Project 1

Sign-Language MNIST and Classification

FAA 2024/25

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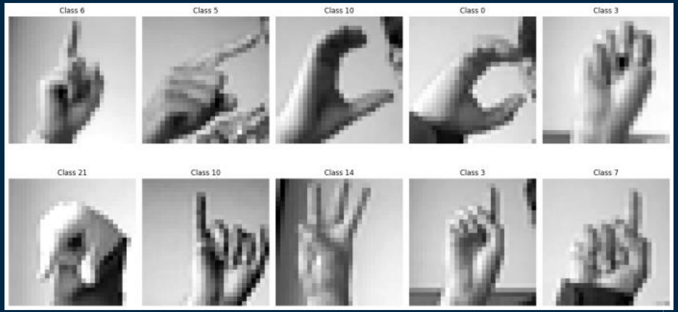
01 Dataset Description

- Dataset is a transformation of another dataset

- Data was presplit into 2 files:

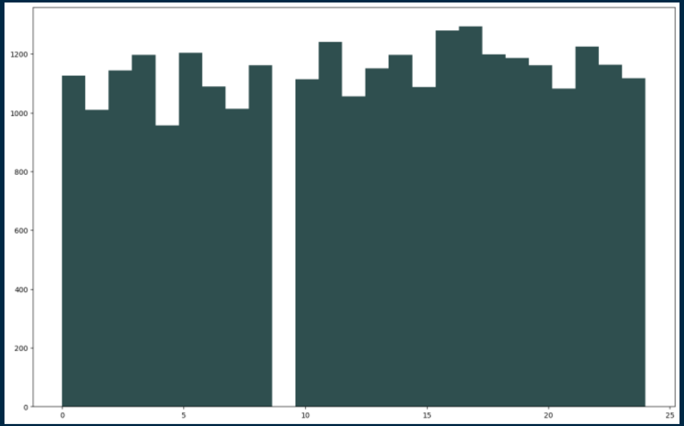
  Train: 27455 examples
  Test: 7172 examples

- 24 classes more or less evenly distributed

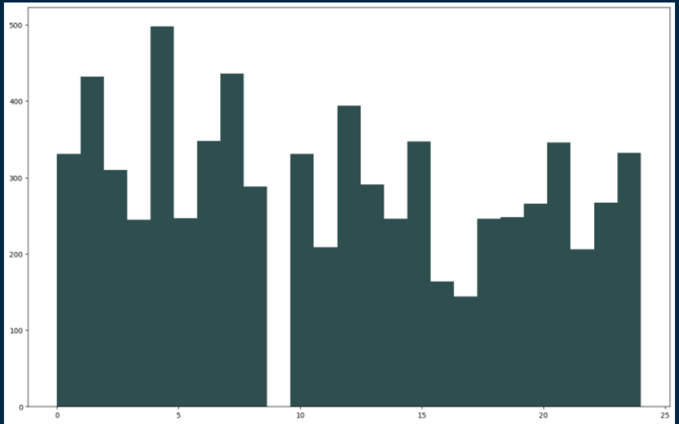


01 Dataset Description

Train

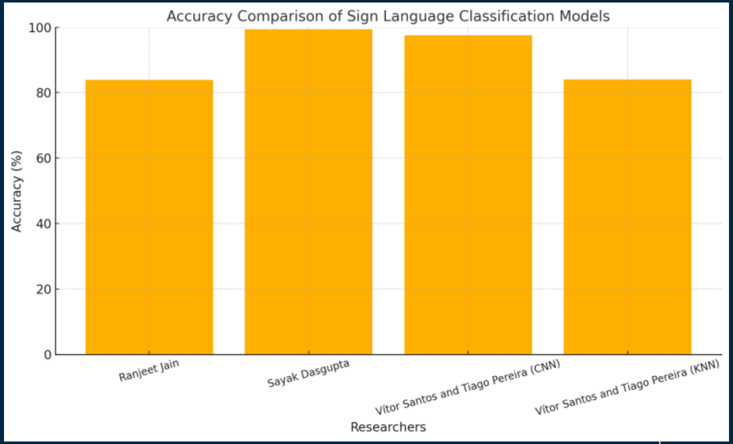


Test



02 State of the art

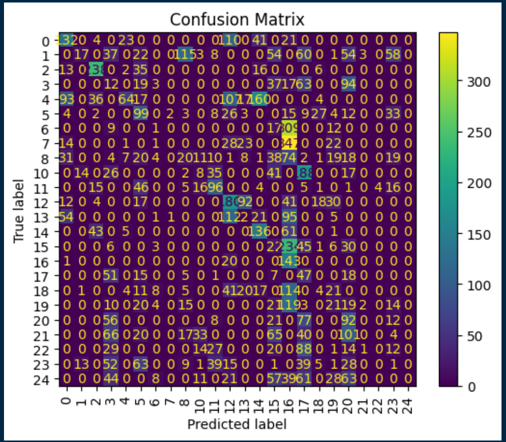
- Ranjeet Jain using CNN has able to achieve 83.87% accuracy
- Sayak Dasgupta using CNN has able to achieve 99.40% accuracy but using data augmentation
- Vitor Santos and Tiago Pereira were able achieve 84% accuracy using a KNN and 97% using a CNN

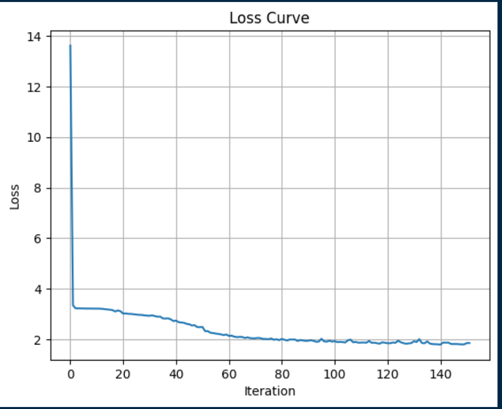


Models

03 Models – NN 1

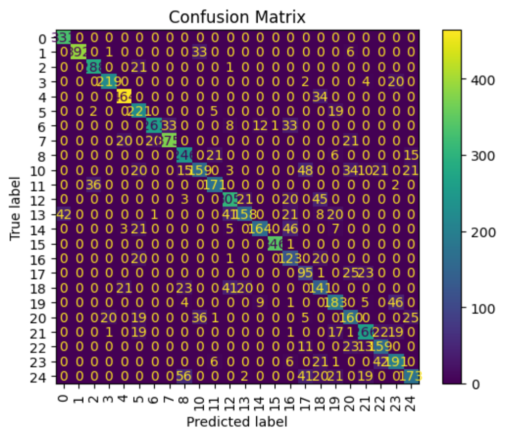
- Model built using most basic parameters, to understand how a simple model will perform
- No data normalization
- No L2 regularization term
- Accuracy 18,61% F1-Score 0.156

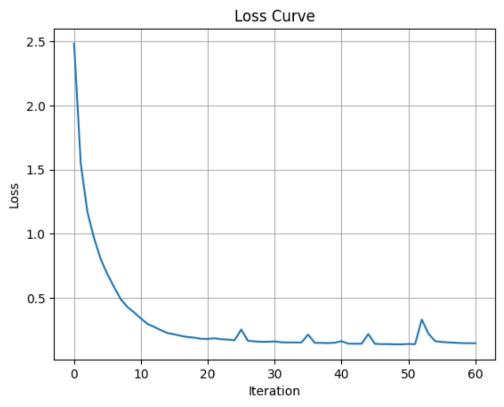




03 Models – NN 2

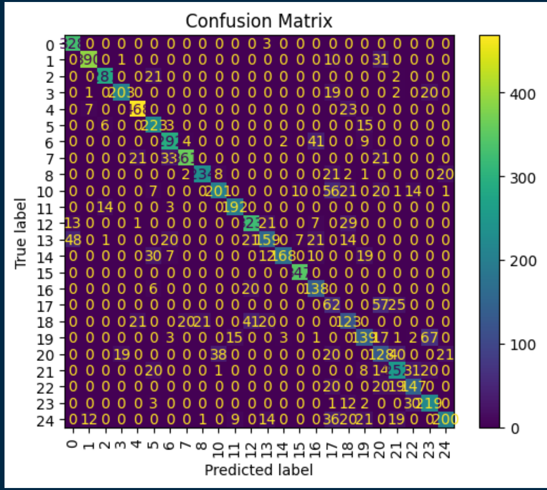
- Added data normalization
- Ran simulations to learn best hidden layer structure (1st 256 , 2nd 128)
- Shows clear improvements comparing to Model 1
- Accuracy 77.96% F1-Score 0.7577

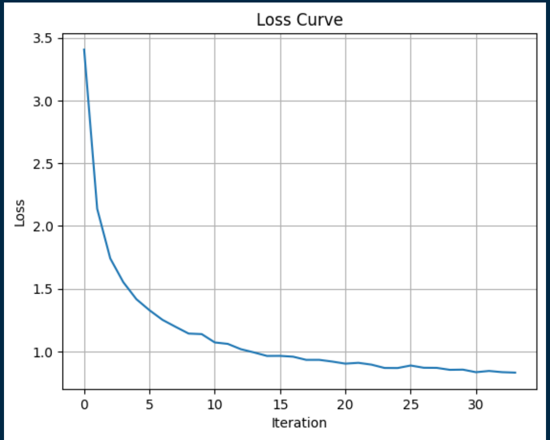




03 Models – NN 3

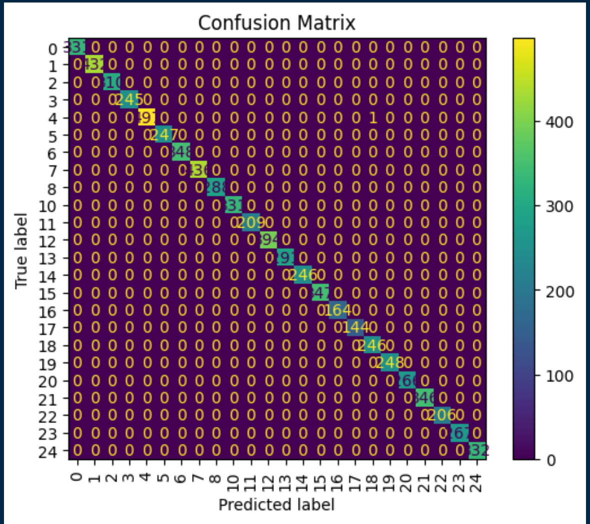
- Added L2 regularization term (alpha)
- Ran simulations to get the best alpha value (0.1)
- Accuracy 77.86% F1-Score 0.7559
- Overfitting still present

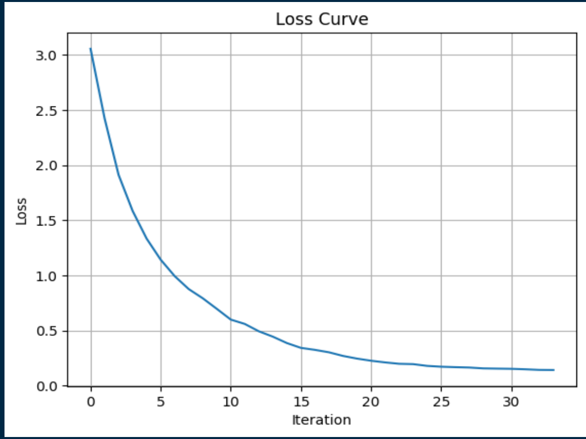




03 Models – NN 4

- Added data augmentation in both training and testing
- Model performance shows clear improvement
- Accuracy 99.48%
- F1-Score 0.9979

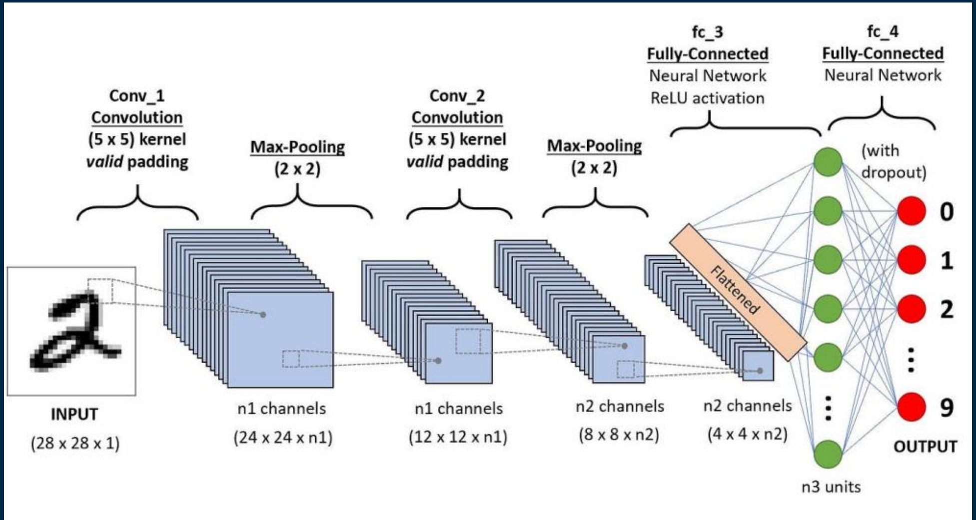




03 Models – CNN What is ?

- Very Good at dealing with images as it makes use of convolutions.

- From the references we know that they perform well on this problem

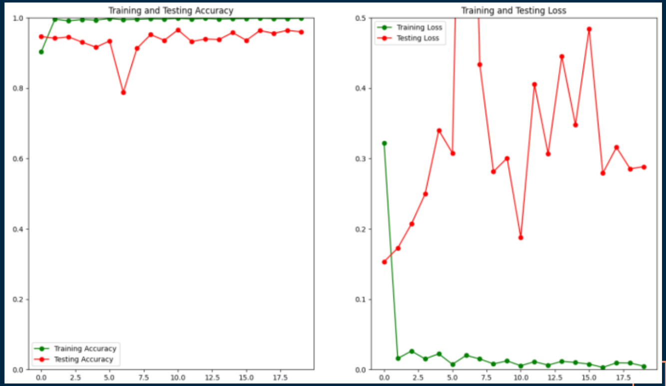


03 Models – CNN 1

- Based on references we built the architecture
- Trained without Data Augmentation and Adaptive learning rate
- Accuracy 90.90%
- F1-score 0.9019

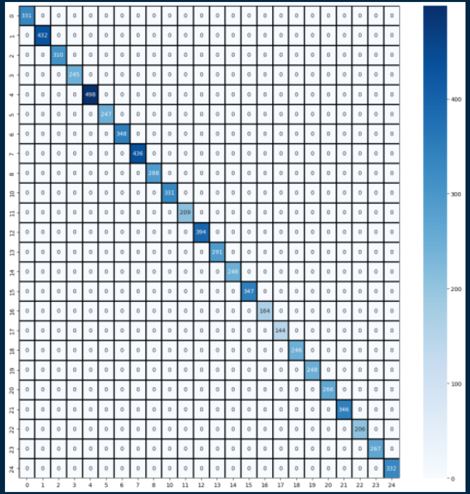
Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 28, 28, 75)	750
batch_normalization_3 (BatchNormalization)	(None, 28, 28, 75)	300
max_pooling2d_3 (MaxPooling2D)	(None, 14, 14, 75)	0
conv2d_4 (Conv2D)	(None, 14, 14, 50)	33,800
dropout_2 (Dropout)	(None, 14, 14, 50)	0
batch_normalization_4 (BatchNormalization)	(None, 14, 14, 50)	200
max_pooling2d_4 (MaxPooling2D)	(None, 7, 7, 50)	0
conv2d_5 (Conv2D)	(None, 7, 7, 25)	11,275
batch_normalization_5 (BatchNormalization)	(None, 7, 7, 25)	100
max_pooling2d_5 (MaxPooling2D)	(None, 4, 4, 25)	0
flatten_1 (Flatten)	(None, 400)	0
dense_2 (Dense)	(None, 512)	205,312
dropout_3 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 24)	12,312

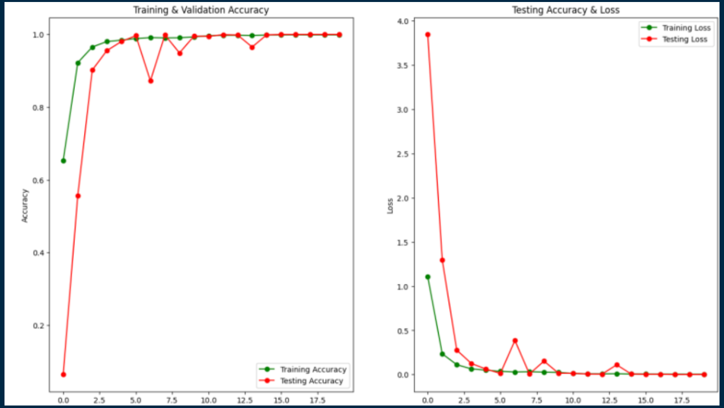
Total params: 264,049 (1.01 MB)



03 Models – CNN 1

- Same Architecture
- But using data augmentation and adaptive learning rate
- Accuracy 100%
- F1-score 1





03 Models – CNN 2

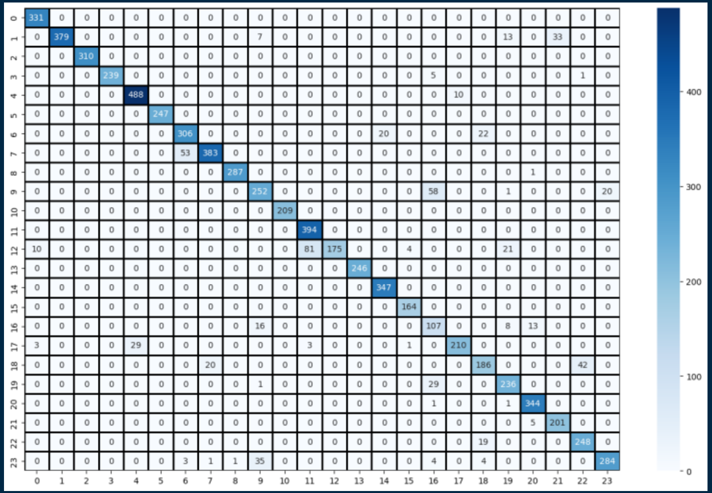
- Smaller model to not overfit without data augmentation
- L2 regularization on dense layers and strength 0.01
- Architecture based on iterations where we adjusted model size and alpha strength

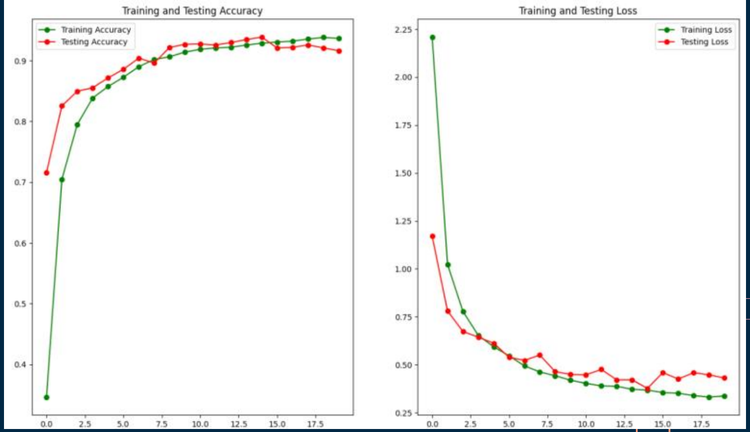
Layer (type)	Output Shape	Param #
conv2d_57 (Conv2D)	(None, 28, 28, 50)	500
max_pooling2d_51 (MaxPooling2D)	(None, 14, 14, 50)	0
conv2d_58 (Conv2D)	(None, 14, 14, 25)	11,275
dropout_38 (Dropout)	(None, 14, 14, 25)	0
max_pooling2d_52 (MaxPooling2D)	(None, 7, 7, 25)	0
conv2d_59 (Conv2D)	(None, 7, 7, 10)	2,260
flatten_19 (Flatten)	(None, 490)	0
dense_38 (Dense)	(None, 32)	15,712
dropout_39 (Dropout)	(None, 32)	0
dense_39 (Dense)	(None, 24)	792

Total params: 30,539 (119.29 KB)

03 Models – CNN 2

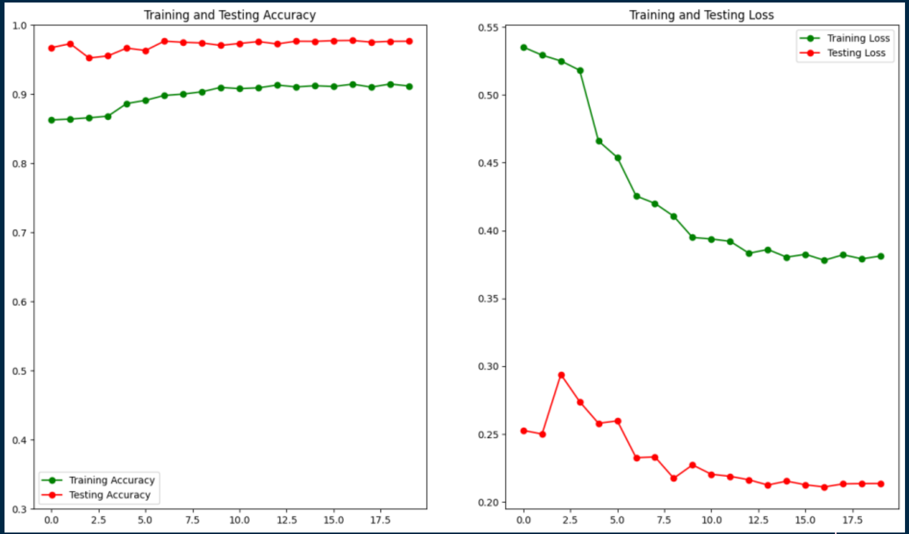
- Loss curve shows that the model didn’t overfit
- Accuracy is less than model 1 with data augmentation
- Hardest classes are 11 and 16
- Accuracy 91.64%
- F1-score 0.9106





03 Models – CNN 2

- Using data augmentation on this model gives an interesting result where train loss > test loss
- Data augmentation introduced patterns than don't occur on test.
- Accuracy 97.65%
- F1-score 0.9737

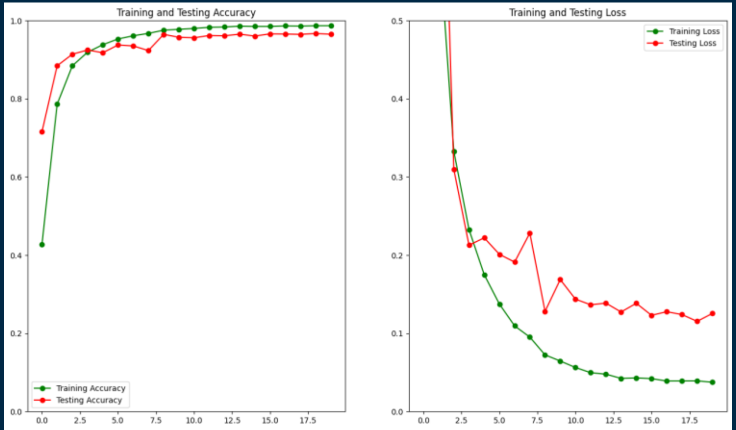


03 Models – CNN3

- Final model meant to be small and precise and with data augmentation in mind
- Needed 3 layers of convolution
- Accuracy 96.52%
- F1-score 0.9660

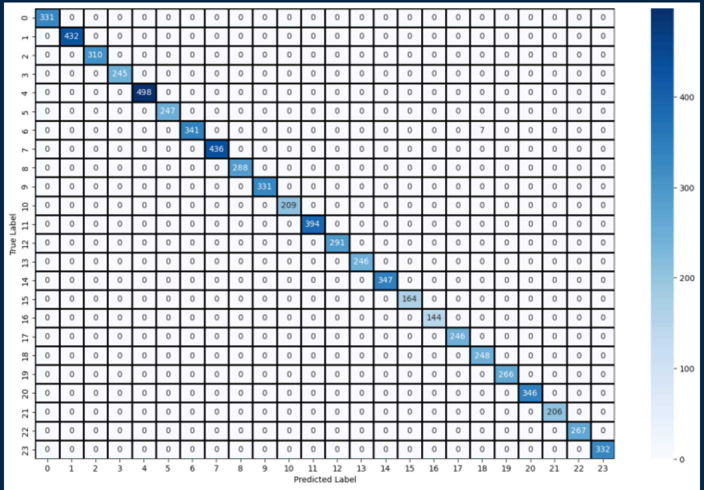
Layer (type)	Output Shape	Param #
conv2d_81 (Conv2D)	(None, 28, 28, 64)	640
batch_normalization_48 (BatchNormalization)	(None, 28, 28, 64)	256
max_pooling2d_70 (MaxPooling2D)	(None, 14, 14, 64)	0
conv2d_82 (Conv2D)	(None, 14, 14, 32)	18,464
dropout_52 (Dropout)	(None, 14, 14, 32)	0
max_pooling2d_71 (MaxPooling2D)	(None, 7, 7, 32)	0
conv2d_83 (Conv2D)	(None, 7, 7, 20)	5,780
max_pooling2d_72 (MaxPooling2D)	(None, 4, 4, 20)	0
conv2d_84 (Conv2D)	(None, 4, 4, 20)	3,620
dropout_53 (Dropout)	(None, 4, 4, 20)	0
flatten_27 (Flatten)	(None, 320)	0
dense_55 (Dense)	(None, 32)	10,272
dropout_54 (Dropout)	(None, 32)	0
dense_56 (Dense)	(None, 24)	792

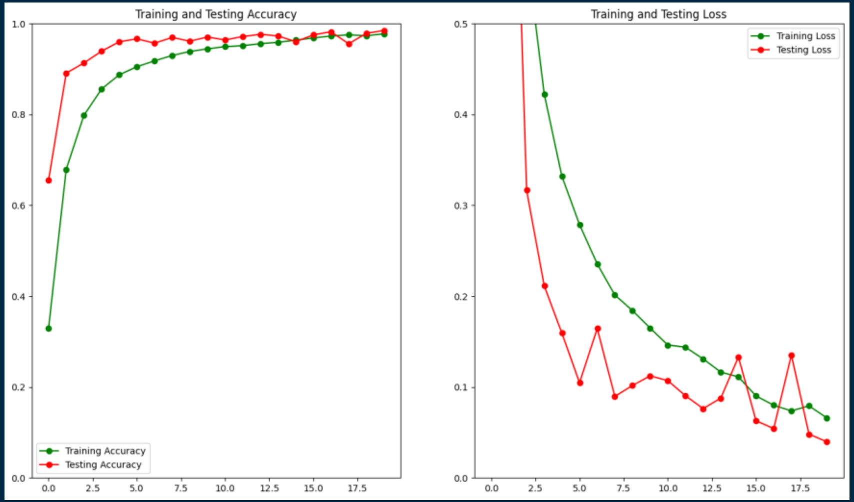
Total params: 39,824 (155.56 KB)



03 Models – CNN3

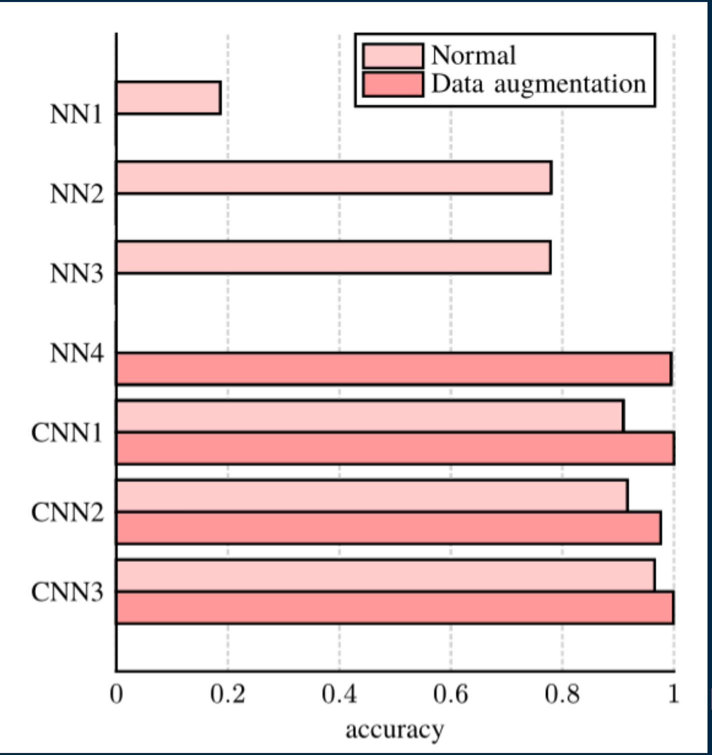
Accuracy:99.90% F1-score:0.9989





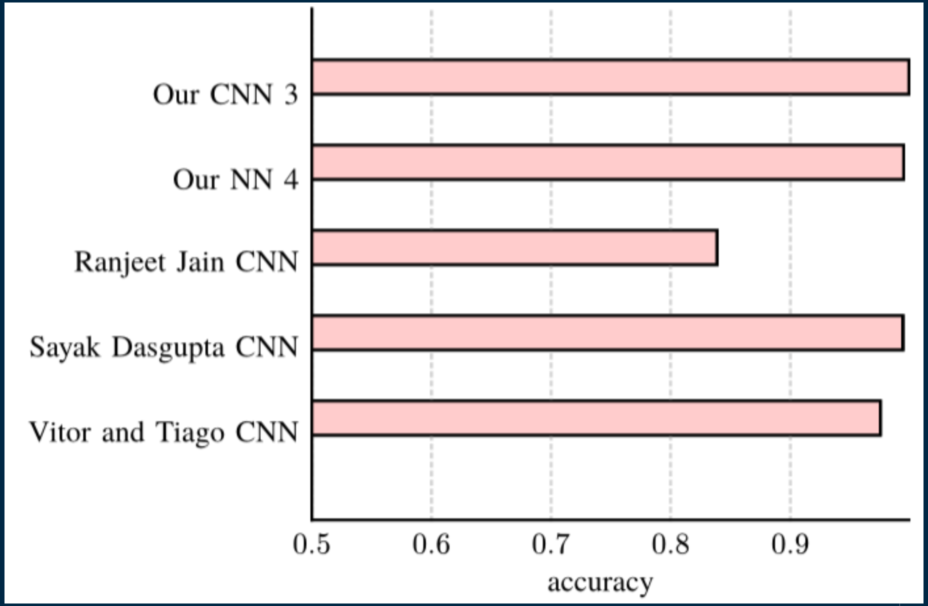
04 Comparison

- Without data augmentation the CNNs performed much better
- Data augmentation had a big effect on this problem



04 Comparison

- Our CNN 3 has 8x less parameters than the best model
- Our NN 4 performed better than we expected



Conclusion

- Data augmentation had a large impact both in CNN and ANN.
- Both approaches produced very good models.
- For further improvements we could experiment with PCA and ensemble of small models.

References:

- [1] R. Jain, “Deep Learning Using Sign Language.” [Online]. Available: https://www.kaggle.com/code/ranjeetjain3/deep-learning-usingsign-language
- [2] S. Dasgupta, “Sign Language Classification - CNN (99.40% Accuracy).” [Online]. Available: https://www.kaggle.com/code/sayakdasgupta/ sign-language-classification-cnn-99-40-accuracy
- [3] V. Santos and T. Pereira, “Exploring Models for Sign Language Classification.” Aveiro, Portugal, 2023.

THANK YOU