Experiment Run

Experiment Run Report

Experiment Title: Numerosity-Based Categorization – Silhouettes Dataset

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1. Experiment Details

Parameter	Value
Seed	42
Dataset Size	3000 samples
Image Size	128x128 pixels
Categories	Few (1-5), Medium (6-15), Many (>16)
Batch Size	256
Learning Rate	0.0001
Epochs	20
Optimizer	AdamW
Dropout Rate	0.4
Weight Decay	5e-4
Loss Function	CrossEntropyLoss
Early Stopping	Yes (Patience = 5)
Device Used	GPU – NVIDIA L4
eps	1e-6
betas	0.9, 0.98
Accumulation steps	2

2. Experiment Setup

- **Dataset:** Synthetic Dot Patterns
- **Model Architecture:** CNN-Transformer architecture
- **Training Strategy:**
  - Train on 70% of data.
  - Validate on 15%.
  - Test on 15%.
- **Evaluation Metrics:**
  - Accuracy
  - Loss Curves
  - Confusion Matrix
  - Precision, Recall, and F1-Score

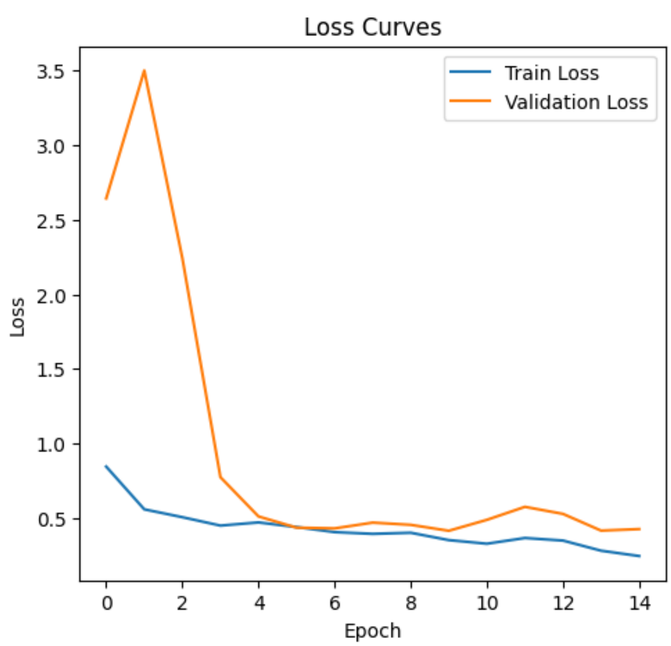
3. Training & Validation Performance

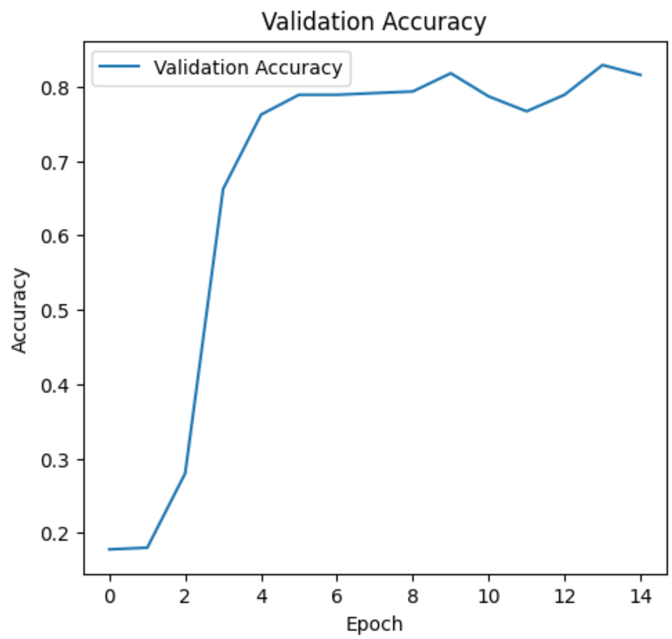
3.1 Loss and Accuracy Trends

Epoch	Train Loss	Validation Loss	Validation Accuracy (%)
1	0.8440	2.6334	17.78%
2	0.5575	3.5014	18.00%
3	0.5048	2.2426	28.00%
4	0.4485	0.7734	66.22%
5	0.4696	0.5100	76.22%
6	0.4386	0.4345	78.89%
7	0.4046	0.4297	78.89%
8	0.3930	0.4684	79.11%
9	0.4004	0.4536	79.33%
10	0.3511	0.4137	81.78%

Epoch	Train Loss	Validation Loss	Validation Accuracy (%)
11	0.3269	0.4871	78.67%
12	0.3652	0.5743	76.67%
13	0.3480	0.5269	78.89%
14	0.2800	0.4147	82.89%
15	0.2442	0.4251	81.56%

3.2 Loss Curve & Accuracy Plot

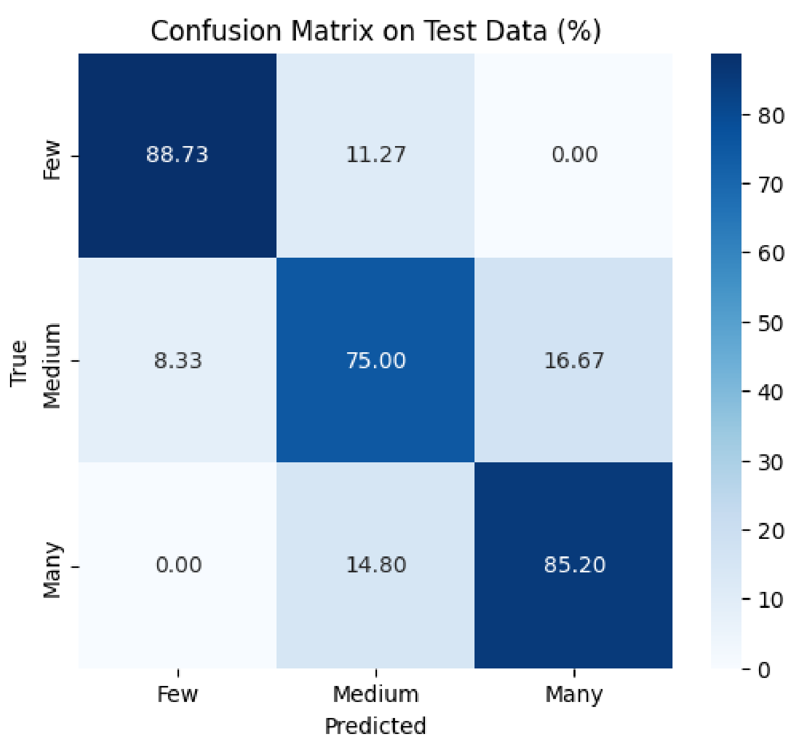




4. Test Set Evaluation

Final Test Accuracy: 82.22%

4.1 Confusion Matrix



4.2 Classification Report

Class	Precision	Recall	F1-Score	Support
Few	0.83	0.89	0.86	71
Medium	0.74	0.75	0.75	156
Many	0.88	0.85	0.87	351

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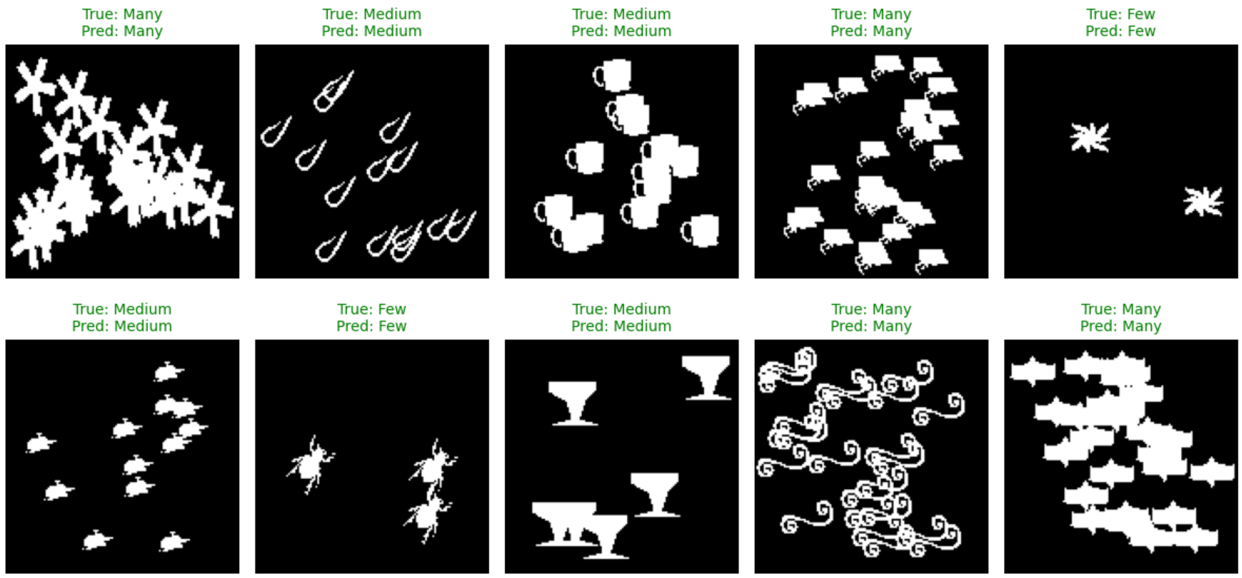
5. Observations & Insights

- **Key Findings:**
  - Model performance improved noticeably over the CNN-only setup.
  - Validation accuracy steadily increased, peaking at 82.89%, indicating good learning and generalization.
  - The final test accuracy is 82.22%, a solid result for categorizing abstract numerosity from silhouettes.
  - The loss trends in both training and validation loss curves are smoother, indicating better convergence and reduced overfitting.
  - All three classes ("Few", "Medium", "Many") were correctly learned to some degree, with the model being particularly strong on the "Few" and "Many" categories.
  - Improved Generalization: The CNN+Transformer model generalizes better than the CNN-only version. Despite earlier training instability (spikes in validation loss), performance stabilized and improved in later epochs.
  - Strong Accuracy in Extremes:
    - Few (Precision: 0.83, Recall: 0.89): High precision and recall suggest the model can easily recognize small object counts.
    - Many (Precision: 0.88, Recall: 0.85): The model reliably identifies cluttered scenes with high object counts.
  - Moderate Handling of Medium:
    - Medium (Precision: 0.74, Recall: 0.75) is slightly weaker, reflecting natural ambiguity in mid-range quantities, which are less visually distinct.

- **Error Analysis:**



  - Confusion between "Medium" and both extremes:
    - 16.67% of "Medium" samples were misclassified as "Many".
    - 8.33% were misclassified as "Few".
  - "Many" misclassified as "Medium" (14.8%): These errors could stem from object overlap, shape complexity, or edge occlusion making dense images appear less populated.
  - No "Few" misclassified as "Many": Indicates model learned a strong separation between lowest and highest counts.

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6. Conclusion

The CNN+Transformer model demonstrates strong capability in abstract numerosity categorization, achieving over 82% accuracy on complex silhouette compositions. Compared to the CNN-only version, it shows:

- Improved accuracy in both validation and test sets.
- Better generalization across numerosity levels, especially at extremes.
- Moderate errors in ambiguous middle cases, which is a known challenge in cognitive-inspired quantification.
