Letter Character Counts from the HASYv2 Dataset
Image Count
0
500
1000
1500
2000
2500
α ξ Σ π φ δ μ γ β σ Δ λ χ ζ Ω Π ε ρ ϕ η θ ω Γ Φ ψ ε Θ Ψ Λ τ Ξ ν ϑ κ ϱ ι ϖ ϰ
Greek Letter

Image Data

Computers view images as arrays.

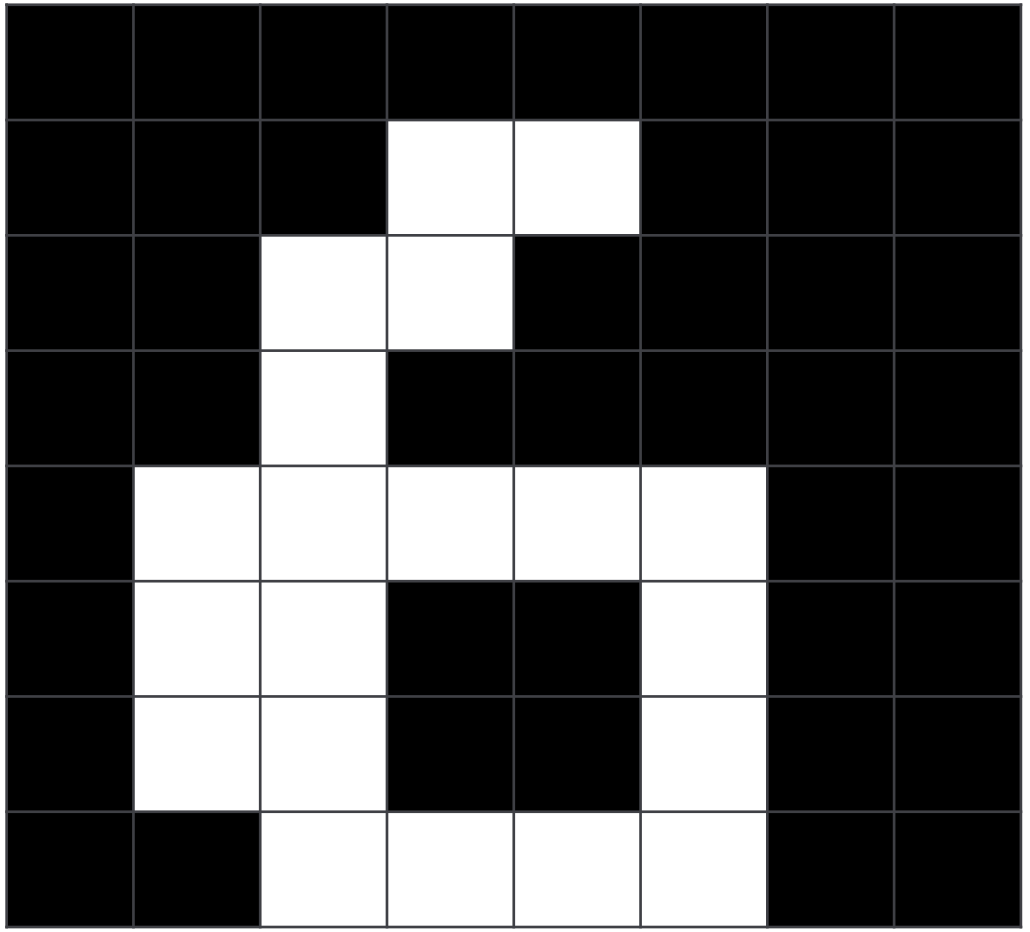


Image Data

Computers view images as arrays.

0	0	0	0	0	0	0	0
0	0	0	255	255	0	0	0
0	0	255	255	0	0	0	0
0	0	255	0	0	0	0	0
0	255	255	255	255	255	0	0
0	255	255	0	0	255	0	0
0	255	255	0	0	255	0	0
0	0	255	255	255	255	0	0

Image Data

Computers view images as arrays.

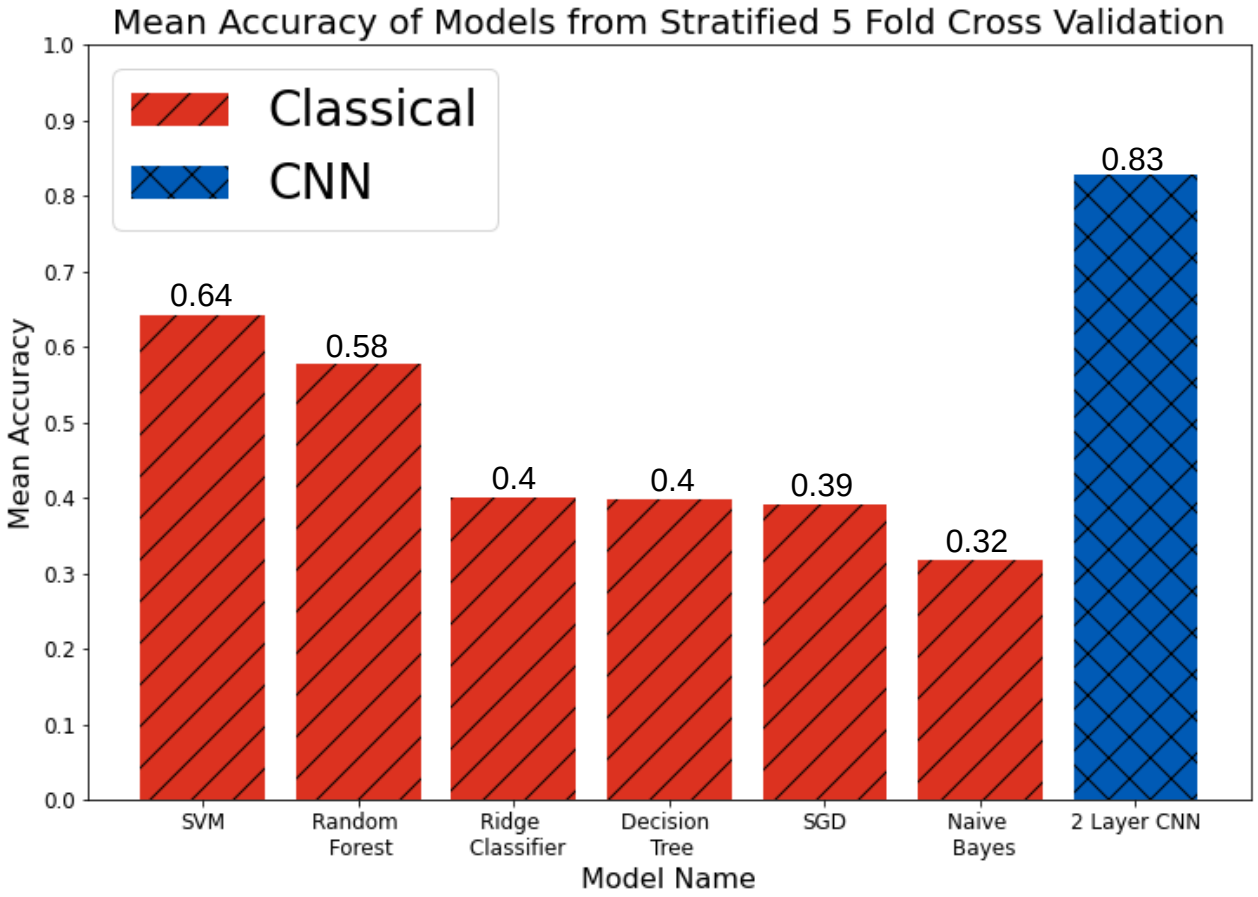
Black and white images require a single array of size equal to the size of the image. Each value in the array ranges in value from 0 to 255 inclusively. 0 represents a black pixel and 255 a white pixel.

0	0	0	0	0	0	0	0
0	0	0	255	255	0	0	0
0	0	255	255	0	0	0	0
0	0	255	0	0	0	0	0
0	255	255	255	255	255	0	0
0	255	255	0	0	255	0	0
0	255	255	0	0	255	0	0
0	0	255	255	255	255	0	0

Modelling

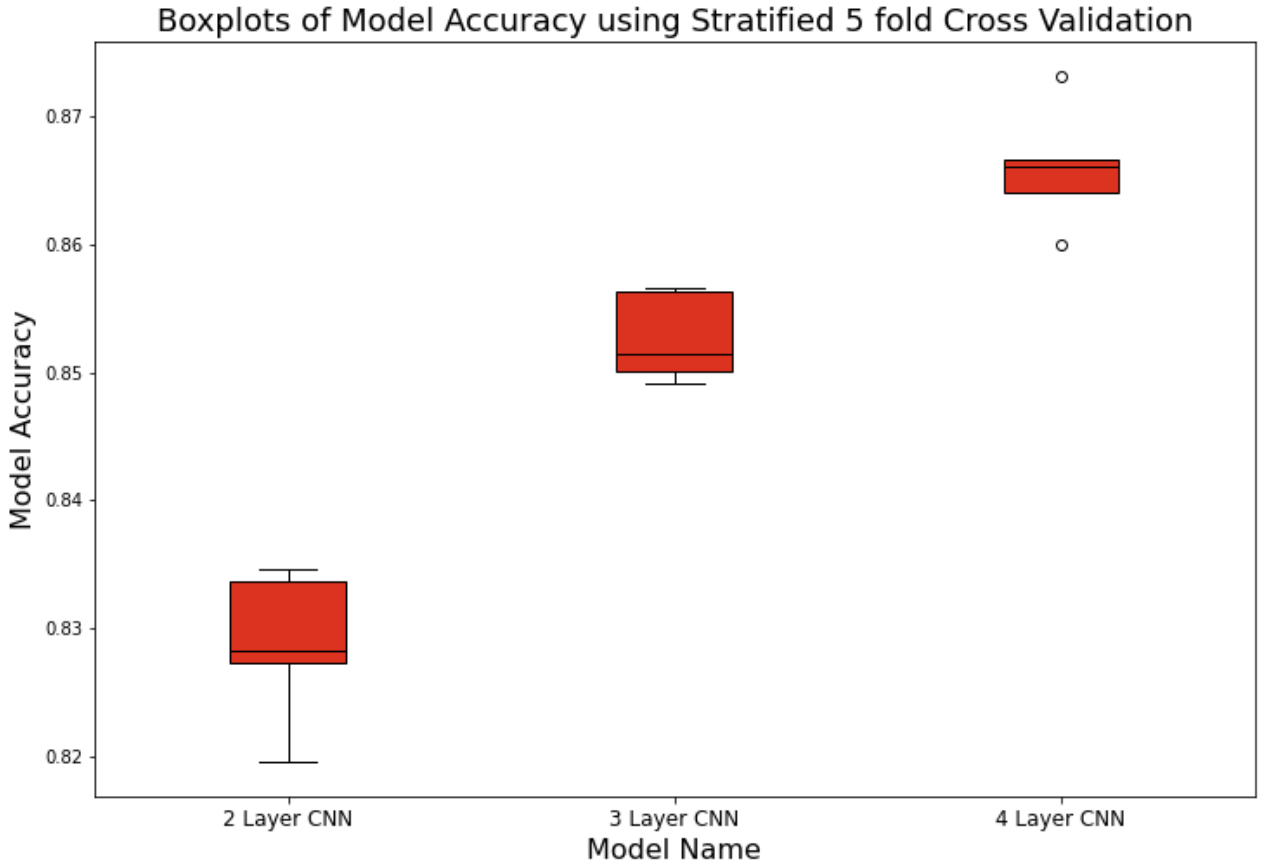
Initial Models

A variety of different classification models were tried initially. These included a variety of “classical” models such as SVM and Random Forests and some Convolutional Neural Networks (CNN).



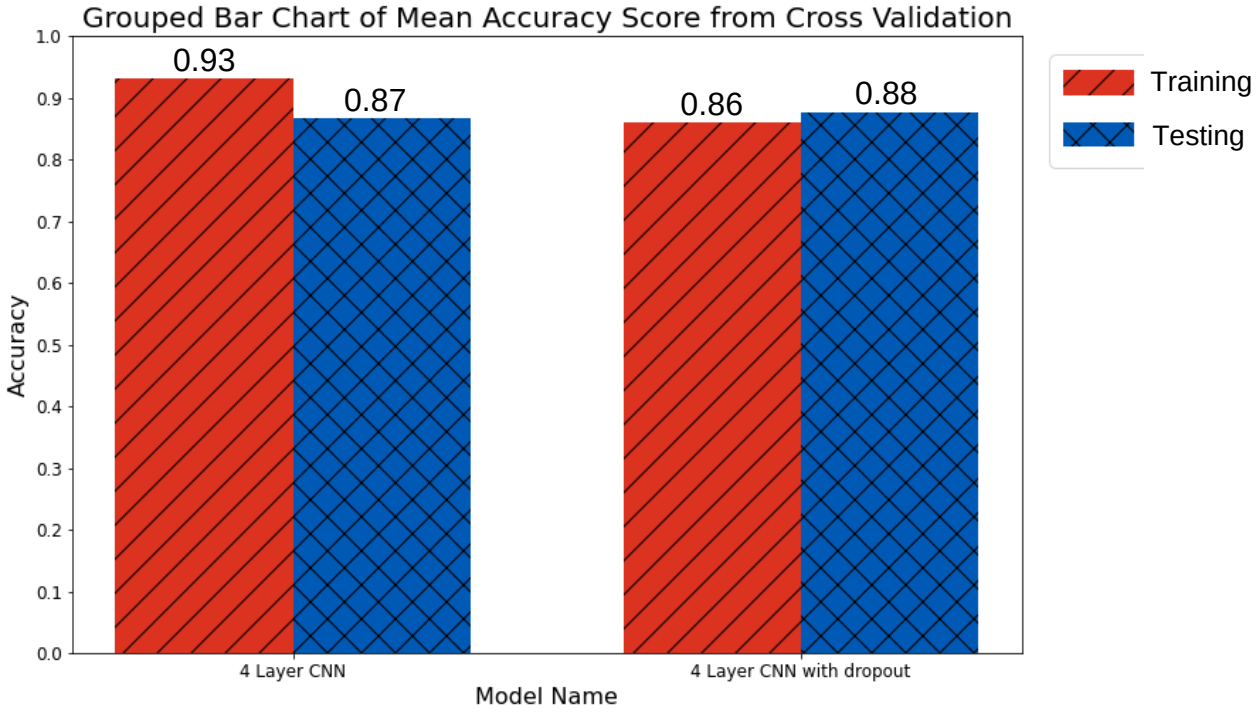
Convolutional Neural Networks (CNNs)

Through trial and error, I built various CNNs and measured their performance.



Fixing Overfitting

To remedy the overfitting I experimented with what's known as dropout. This is a regularisation technique that helps reduce overfitting.



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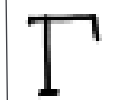
Metric	Test Result (%)
Accuracy	89.48
Precision	88.18
Recall	84.23
F1 Score	85.64

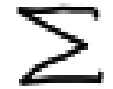
The Final Test

My Handwriting

The model performs well on the data but can it successfully classify my handwriting?

Letter	Predicted
 alpha	
 beta	
 gamma	
 delta	
 epsilon	
 zeta	
 eta	
 theta	
 iota	
 kappa	
 lambda	
 mu	
 nu	

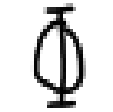
Letter	Predicted
 xi	
 pi	
 rho	
 sigma	
 tau	
 phi	
 chi	
 psi	
 omega	
 Gamma	
 Delta	
 Theta	
 Lambda	

Letter	Predicted
 Xi	
 Pi	
 Sigma	
 Phi	
 Psi	
 Omega	
 varepsilon	
 varkappa	
 varpi	
 varrho	
 varphi	
 vartheta	

My Handwriting

The model performs well on the data but can it successfully classify my handwriting?

The model achieved a 76.3% (29/38) accuracy score on my letters.

	Letter	Predicted		Letter	Predicted		Letter	Predicted
	alpha	alpha ✓		xi	xi ✓		Xi	Xi ✓
	beta	beta ✓		pi	pi ✓		Pi	Pi ✓
	gamma	gamma ✓		rho	rho ✓		Sigma	Sigma ✓
	delta	xi ✗		sigma	sigma ✓		Phi	Phi ✓
	epsilon	Xi ✗		tau	tau ✓		Psi	psi ✗
	zeta	xi ✗		phi	Phi ✗		Omega	Omega ✓
	eta	eta ✓		chi	chi ✓		varepsilon	xi ✗
	theta	theta ✓		psi	psi ✓		varkappa	kappa ✗
	iota	iota ✓		omega	omega ✓		varpi	sigma ✗
	kappa	kappa ✓		Gamma	Gamma ✓		varrho	varrho ✓
	lambda	lambda ✓		Delta	Delta ✓		varphi	varphi ✓
	mu	mu ✓		Theta	Theta ✓		vartheta	theta ✗
	nu	nu ✓		Lambda	Lambda ✓			

Thank You