QUANTUM IMAGE CLASSIFICATION

Presentated by Huzaifah Tariq Ahmed, Lyeba Abid, Sadiqah Mushtaq

LITERATURE REVIEW

1. Hybrid Quantum-Classical CNNs
- Quanvolutional Neural Networks: Quantum circuits for feature extraction.
- Speedups in specific tasks, e.g., image classification (Mattern et al., 2021).

2. **Quantum Generative Adversarial Networks (QGANs)**
- Quantum circuits for generating images (e.g., MNIST).
- Efficiency in high-dimensional data (Tsang, 2023).

3. **Quantum Activation Functions**
- QReLU, m-QReLU outperform traditional ReLU.
- Improve convergence and generalization (Parisi et al., 2022).

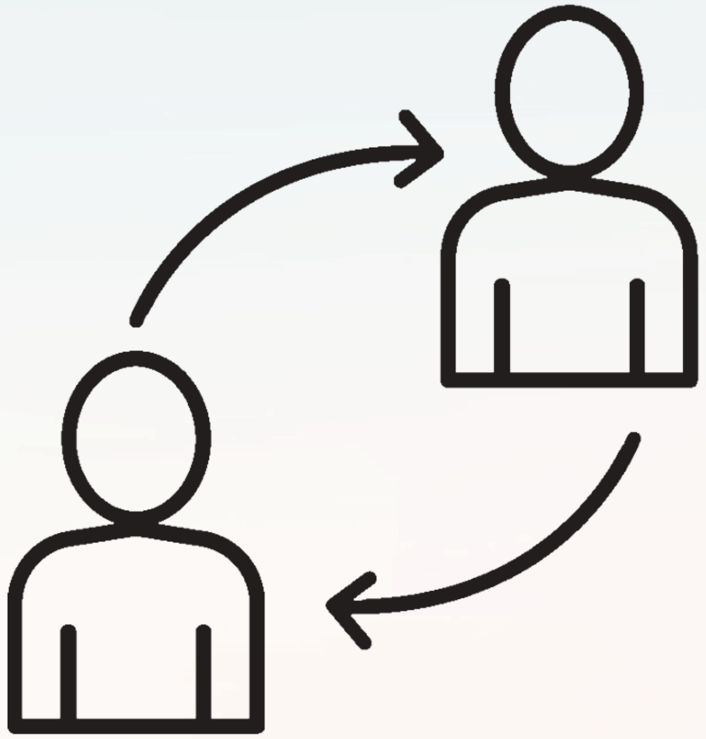
4**. Quantum Convolutional Layers**
- Use quantum circuits for image convolution operations.
- Significant potential for parallel processing and dimensionality reduction (Mattern et al., 2021).

5**. Quantum Image Processing**
- Quantum Fourier transform for image compression.
- Increased speed for edge detection and enhancement (Qin & Zhang, 2022).

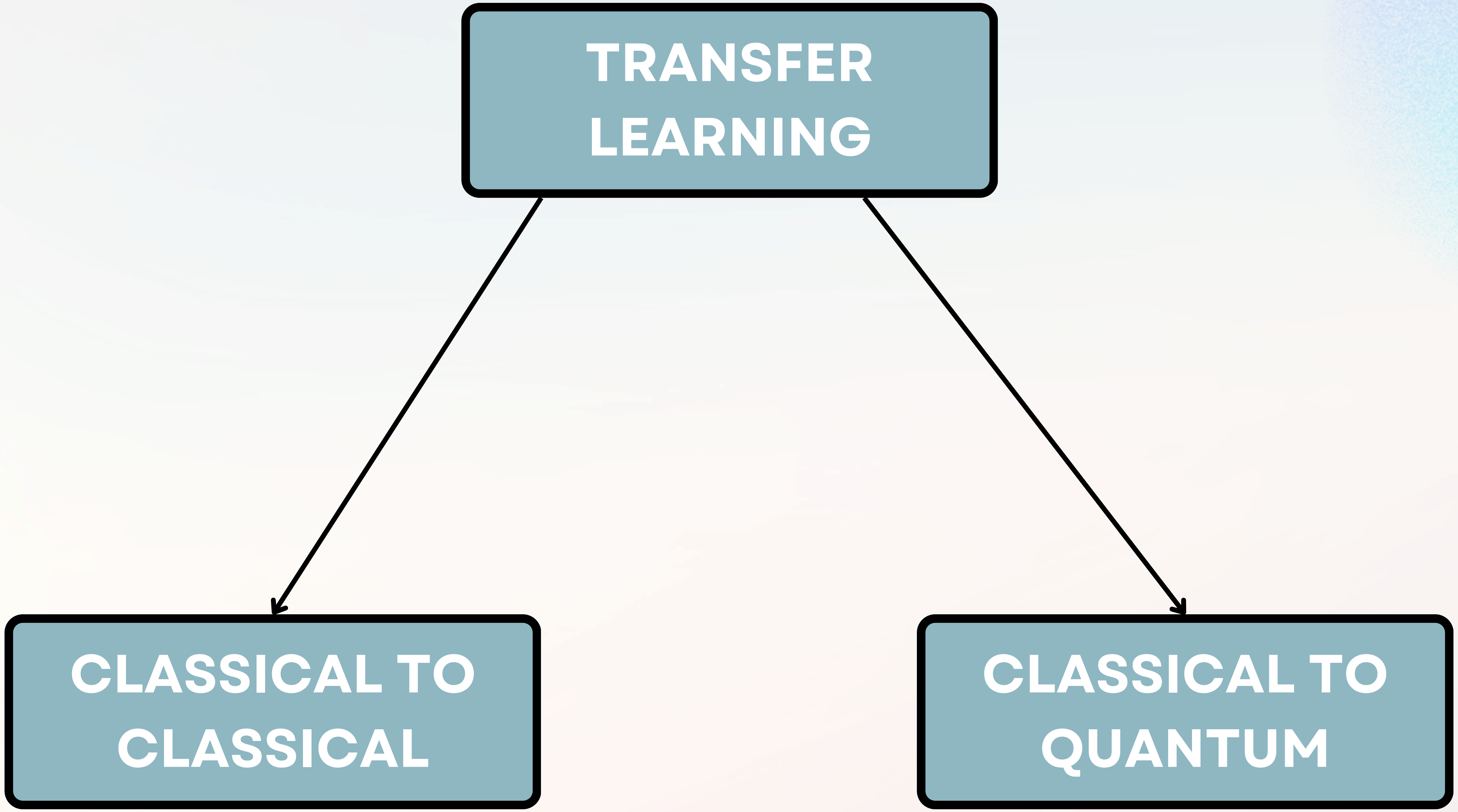
6**. Challenges**
- Hardware limitations restrict scalability.
- Difficulty in integrating quantum models with classical deep learning tools.
- Need for more robust quantum error correction (Nielsen & Chuang, 2020).

TRANSFER LEARNING

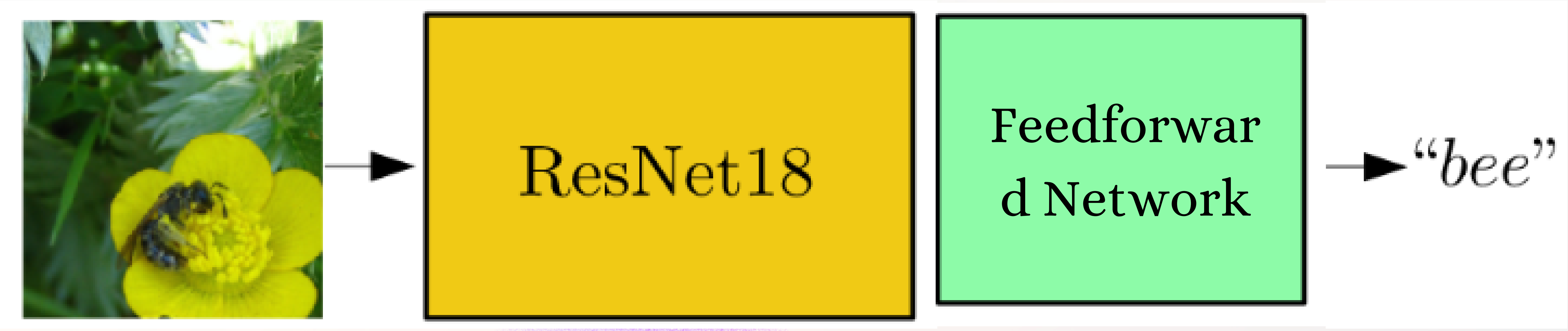
TRANSFER LEARNING



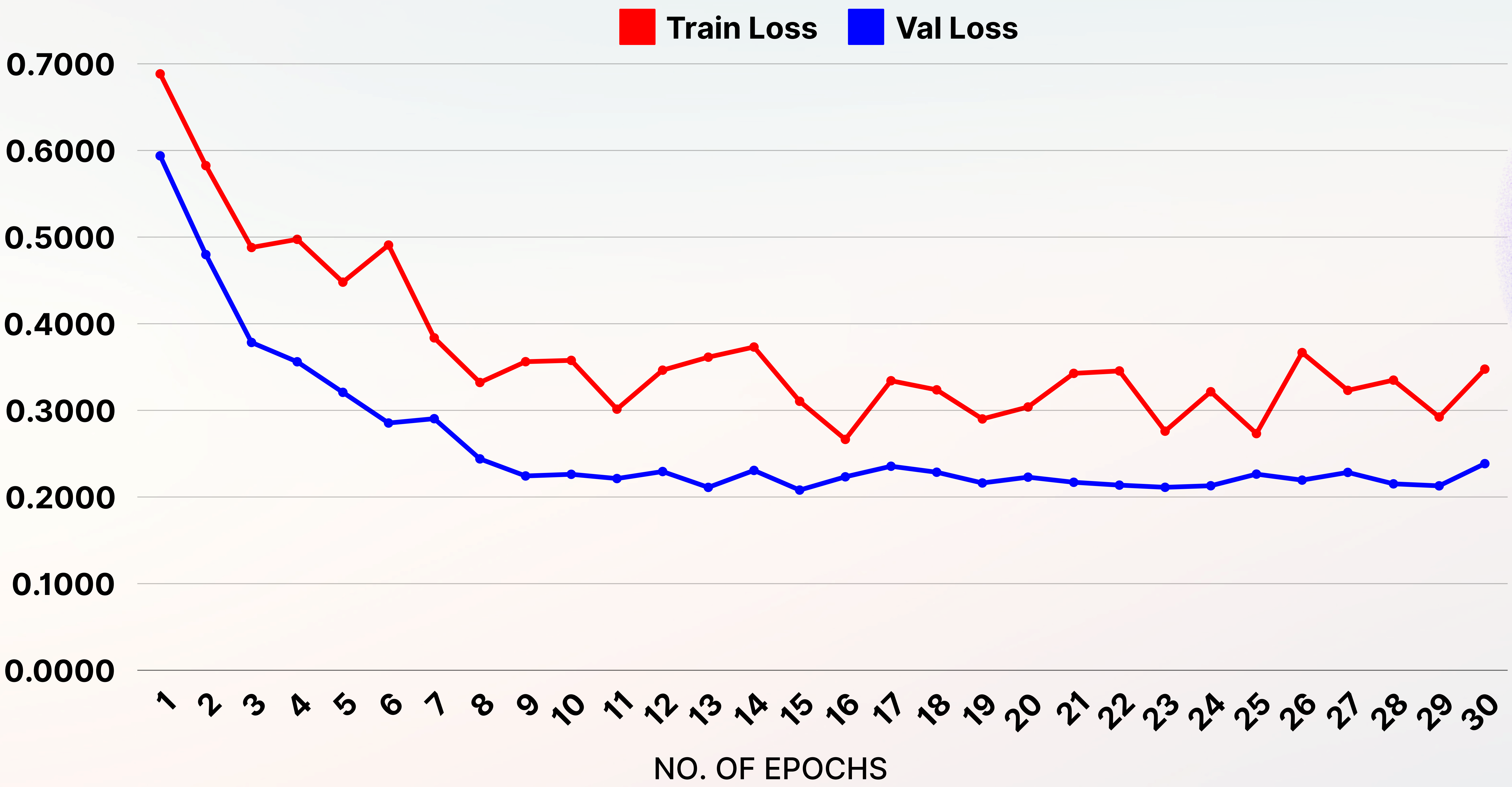
Transfer learning is like building on what you already know to learn something new faster, similar to riding a motorbike after mastering a bicycle. Technically, it is a machine learning method where a pre-trained model from one task is fine-tuned to solve a related task, saving time and resources.


TRANSFER LEARNING
CLASSICAL TO CLASSICAL
CLASSICAL TO QUANTUM

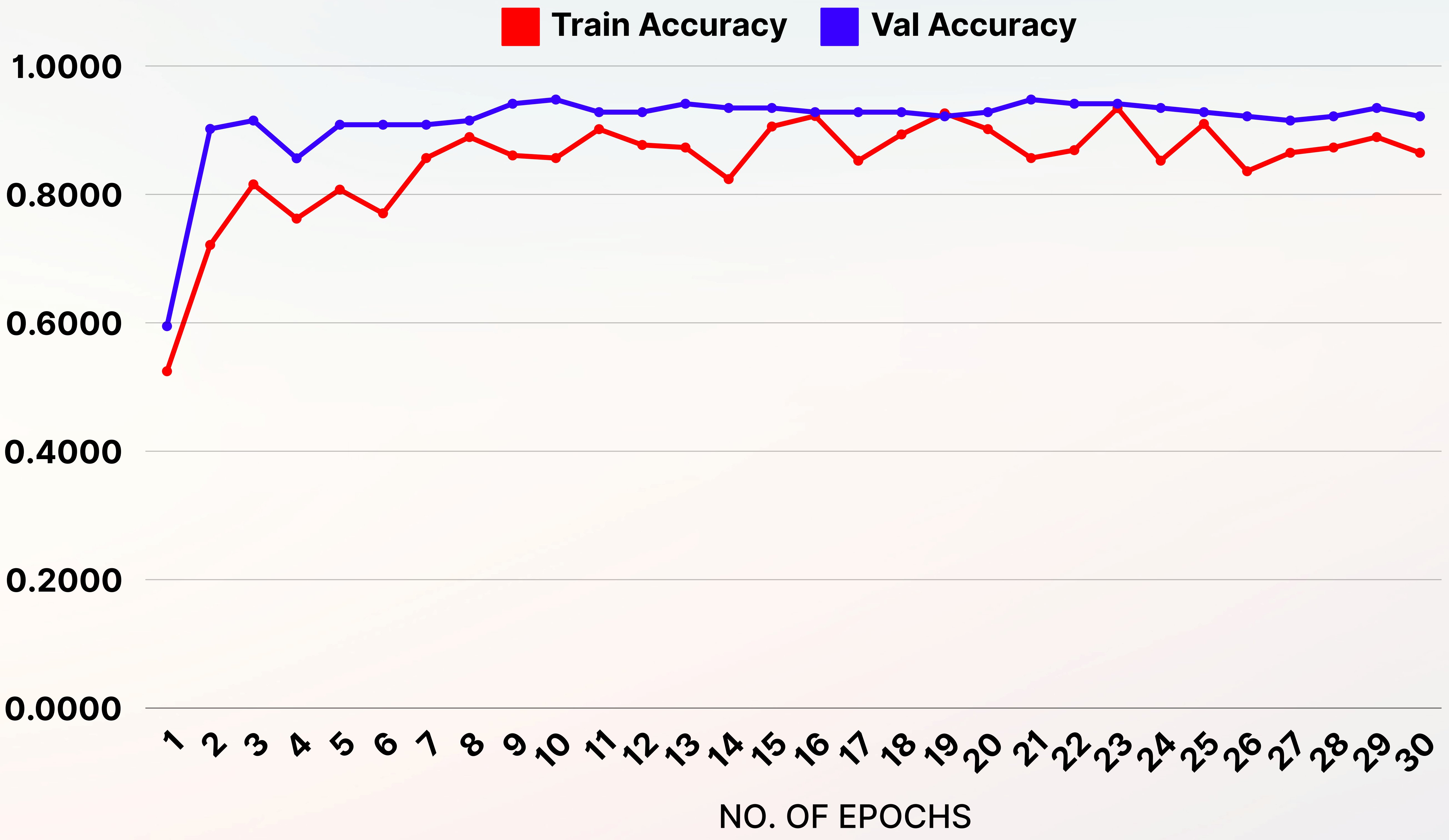
CLASSICAL TO CLASSICAL TRANSFER LEARNING



ANTS & BEES C2C (LOSS)



ANTS & BEES C2C (ACCURACY)

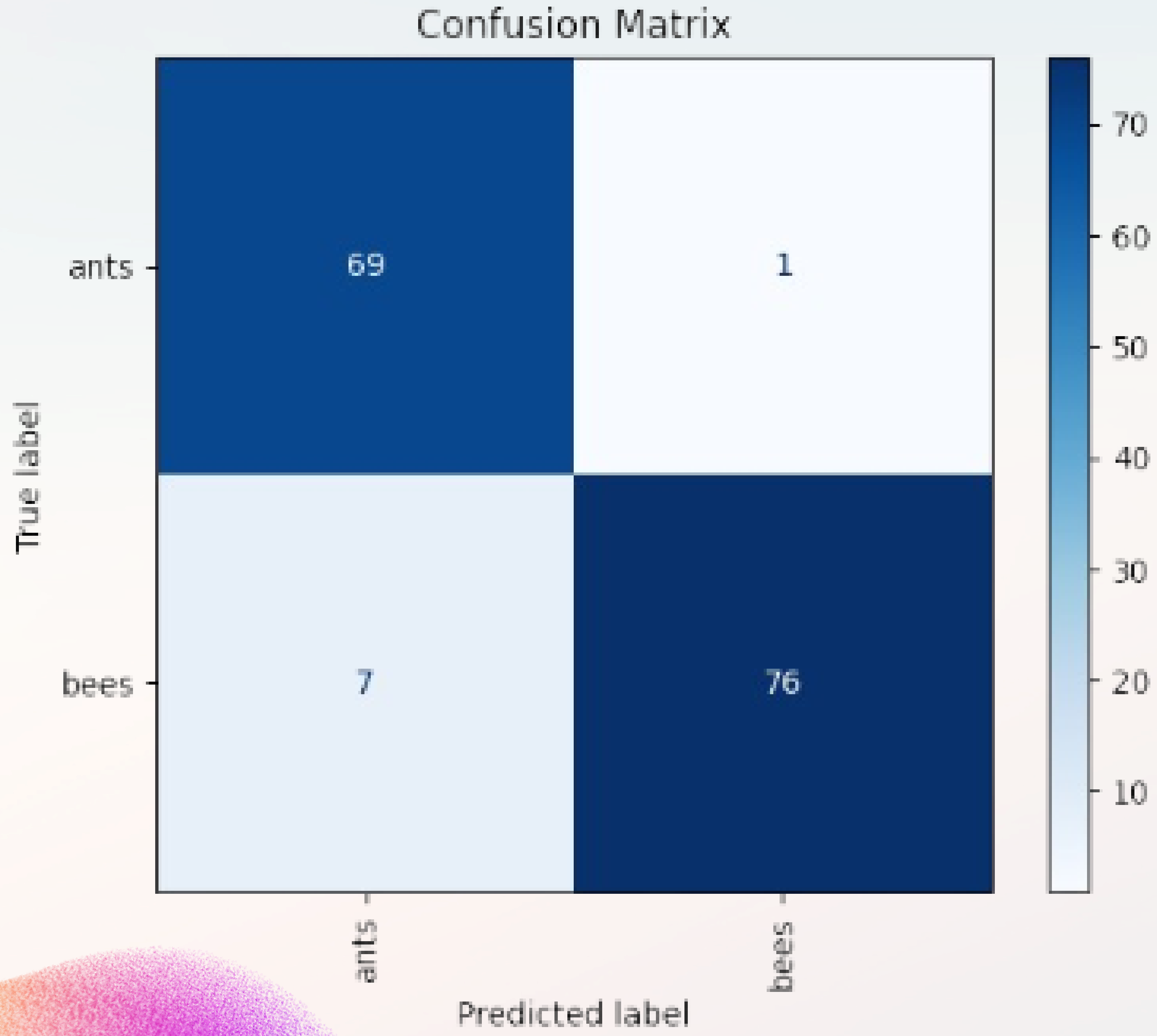


TEST ACCURACY 94.77%

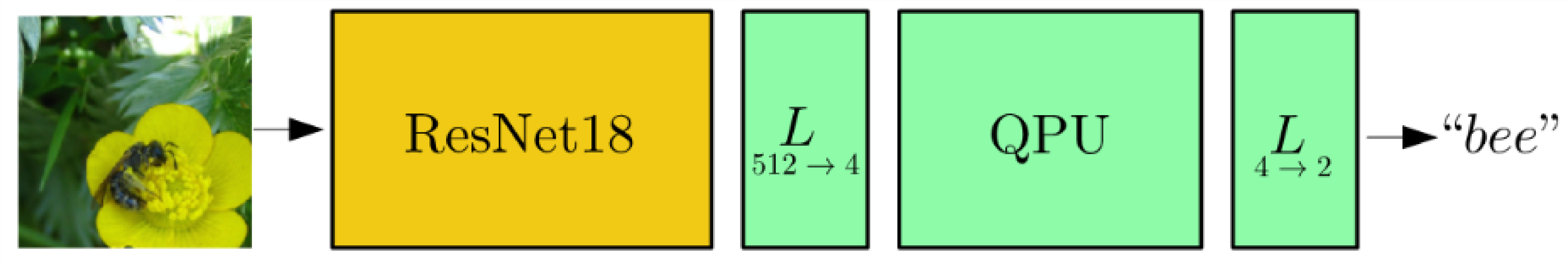
VAL ACCURACY 94.77%

TRAIN ACCURACY 93.44%

ANTS & BEES C2C (ACCURACY)



CLASSICAL TO QUANTUM TRANSFER LEARNING



VARIATIONAL QUANTUM CIRCUITS

CLASSICAL LAYER EQUATION:

$$L_{n_0 \to n_1}: \ \mathbf{x} \to \mathbf{y} = \varphi(W\mathbf{x} + \mathbf{b}).$$

QUANTUM LAYER EQUATION:

$$\mathcal{L}: \ |x\rangle \to |y\rangle = U(\mathbf{w})|x\rangle,$$

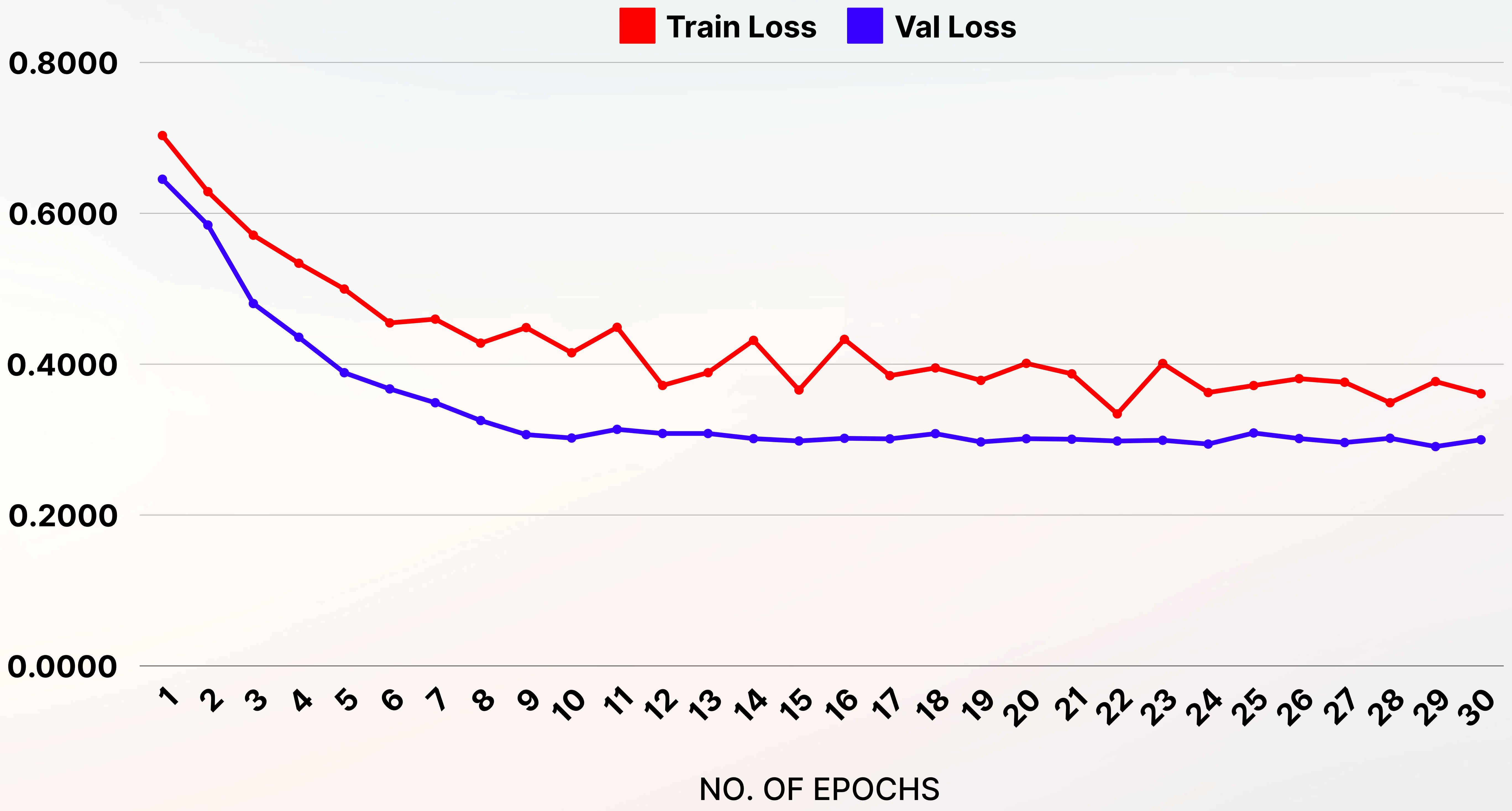
QUANTUM MODEL:

$$Q = \mathcal{M} \circ \mathcal{Q} \circ \mathcal{E}.$$

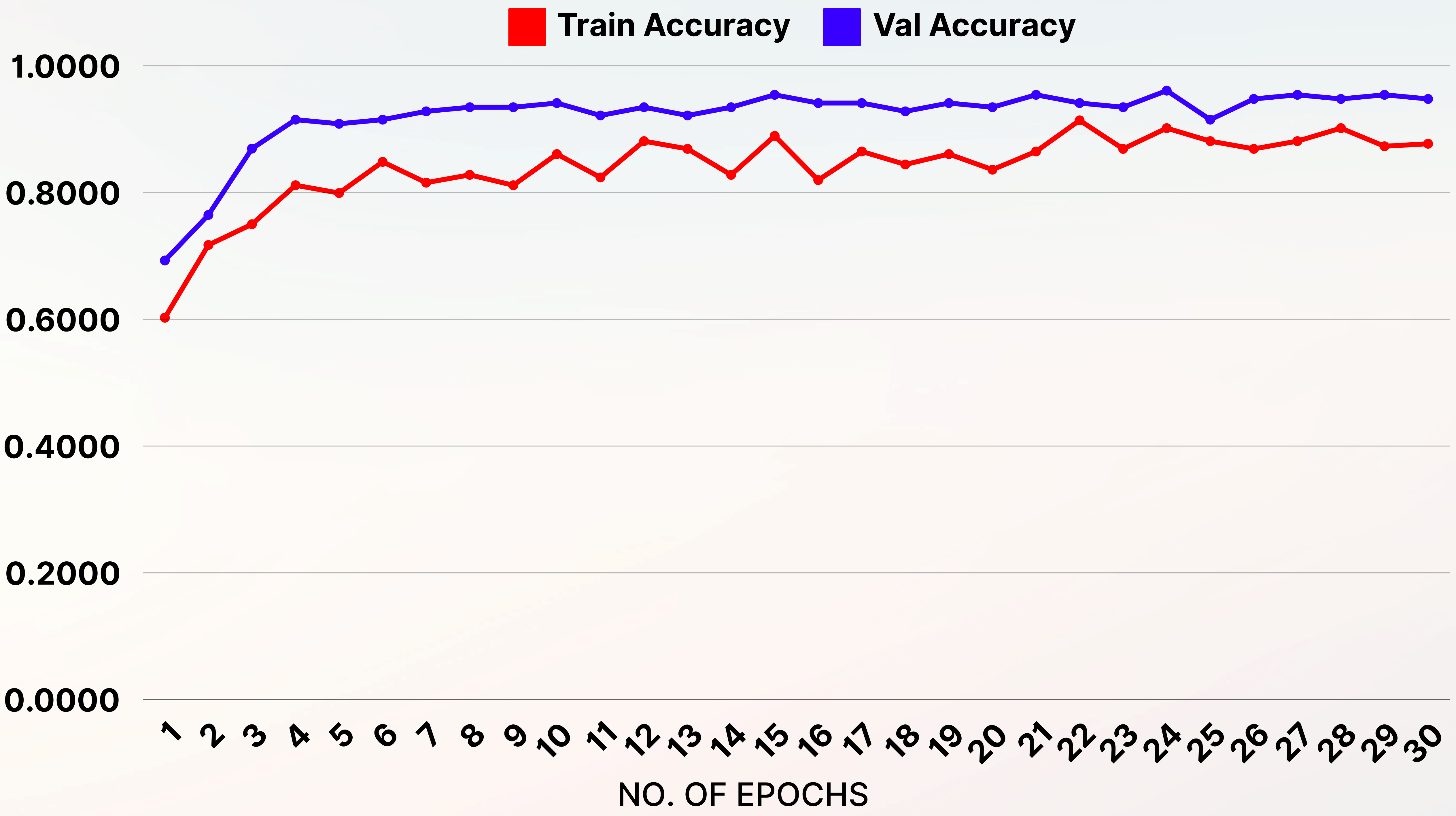
$$\mathcal{M}: \ |x\rangle \to \mathbf{y} = \langle x|\hat{\mathbf{y}}|x\rangle.$$

$$\mathcal{E}: \ \mathbf{x} \to |x\rangle = E(\mathbf{x})|0\rangle.$$

ANTS & BEES C2Q (LOSS)



ANTS & BEES C2Q (ACCURACY)

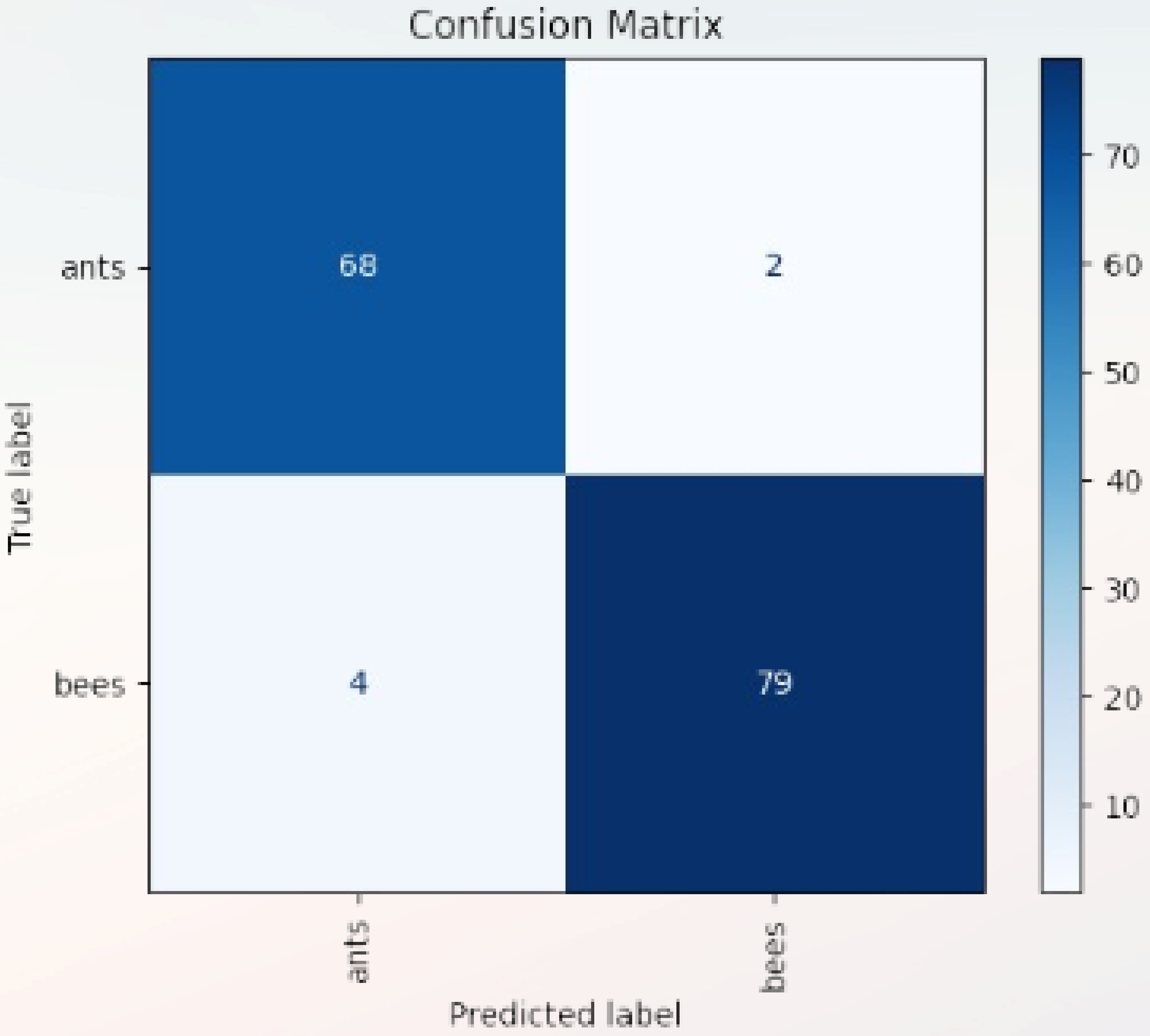


TEST ACCURACY 96.08%

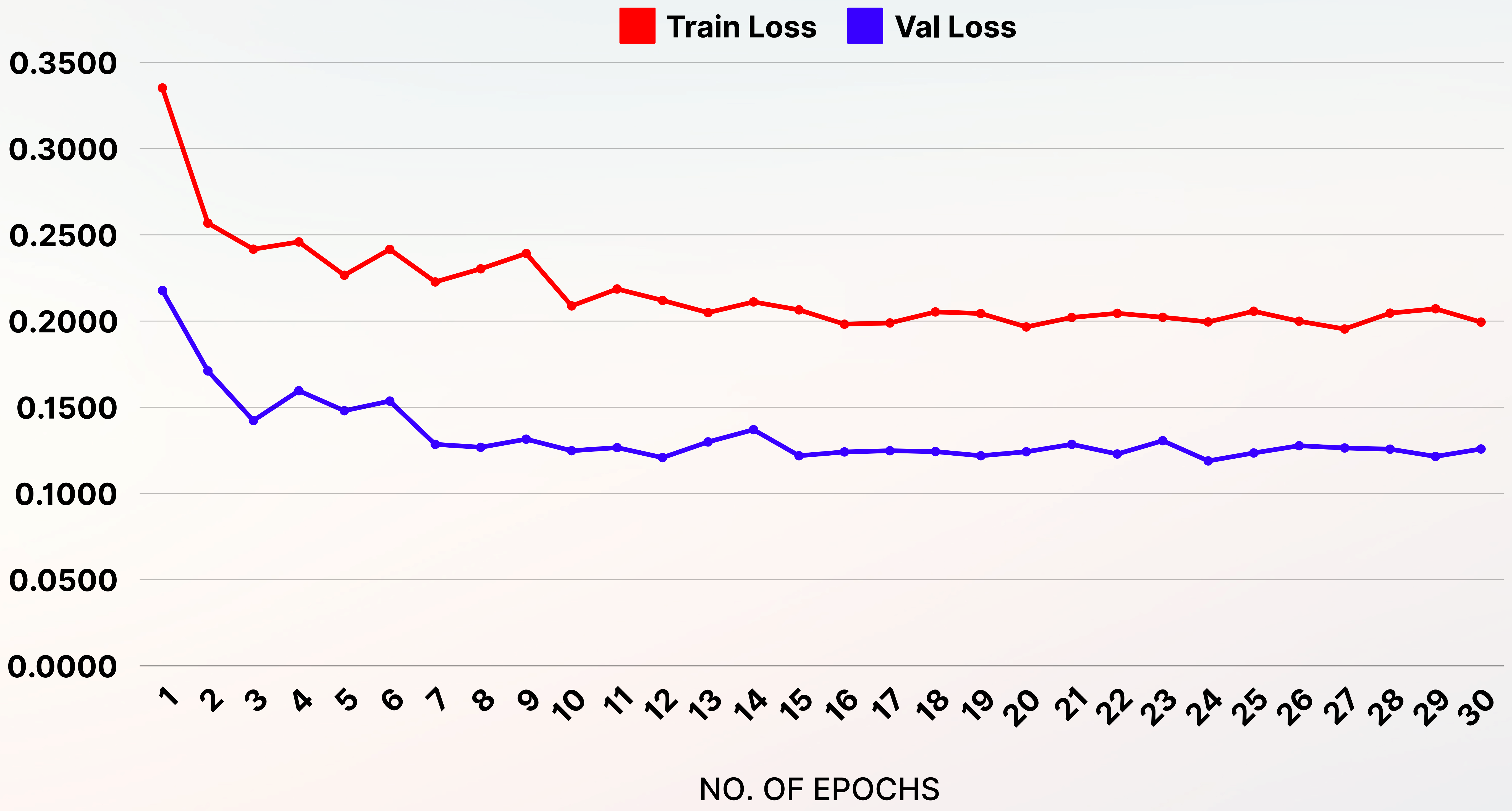
VAL ACCURACY 96.08%

TRAIN ACCURACY 91.39%

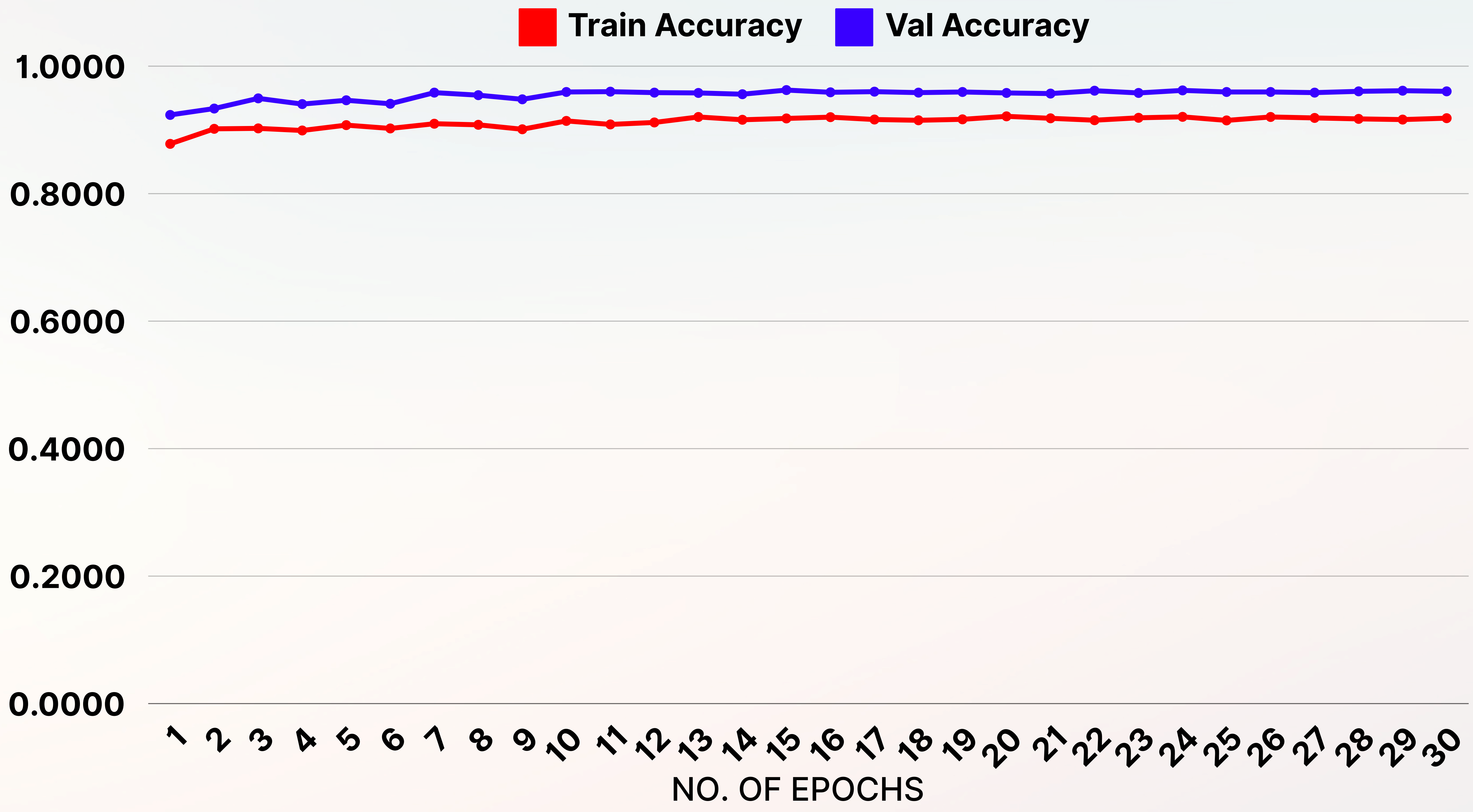
ANTS & BEES C2Q (ACCURACY)



PLANES VS CARS C2Q (LOSS)



PLANES VS CARS C2Q (ACCURACY)



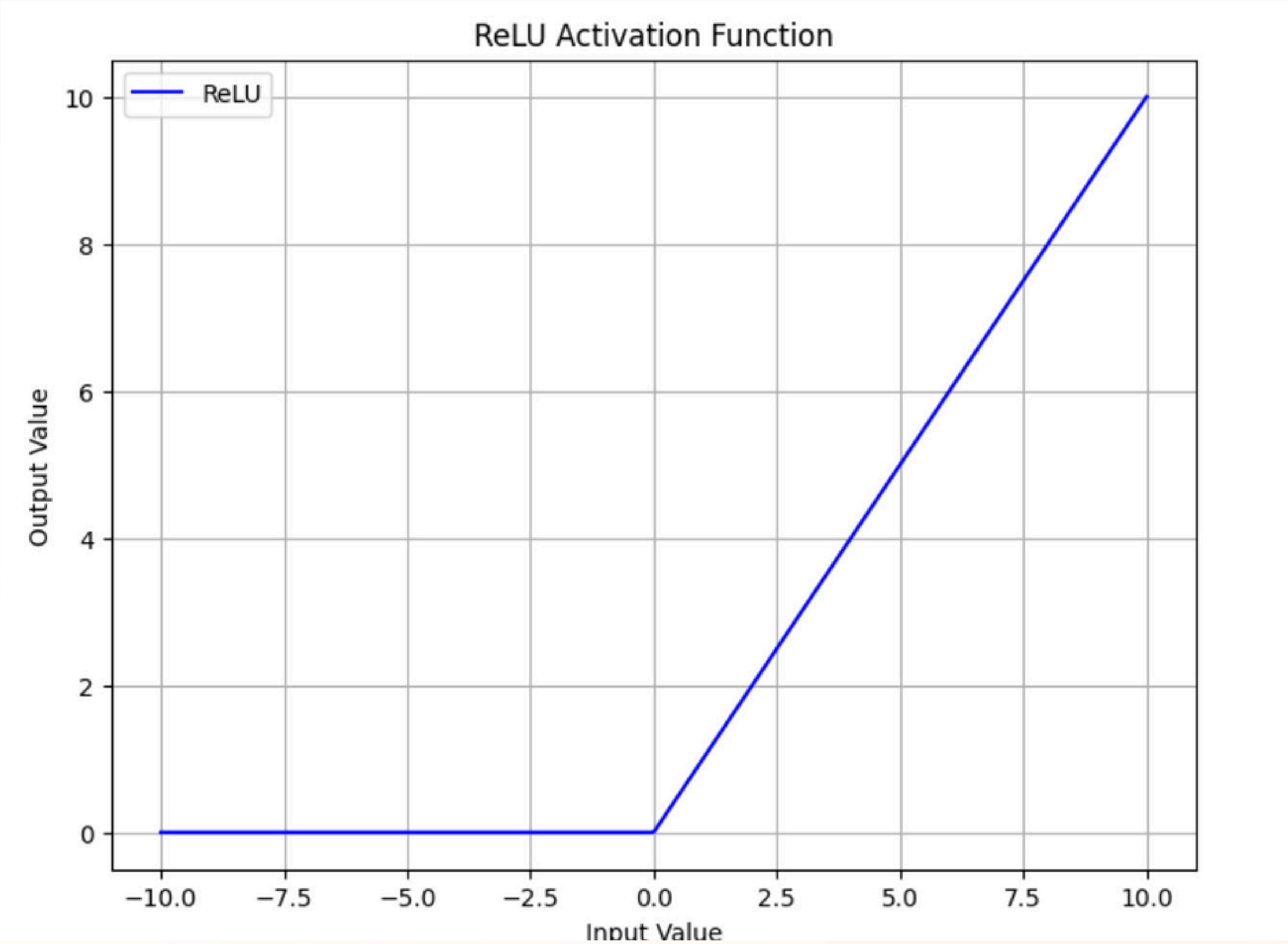
TEST ACCURACY 96.25%

VAL ACCURACY 96.20%

TRAIN ACCURACY 92.13%

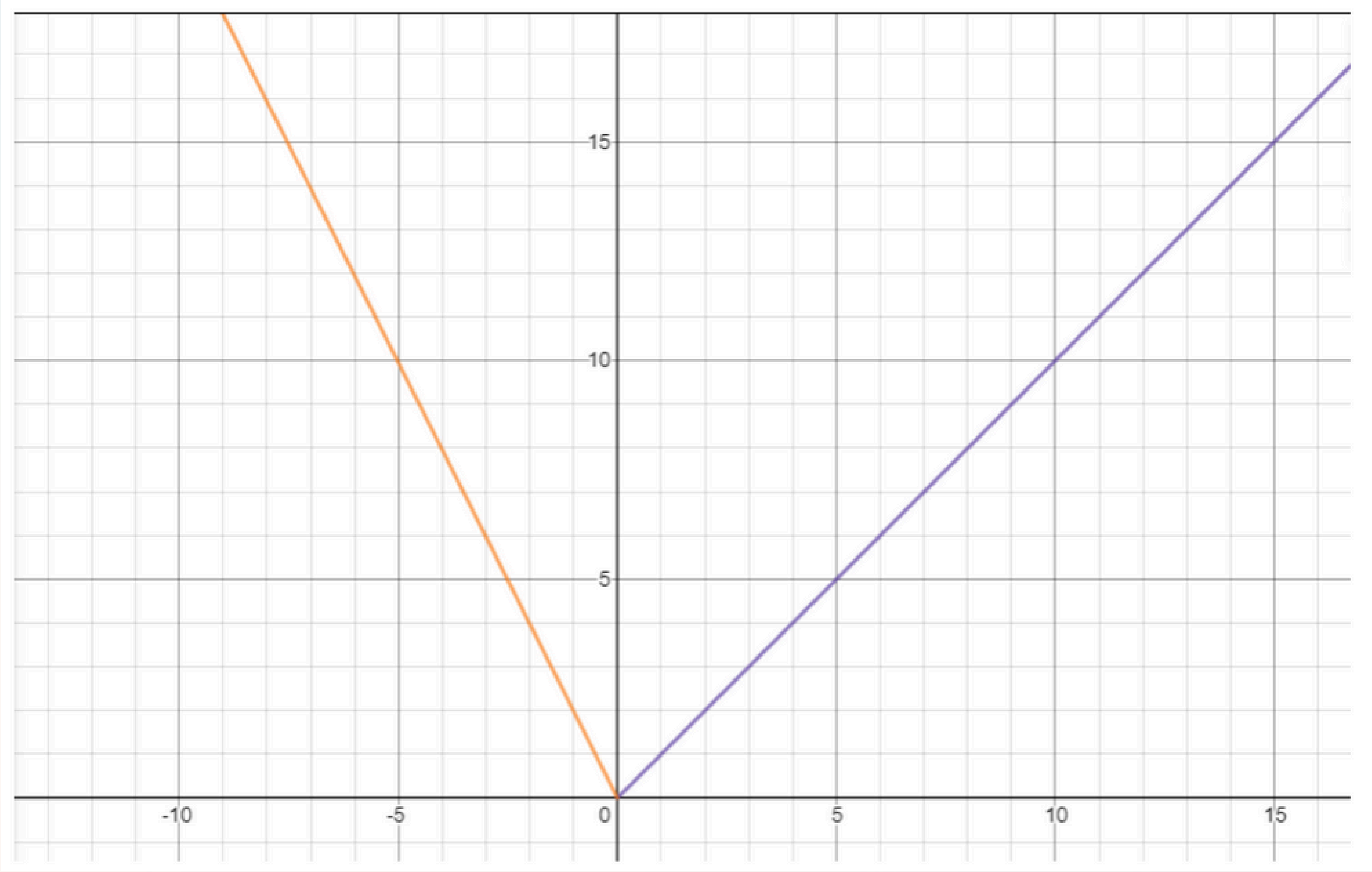
QRELU VS RELU

RELU



- OUTPUTS R(Z)=ZR(Z) = ZR(Z)=Z FOR Z>0Z > 0Z>0, AND R(Z)=0R(Z) = 0R(Z)=0 FOR Z≤0Z \LEQ 0Z≤0.
- **PROBLEM:** NEURONS WITH NEGATIVE INPUTS "DIE" (OUTPUT ALWAYS 0), CAUSING THE DYING RELU PROBLEM AND HALTING LEARNING.
- LEAKY RELU GIVES SMALL NEGATIVE OUTPUTS

QRELU

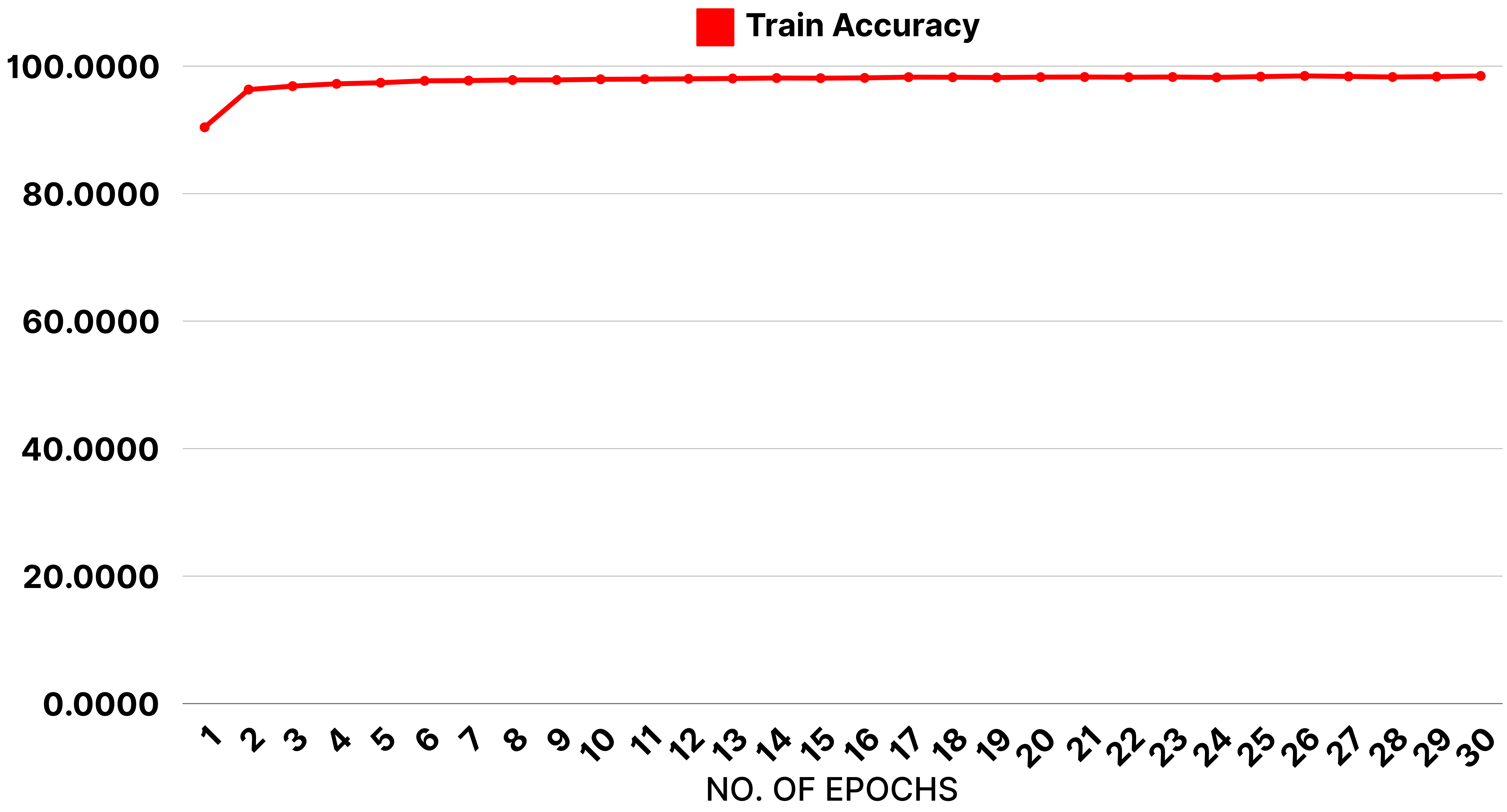


- USES THE **PRINCIPLE OF ENTANGLEMENT** TO COMBINE **RELU** (POSITIVE INPUTS) AND **LEAKY RELU** (SMALL NEGATIVE INPUTS).
- **SOLUTION:** PREVENTS DEAD NEURONS BY ENSURING NON-ZERO OUTPUTS FOR NEGATIVE INPUTS, ENHANCING LEARNING AND GENERALIZATION.

Q-RELU (LOSS)

Train Loss
0.3000
0.2500
0.2000
0.1500
0.1000
0.0500
0.0000
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
NO. OF EPOCHS

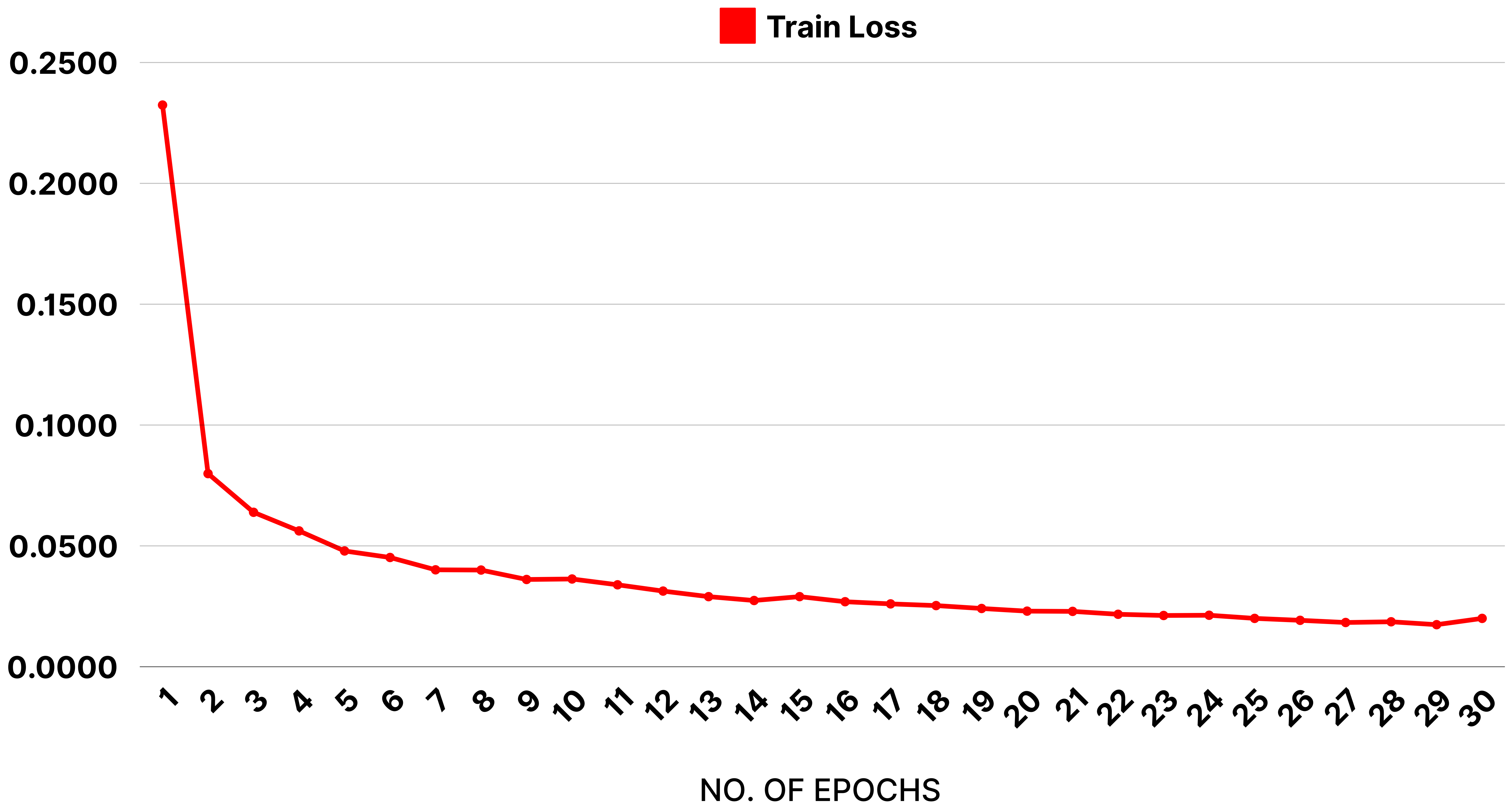
Q-RELU (ACCURACY)



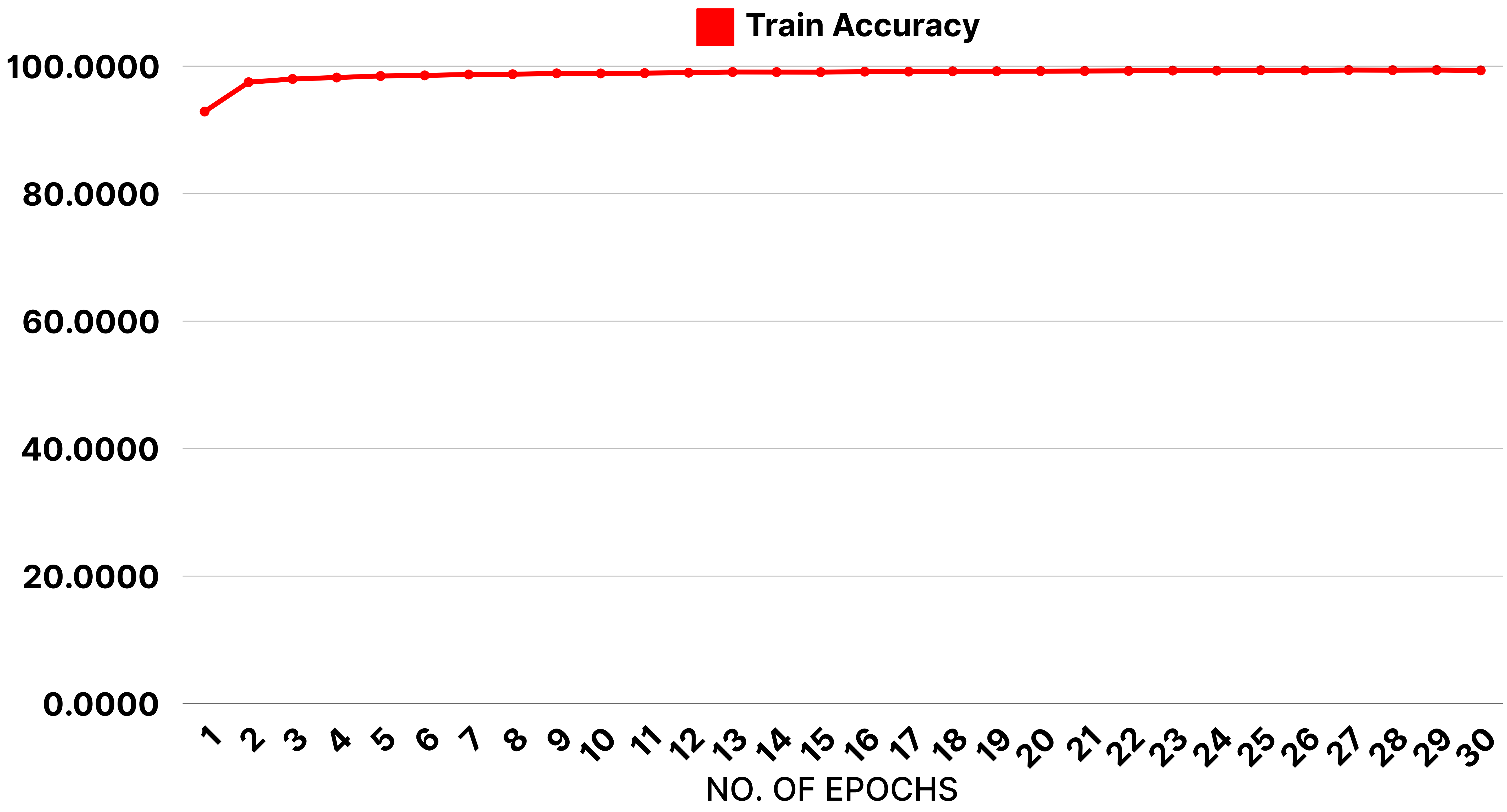
TEST ACCURACY 99.20%

TRAIN ACCURACY 98.47%

RELU (LOSS)


Train Loss
0.2500
0.2000
0.1500
0.1000
0.0500
0.0000
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30
NO. OF EPOCHS

RELU (ACCURACY)



TEST ACCURACY 99.32%

TRAIN ACCURACY 99.30%

THANK YOU

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