DA 675 Fuzzy Systems and Applications

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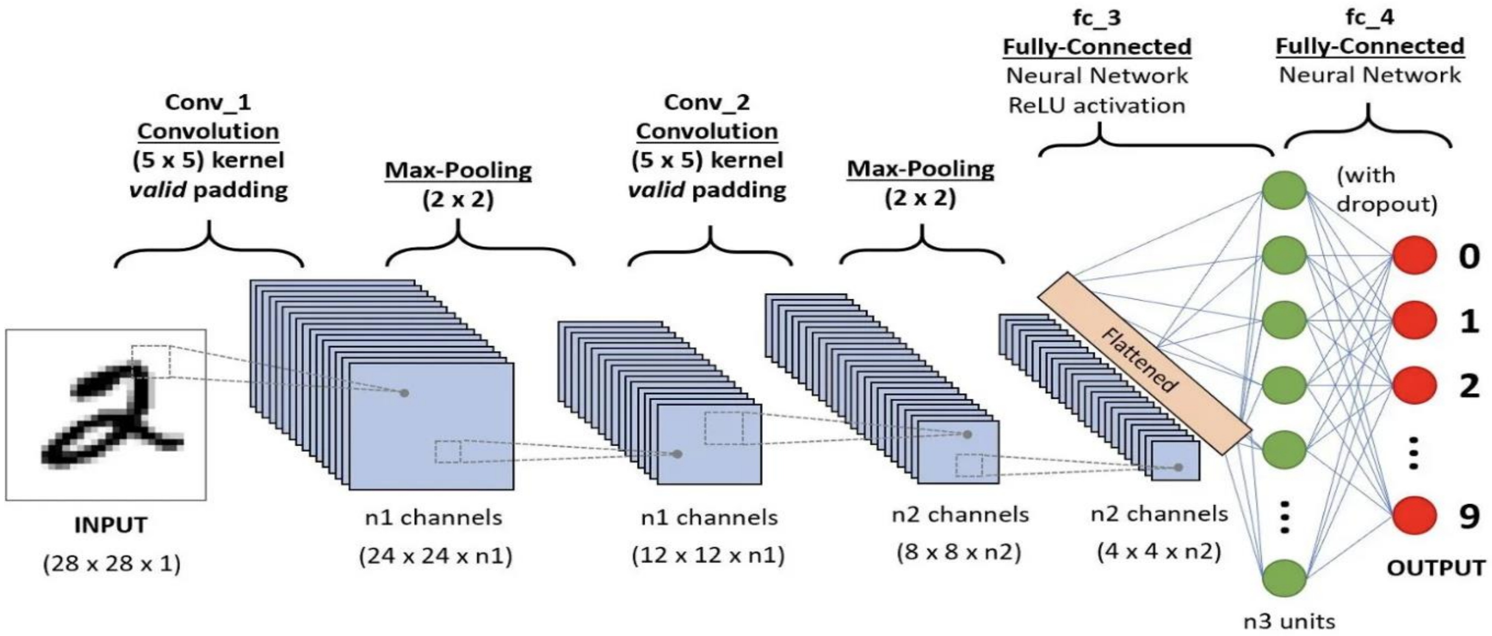
INTRODUCTION

- CNNs utilize convolution and pooling for feature extraction and dimension reduction in image classification.
- Traditional pooling methods overlook uncertainty that can propagate through layers.
- A novel fuzzy pooling approach, based on type-1 fuzzy sets, addresses **local imprecision** in feature maps.
- Fuzzy pooling includes **fuzzification**, **aggregation**, and **defuzzification** steps, acting as a drop-in replacement for standard pooling layers.

CNN ARCHITECTURE



Why to use Pooling Layers?

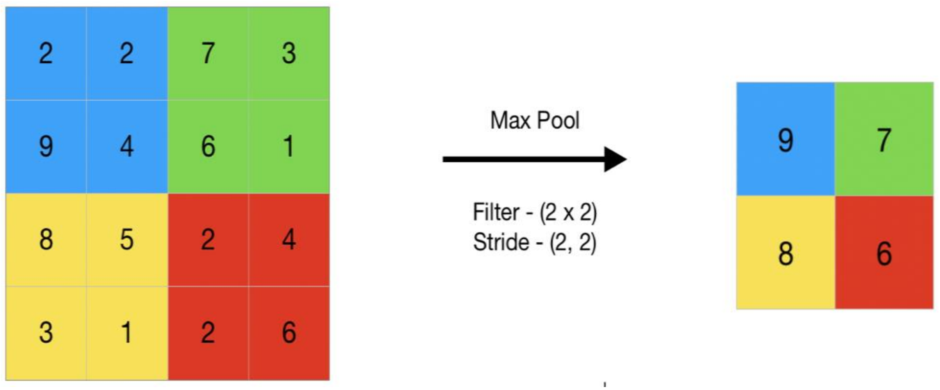
- Pooling layers are used to reduce the dimensions of the feature maps. It reduces the number of parameters to learn, and the amount of computation performed in the network.

- The pooling layer summarizes the features present in a region of the feature map generated by a convolution layer.

Max Pooling

- Max pooling is a pooling operation that selects the maximum element from the region of the feature map covered by the filter.

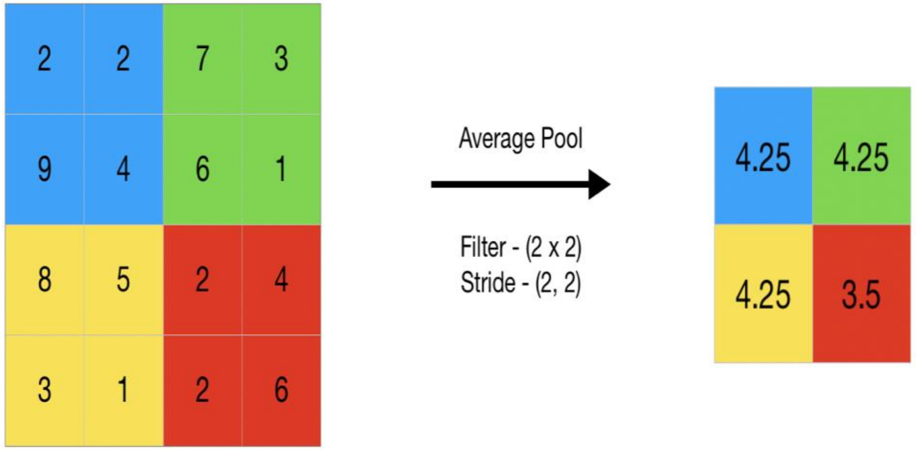
$$f_{\max}(\mathbf{z}) = \max_{m}(z_m)$$



Average Pooling

Average pooling computes the average of the elements present in the region of feature map covered by the filter.

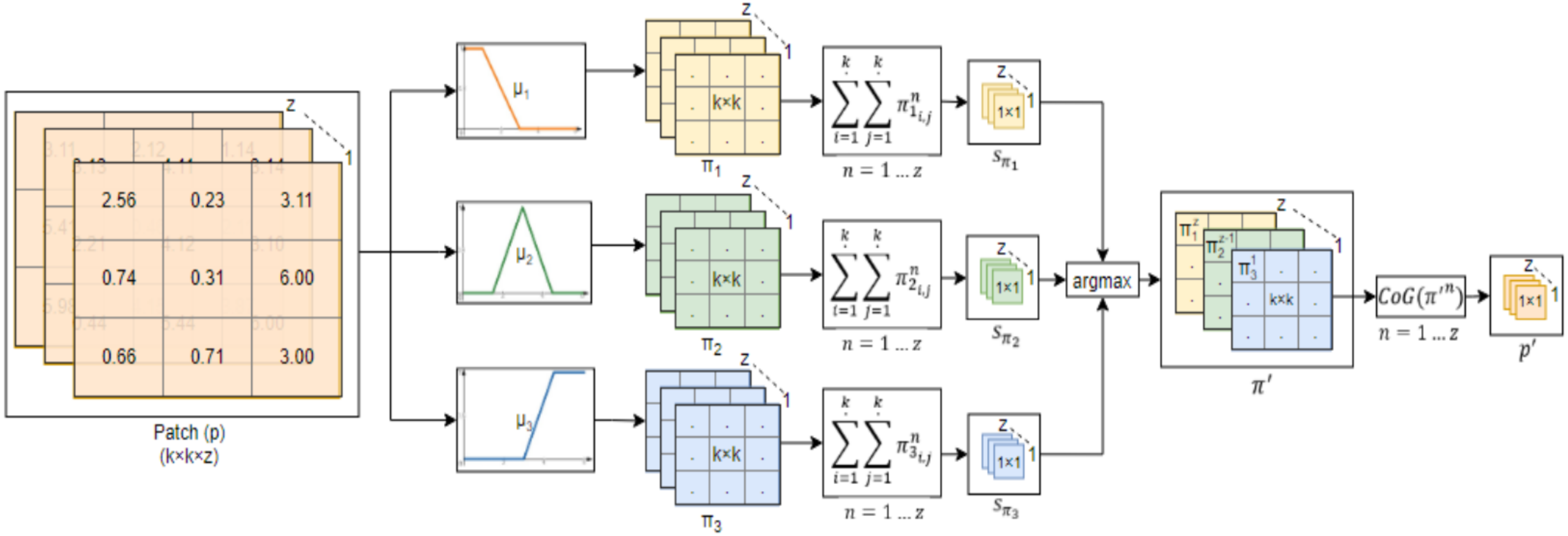
$$f_{\text{avg}}(\mathbf{z}) = \frac{1}{M}\sum_{m=1}^{M} z_m$$



Fuzzy Pooling

- **Fuzzification**: Converts numerical values in a pooling region into fuzzy values based on defined membership functions.
- **Aggregation**: Combines the fuzzy values in each pooling window, often using a mathematical operation like a fuzzy algebraic sum.
- **Defuzzification**: Produces a single representative value for the pooling region, based on the aggregated fuzzy values.

Fuzzy Pooling



MNIST DATASET

- MNIST dataset consists of 70.000 grayscale 28×28 pixels in size images of handwritten digits.
- It is split into two subsets from which 60.000 are used for training and 10.000 for testing.

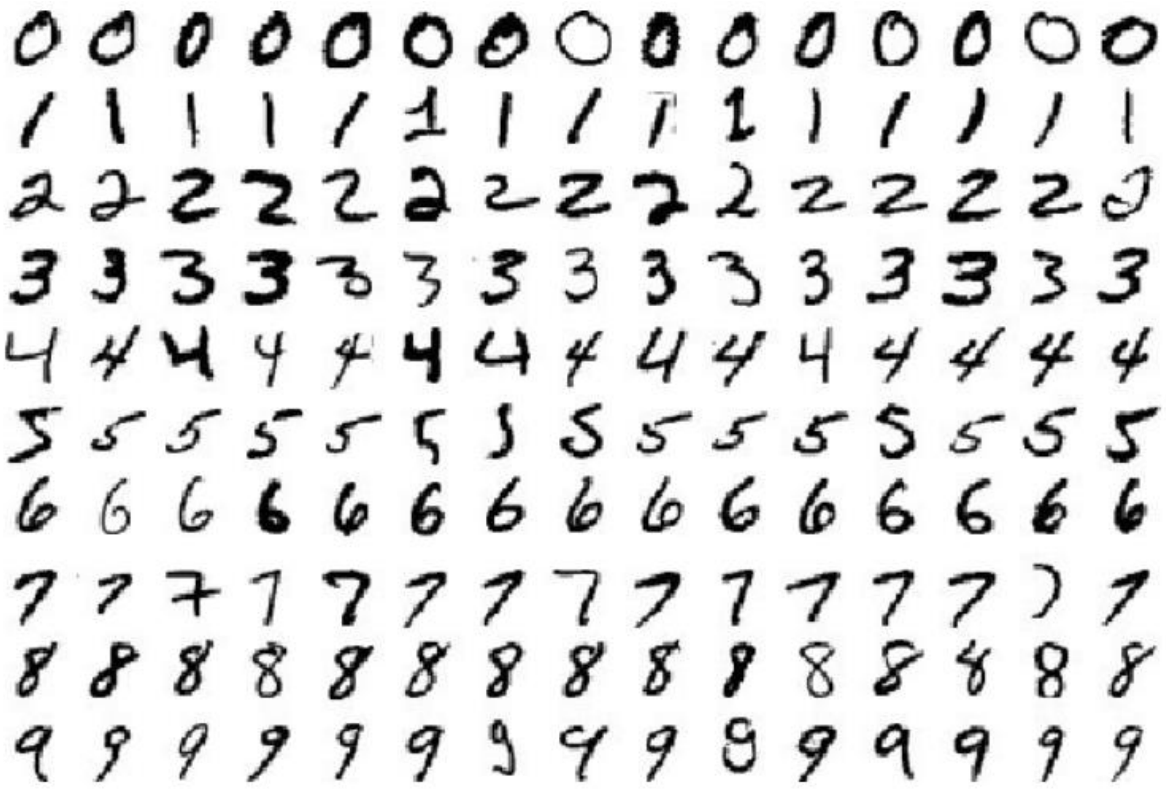


Fig. 2. Sample images of the 10 classes from MNIST [32] dataset

CIFAR- 10 DATASET

- CIFAR- 10 dataset is consisting of 60.000 natural RGB images of 32×32 pixels in size from 10 different classes.
- It is split into two subsets from which, 50.000 are used for training and 10.000 for testing.
- The dataset contains 6.000 images per class.

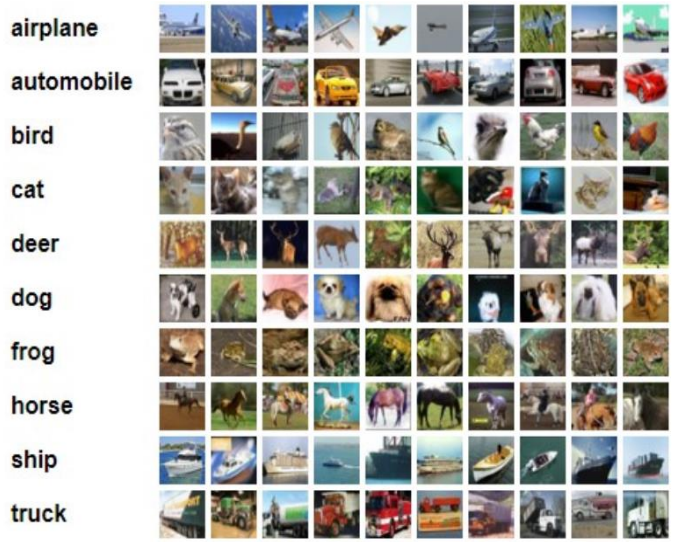


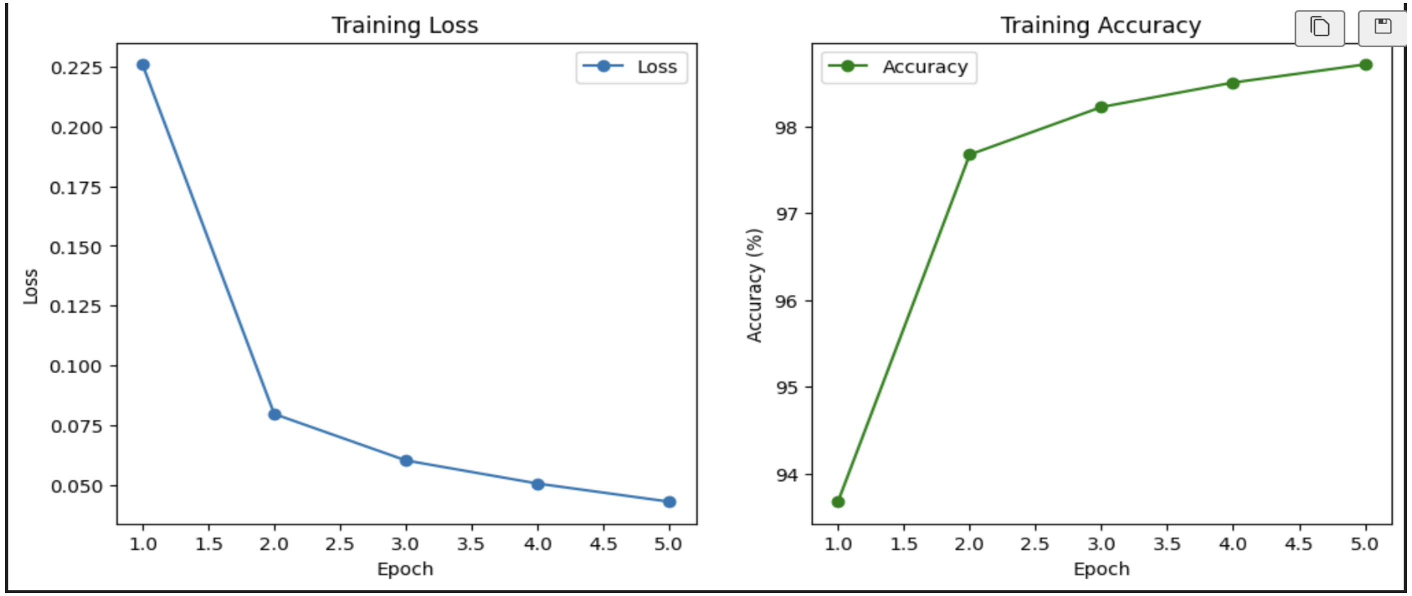
Fig. 4. Sample images from the 10 classes of CIFAR-10 [34] dataset

MODEL EVALUATION

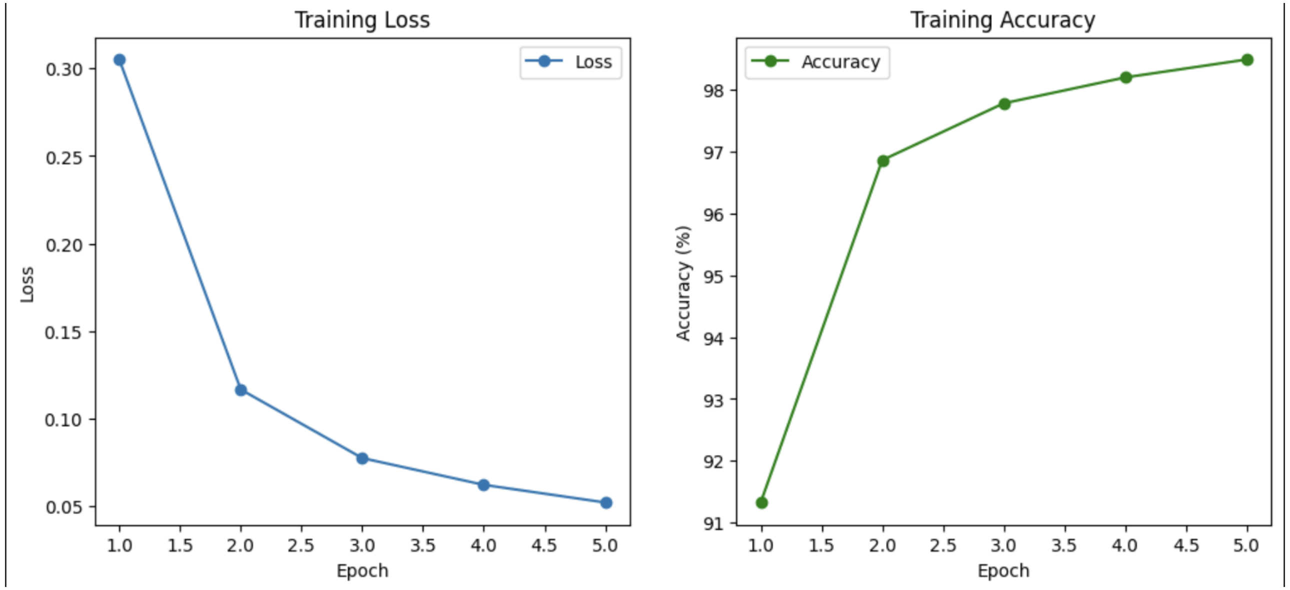
COMPARATIVE ACCURACY RESULTS OF THE PROPOSED TYPE-1 FUZZY POOLING METHODOLOGY ON MNIST DATASET

Methodology	Loss	Accuracy
Max Pooling	0.0430	98.12%
Average Pooling	0.0521	98.26%
RegP	0.0700	97.96%
Proposed	0.0681	98.85%

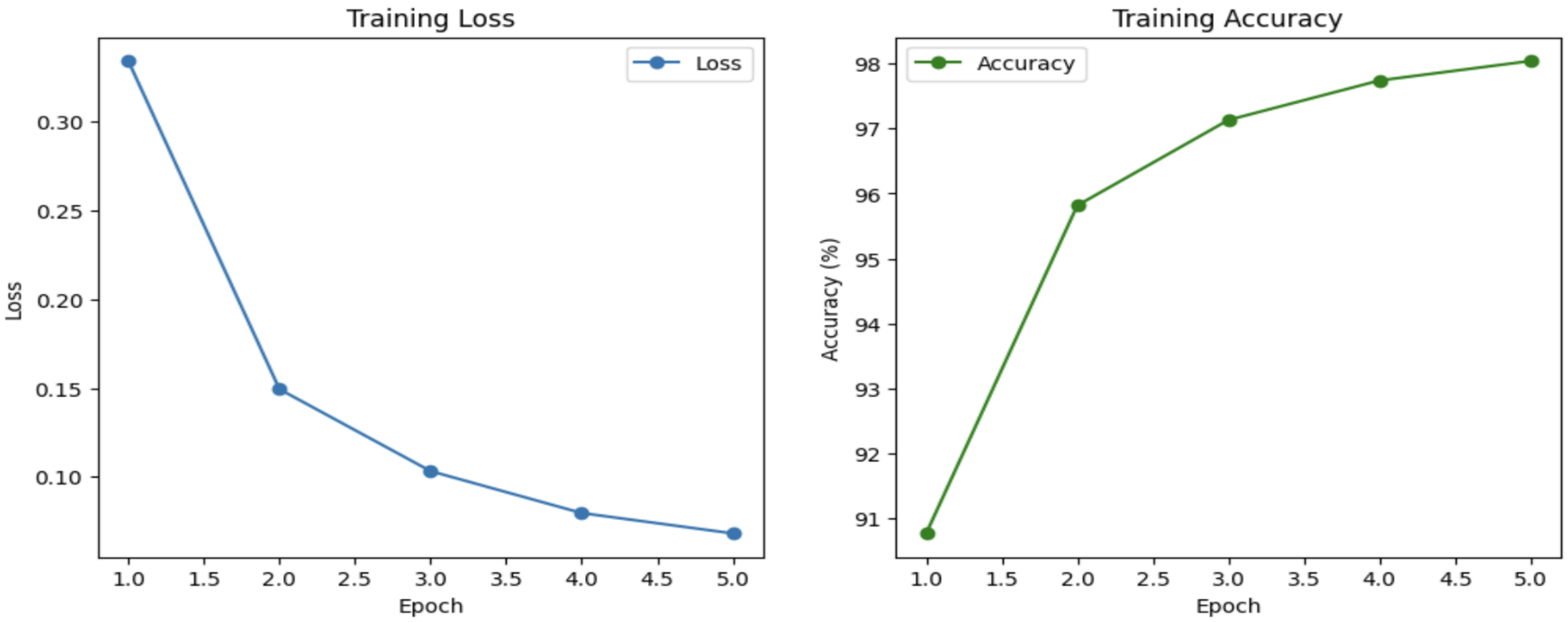
Max Pooling


Training Loss
Loss
0.225
0.200
0.175
0.150
0.125
0.100
0.075
0.050
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Epoch
Training Accuracy
Accuracy
Accuracy (%)
98
97
96
95
94
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Epoch

Average pooling



Fuzzy Pooling



MODEL EVALUATION

COMPARATIVE ACCURACY RESULTS OF THE PROPOSED TYPE-1 FUZZY POOLING METHODOLOGY ON CIFAR-10 DATASET

Methodology	Loss	Accuracy
Max Pooling	0.0530	75.03%
Average Pooling	0.0621	62.94%
RegP	0.0534	58.52%
Proposed	0.0581	78.14%

CONCLUSION

- A novel fuzzy pooling operation for CNNs is introduced, addressing feature uncertainty.
- Experiments demonstrate significant improvements in CNN classification performance over traditional pooling methods.
- Fuzzy pooling can replace standard pooling layers, enhancing generalization and retaining important features.
- Visual and statistical validation confirm improved feature preservation.

REFERENCES

- H.-J. Zimmermann, *Fuzzy set theory—and its applications*. Springer Science & Business Media, 2011.
- K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.
- Mixed fuzzy pooling in convolutional neural networks for image classification.
- Fuzzy based Pooling in Convolutional Neural Network for Image Classification.

THANK YOU