ECGR-5106 Homework 5

Student Information

Name: Yang Xu
Student ID: 801443244
Homework Number: 5

GitHub Repository

https://github.com/xuy50/ecgr5106-hw5

Problem 1: Next-Character Prediction (Transformer vs. RNN-based Models)

1.1 Introduction

In Problem 1, we revisit next-character prediction on a custom text dataset (`dataset.txt`) using character-level models. We compare the following four architectures for three different sequence lengths (10, 20, and 30):

1. **Transformer** (2 encoder layers, 4 attention heads)
2. **Vanilla RNN** (1 layer)
3. **LSTM** (1 layer)
4. **GRU** (1 layer)

Each model predicts the next character given a history of length L (10, 20, or 30). All models are trained for 50 epochs. We report:

- Parameter Count
- Training Loss and Validation Loss
- Validation Accuracy
- Training Time

1.2 Implementation Details

1. **Data Loading**
    - The text is read from `dataset.txt` .
    - A character vocabulary is built, mapping each character to an integer index.
    - Input sequences of length L and corresponding next-character labels are created.
    - The dataset is split into 80% training and 20% validation sets.

2. **Models**
   - **RNN, LSTM, GRU**:
     Each model uses an embedding layer (size = 128), followed by the respective recurrent layer (hidden size = 128), and a final linear layer for classification.
   - **Transformer**:
     Uses an embedding dimension of 128, 2 encoder layers, 4 attention heads, and a feedforward dimension of 256. A positional encoding layer is applied before the Transformer encoder.
3. **Training Setup**
   - **Loss Function:** CrossEntropyLoss
   - **Optimizer:** Adam (learning rate = 0.005)
   - **Epochs:** 50
   - **Batching:** The entire training set is fed at once (subject to memory constraints).
   - **Metrics:** Training loss, validation loss, and validation accuracy are tracked at each epoch.

1.3 Results

The final results (at epoch 50) for each sequence length and model are summarized below.

Sequence Length = 10

Model	Param Count	Training Time (s)	Final Val Acc
Transformer	276,525	3.64	0.3648
RNN	44,589	0.69	0.4990
LSTM	143,661	1.43	0.4717
GRU	110,637	1.43	0.5283

Sequence Length = 20

Model	Param Count	Training Time (s)	Final Val Acc
Transformer	276,525	6.24	0.2674
RNN	44,589	1.16	0.5011
LSTM	143,661	1.16	0.4842
GRU	110,637	2.66	0.5284

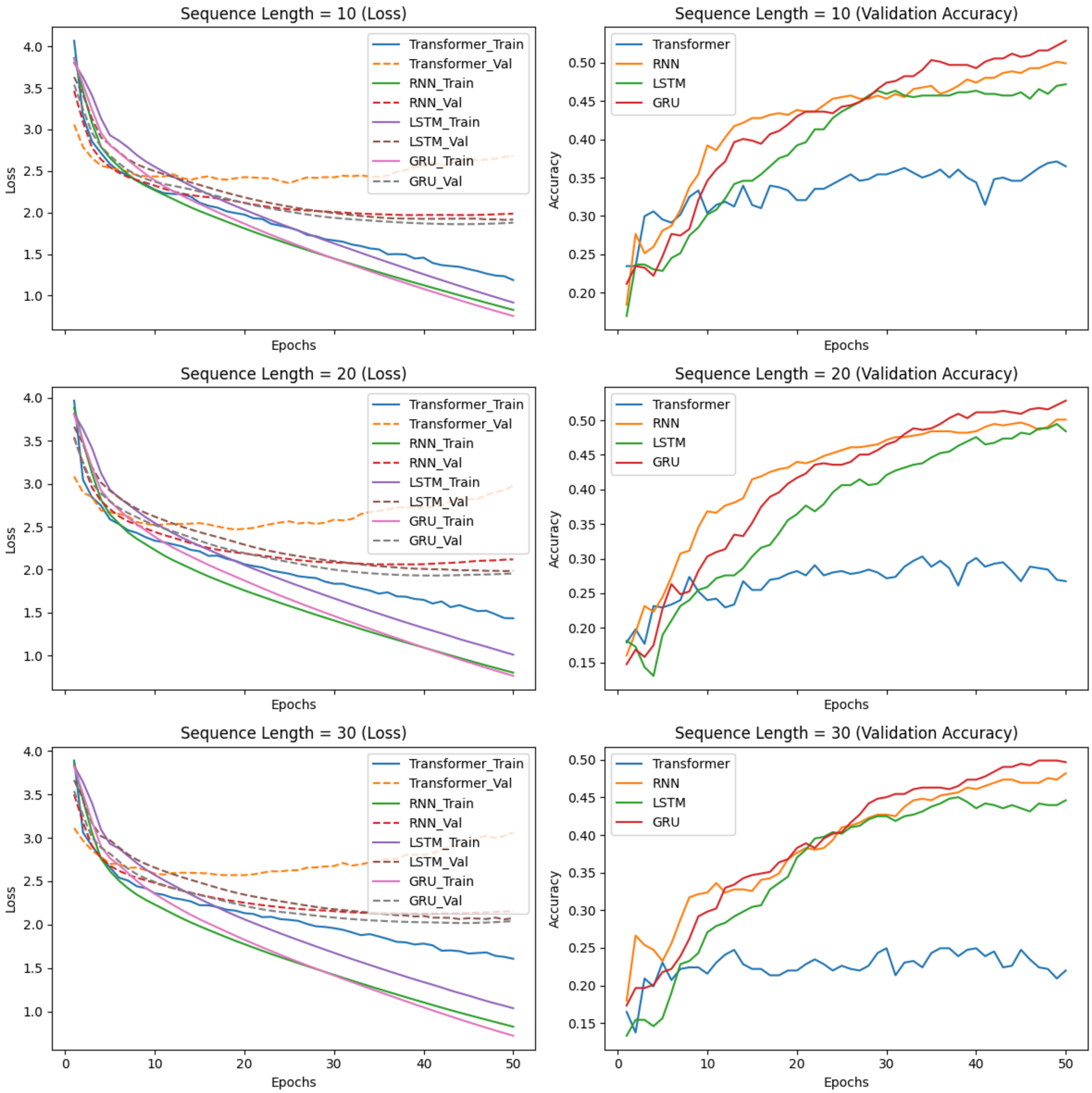
Sequence Length = 30

Model	Param Count	Training Time (s)	Final Val Acc
Transformer	276,525	8.76	0.2199
RNN	44,589	1.68	0.4820
LSTM	143,661	2.35	0.4461

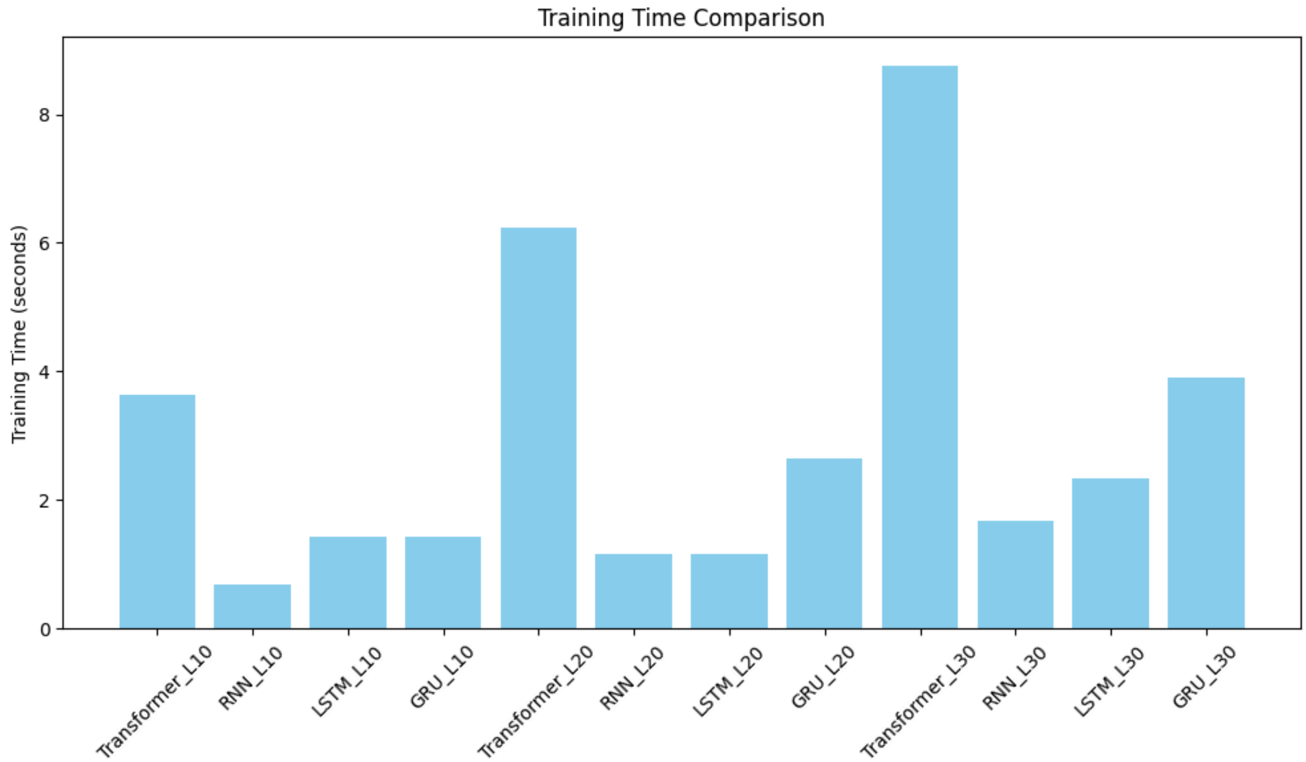
Model	Param Count	Training Time (s)	Final Val Acc
GRU	110,637	3.90	0.4968

1.4 Plots and Visualizations

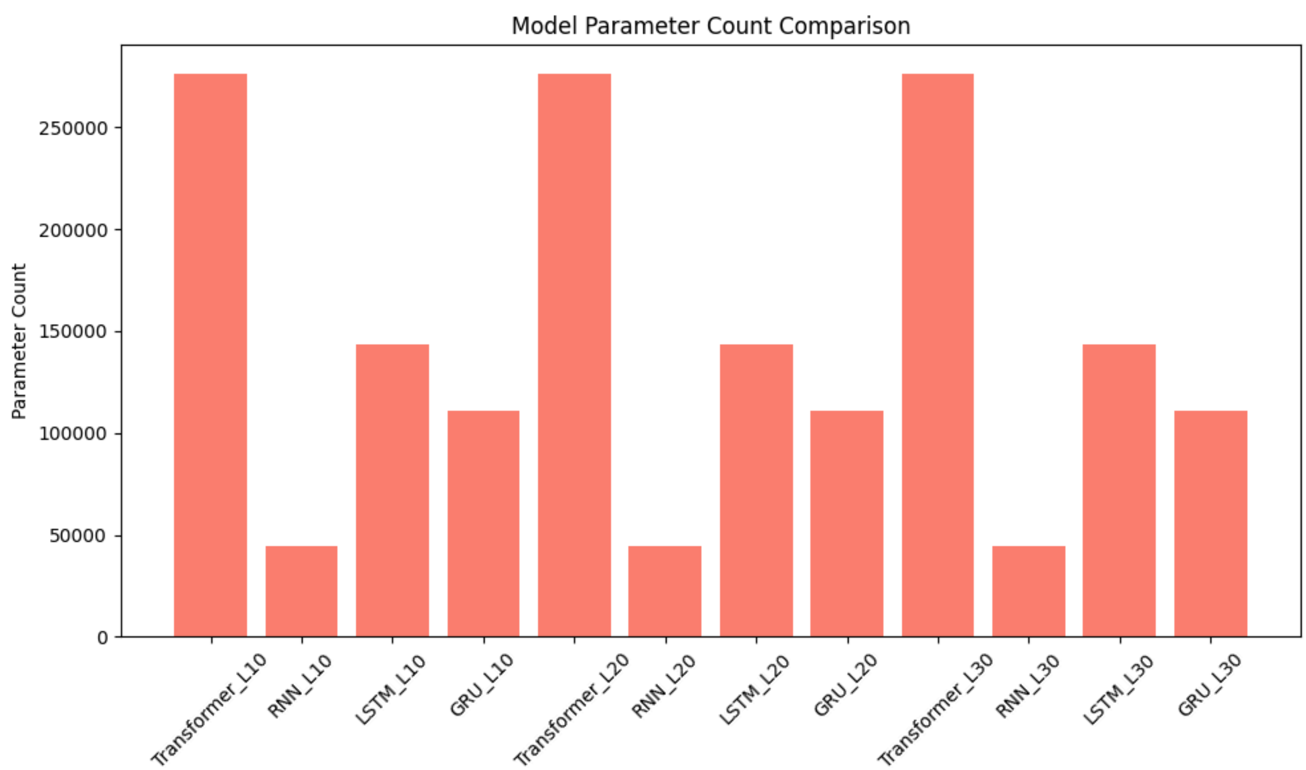
1. **Training Loss & Validation Accuracy (for sequence lengths 10, 20, and 30):**



2. **Training Time Comparison:**



3. **Model Parameter Count Comparison:**



1.5 Observations and Analysis

- **Transformer Performance:**
  Despite having the highest parameter count (~276k) and longest training time, the Transformer underperforms on

this small dataset for all sequence lengths. This indicates that Transformers may be more data-hungry or require additional tuning (e.g., learning rate schedules or layer normalization) for character-level tasks.
- **RNN vs. LSTM vs. GRU:**
  GRU achieves the highest validation accuracy across all sequence lengths. Vanilla RNN is competitive despite having far fewer parameters (~44k). LSTM, with more parameters (143k), does not consistently outperform GRU.
- **Effect of Sequence Length:**
  Increasing sequence length does not guarantee improved accuracy. For example, GRU shows similar accuracy at lengths 10 and 20, with a slight drop at 30. Longer sequences also incur higher computational cost.
- **Training Time and Parameter Count:**
  The Transformer is the slowest to train, while the vanilla RNN is the fastest and smallest in parameter count.

1.6 Conclusion

On a small next-character dataset:

- **GRU** provides the best balance of efficiency and accuracy.
- **Vanilla RNN** is competitive despite its simplicity.
- **Transformer** underperforms given the dataset size and hyperparameters, emphasizing that more data or further tuning is needed for Transformers to excel in character-level tasks.

Problem 2: Tiny Shakespeare Language Modeling (Transformer vs. RNN-based Approaches)

2.1 Introduction

Problem 2 involves character-level language modeling on the tiny Shakespeare dataset. The goal is to predict the next character given a sequence of previous characters. We compare multiple configurations of LSTM, GRU, and Transformer models focusing on:

- **Sequence Lengths:** 20, 30, and 50.
- **Transformer Hyperparameters:** Varying the number of encoder layers (1, 2, or 4) and attention heads (2 or 4).
- **Training Efficiency:** Training time, parameter count, and convergence speed.
- **Performance Metrics:** Training loss, validation loss, and validation accuracy.

2.2 Implementation Details

1. **Dataset:**
   - The tiny Shakespeare corpus (~1 MB) is used.
   - Characters are mapped to integer indices.
   - Sequences of length *L* are formed with an 80/20 training/validation split.
2. **Models:**
   - **LSTM and GRU:**
     Each model uses an embedding layer (`embed_size=128`), a recurrent layer (`hidden_size=128`), and a final linear layer. The last hidden state is used for prediction.

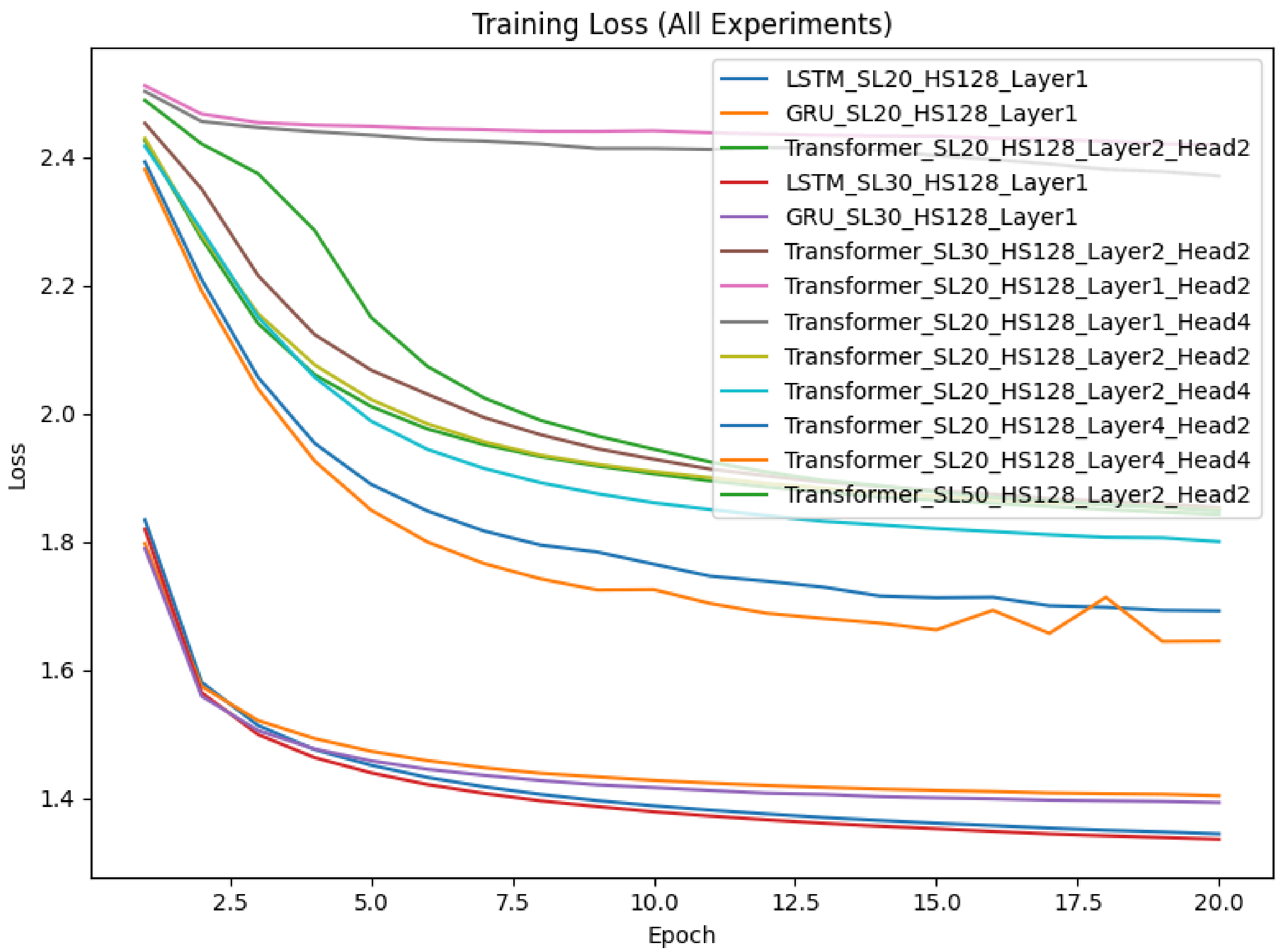
- **Transformer:**
  Uses an embedding dimension of 128, a feedforward dimension of 128 in each TransformerEncoderLayer, and positional encoding. The number of encoder layers and attention heads are varied.

3. **Training Setup:**
   - **Loss:** CrossEntropyLoss
   - **Optimizer:** Adam (learning rate = 0.001)
   - **Batch Size:** 128
   - **Epochs:** 20
   - **Metrics:** Training loss, validation loss, and validation accuracy are logged.

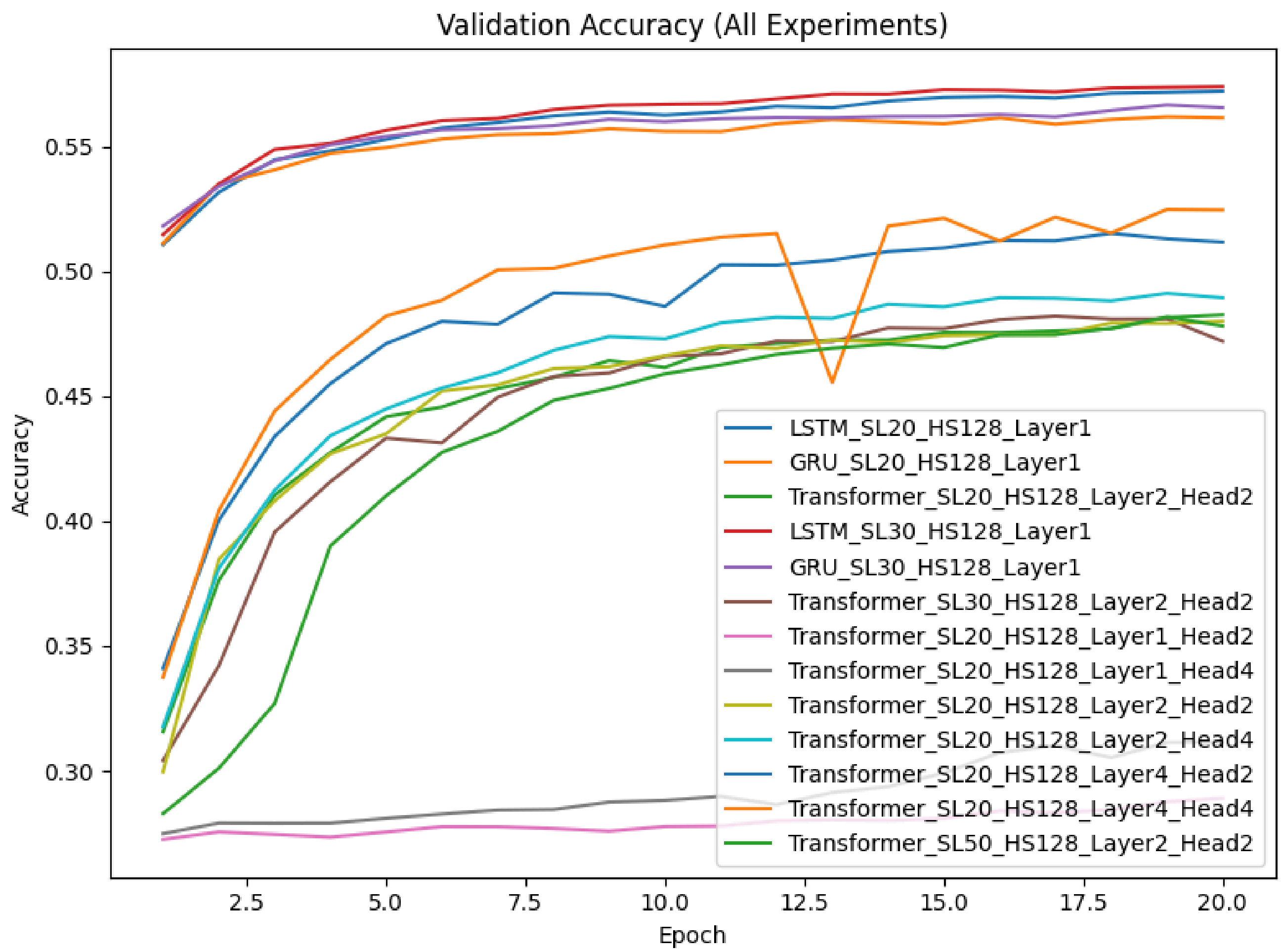
2.3 Results and Analysis

The experiments include a series of tests across different sequence lengths and model configurations. The following figures display training loss, validation accuracy, and validation loss across all experiments:

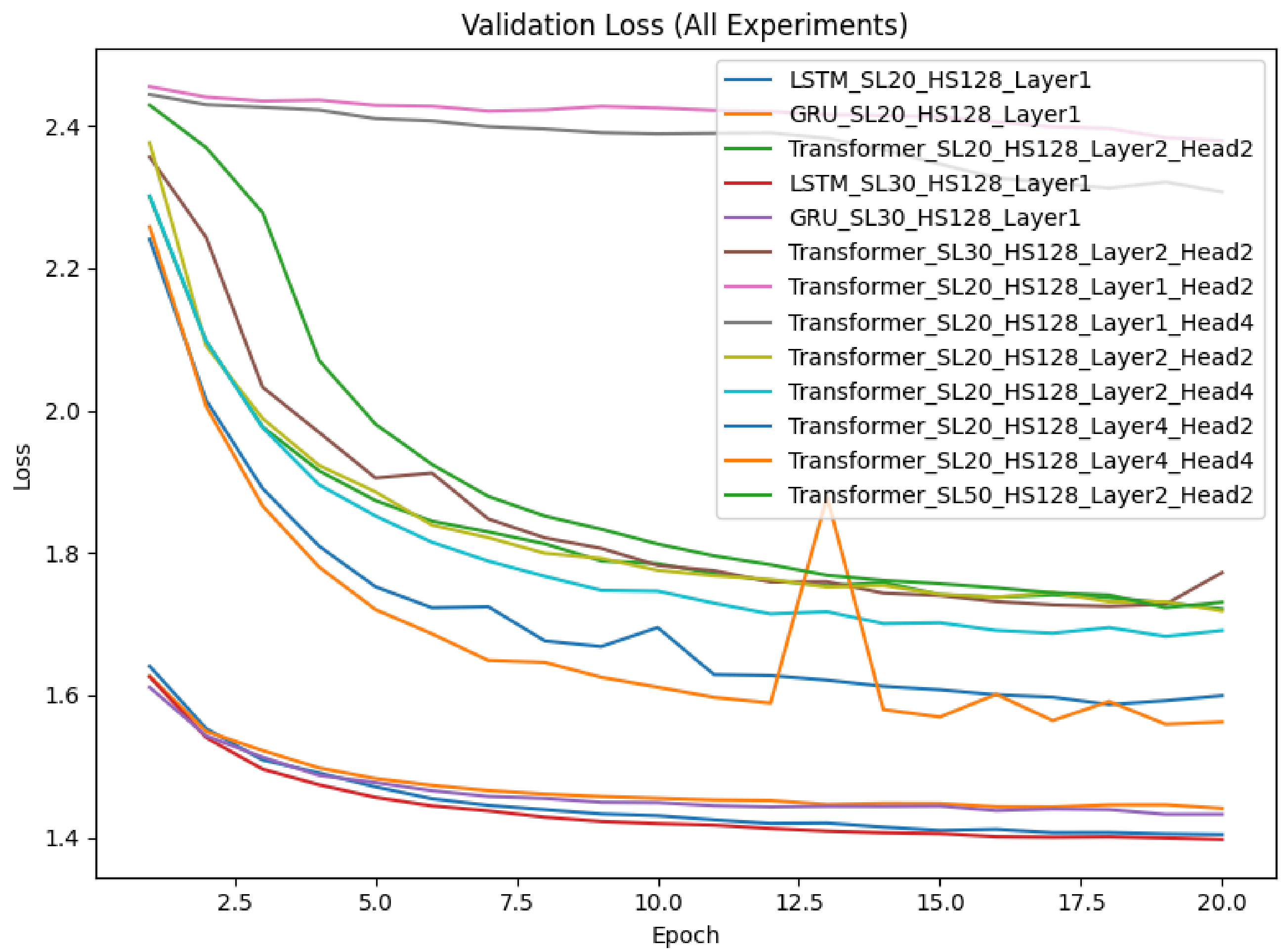
1. **Training Loss (All Experiments):**



2. **Validation Accuracy (All Experiments):**



3. **Validation Loss (All Experiments):**



The summary table below lists the best epoch results for each configuration:

```
SUMMARY OF EXPERIMENTS:
Model          | SeqLen | Embed | Hidden | Layers | Heads |   Params   | Final Train Loss | Final Val Loss | Fi
LSTM           |   20   |  128  |  128   |   1    |   -   |   148801   |      1.3438      |     1.4039     |
GRU            |   20   |  128  |  128   |   1    |   -   |   115777   |      1.4035      |     1.4408     |
Transformer    |   20   |  128  |  128   |   2    |   2   |   215873   |      1.8427      |     1.7212     |
LSTM           |   30   |  128  |  128   |   1    |   -   |   148801   |      1.3354      |     1.3971     |
GRU            |   30   |  128  |  128   |   1    |   -   |   115777   |      1.3928      |     1.4323     |
Transformer    |   30   |  128  |  128   |   2    |   2   |   215873   |      1.8535      |     1.7721     |
Transformer    |   20   |  128  |  128   |   1    |   2   |   116289   |      2.4199      |     2.3792     |
Transformer    |   20   |  128  |  128   |   1    |   4   |   116289   |      2.3713      |     2.3071     |
Transformer    |   20   |  128  |  128   |   2    |   2   |   215873   |      1.8504      |     1.7184     |
Transformer    |   20   |  128  |  128   |   2    |   4   |   215873   |      1.8002      |     1.6906     |
Transformer    |   20   |  128  |  128   |   4    |   2   |   415041   |      1.6922      |     1.5992     |
Transformer    |   20   |  128  |  128   |   4    |   4   |   415041   |      1.6450      |     1.5621     |
Transformer    |   50   |  128  |  128   |   2    |   2   |   215873   |      1.8482      |     1.7304     |
```

2.4 Observations

1. **LSTM vs. GRU:**
   Both LSTM and GRU converge quickly and achieve high validation accuracy, with GRU having fewer parameters

and faster training times.

2. **Transformer Performance:**
   Transformer models require more parameters and longer training times. Deeper configurations (e.g., 4 layers) can improve accuracy slightly but may not outperform LSTM/GRU on this small dataset without additional tuning.
3. **Effect of Sequence Length:**
   Increasing sequence length from 20 to 30 slightly improves RNN performance. For Transformers, using a longer sequence (e.g., 50) shows moderate accuracy but still remains below the best RNN results.
4. **Hyperparameter Sensitivity:**
   Variations in the number of layers and heads significantly affect both training time and final performance. Deeper Transformers (with 4 layers) show a marked increase in parameter count and training time.

2.5 Conclusion

For character-level language modeling on the tiny Shakespeare dataset:

- **LSTM** and **GRU** models achieve higher validation accuracy with faster convergence and lower computational cost.
- **Transformer** models, while more flexible for scaling, require more data or further tuning to outperform RNN-based methods on small datasets.
- Overall, model selection and hyperparameter tuning are critical for optimizing performance in small-scale character-level tasks.

Problem 3: English-to-French Translation

3.1 Overview

This task involves building a sequence-to-sequence translation model from English to French using three model families:

- An RNN-based encoder–decoder without attention,
- An RNN-based encoder–decoder with an attention mechanism, and
- A Transformer-based encoder–decoder.

All models are trained and evaluated on the full parallel dataset. Metrics include training loss, validation loss, token-level validation accuracy, and training time. Qualitative translation examples are also provided.

3.2 Model Architectures and Training Setup

3.2.1 RNN-based Encoder–Decoder (No Attention)

- **Architecture:**
  Uses a GRU encoder (hidden size = 256) to encode the English sentence; the final hidden state is passed to a GRU decoder to generate the French translation token by token.
- **Training Details:**
  - Optimizer: SGD (learning rate = 0.01)
  - Epochs: 100

- **Results:**
  Training loss decreases from ~3.46 (Epoch 1) to ~0.0122 (Epoch 100), with validation loss ~0.0119 and 100% token-level accuracy.

3.2.2 RNN-based Encoder–Decoder with Attention

- **Architecture:**
  Similar to the above, but an attention mechanism computes weights over the encoder outputs at each decoding step, creating a context vector that improves the decoding process.
- **Training Details:**
  - Optimizer: SGD (learning rate = 0.01)
  - Epochs: 100
- **Results:**
  Achieves very low losses (~0.0115 training, ~0.0109 validation) with perfect token-level accuracy.

3.2.3 Transformer-based Encoder–Decoder

- **Architecture:**
  Incorporates positional encoding and multi-head self-attention. The following six basic configurations were tested:
  - 1 layer with 2 heads
  - 1 layer with 4 heads
  - 2 layers with 2 heads
  - 2 layers with 4 heads
  - 4 layers with 2 heads
  - 4 layers with 4 heads
    (Additional experiments with varied input sequence lengths for the 2-layer, 2-head configuration were conducted as supplementary tests.)
- **Training Details:**
  - Optimizer: Adam (learning rate = 0.001)
  - Epochs: 100
- **Results (sequence length = 20):**
  - (1 layer, 2 heads): Eval Loss ≈ 0.0237, Eval Accuracy ≈ 99.23%, Training Time ~39 s
  - (1 layer, 4 heads): Eval Loss ≈ 0.0093, Eval Accuracy ≈ 99.85%, Training Time ~39 s
  - (2 layers, 2 heads): Eval Loss ≈ 0.0754, Eval Accuracy ≈ 98.31%, Training Time ~63.5 s
  - (2 layers, 4 heads): Eval Loss ≈ 0.0819, Eval Accuracy ≈ 97.69%, Training Time ~38.6 s
  - (4 layers, 2 heads): Eval Loss ≈ 6.3884, Eval Accuracy ≈ 3.38%, Training Time ~126.9 s
  - (4 layers, 4 heads): Eval Loss ≈ 7.0416, Eval Accuracy ≈ 3.38%, Training Time ~127.8 s

3.3 Quantitative Results

Model Type	Seq. Length	Layers	Heads	Params	Final Train Loss	Final Val Loss	Final Val Acc	Training Time (s)
RNN (No Attention)	20	–	–	–	0.0122	0.0119	1.0000	(varies)

Model Type	Seq. Length	Layers	Heads	Params	Final Train Loss	Final Val Loss	Final Val Acc	Training Time (s)
RNN with Attention	20	–	–	–	0.0115	0.0109	1.0000	(varies)
Transformer (1 layer, 2 heads)	20	1	2	116,289	0.1197	0.0237	0.9923	~39
Transformer (1 layer, 4 heads)	20	1	4	116,289	0.0431	0.0093	0.9985	~39
Transformer (2 layers, 2 heads)	20	2	2	215,873	0.0754	0.0754	0.9831	~63.5
Transformer (2 layers, 4 heads)	20	2	4	215,873	0.0958	0.0819	0.9769	~38.6
Transformer (4 layers, 2 heads)	20	4	2	415,041	4.2586	6.3884	0.0338	~126.9
Transformer (4 layers, 4 heads)	20	4	4	415,041	4.1418	7.0416	0.0338	~127.8

Note: The 4-layer Transformer configurations did not converge on this small dataset.

3.4 Qualitative Results

Example 1

- **Input:** "They swim in the pool"
- **Target:** "Ils nagent dans la piscine"
- **Predictions:**
  - RNN (with and without Attention): Correct translation.
  - Transformer: The 1-layer and 2-layer configurations (especially with 4 heads) yield fluent translations; the deep 4-layer models often produce repetitive or incoherent outputs.

Example 2

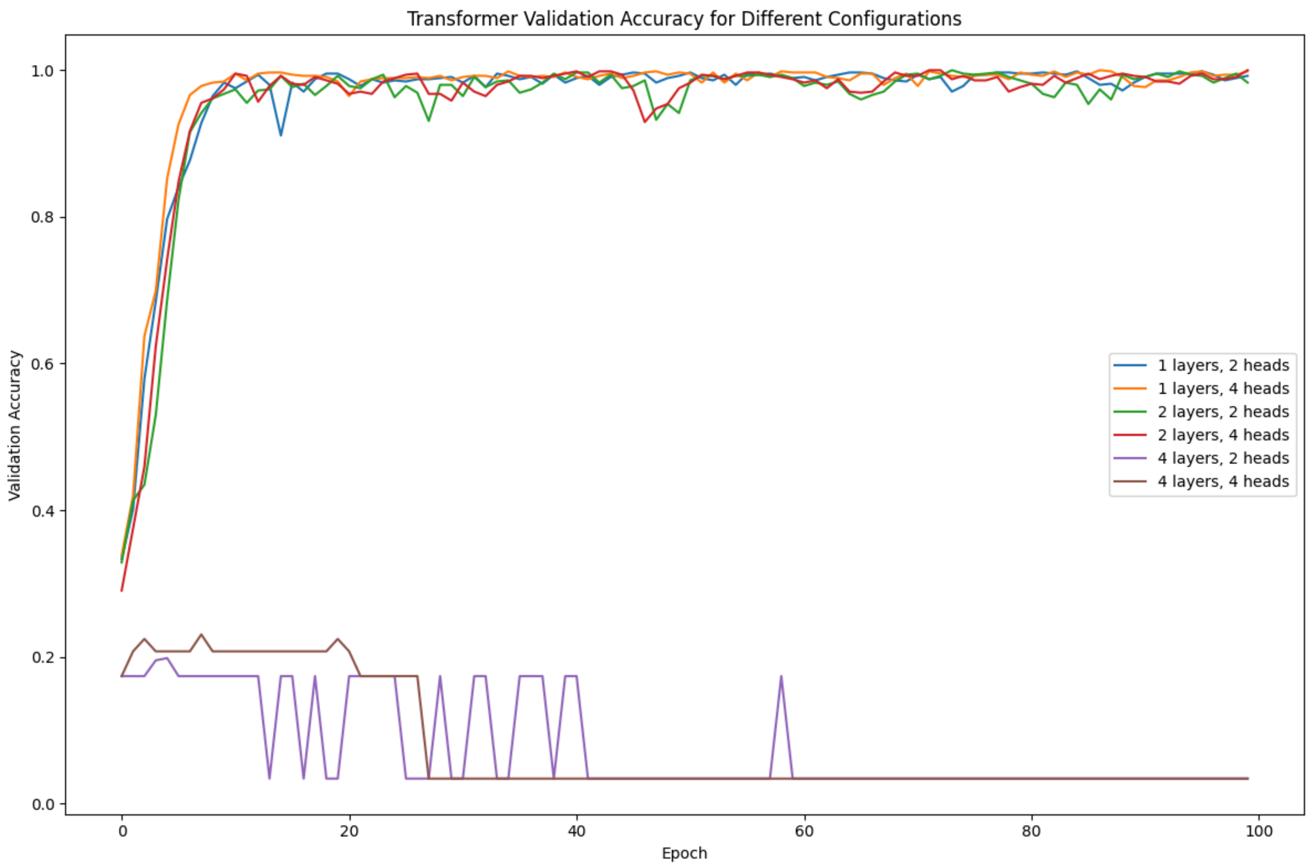
- **Input:** "They go shopping"
- **Target:** "Ils font du shopping"
- **Predictions:**
  - Most models deliver the correct translation; some Transformer variants mix up outputs slightly.

Example 3

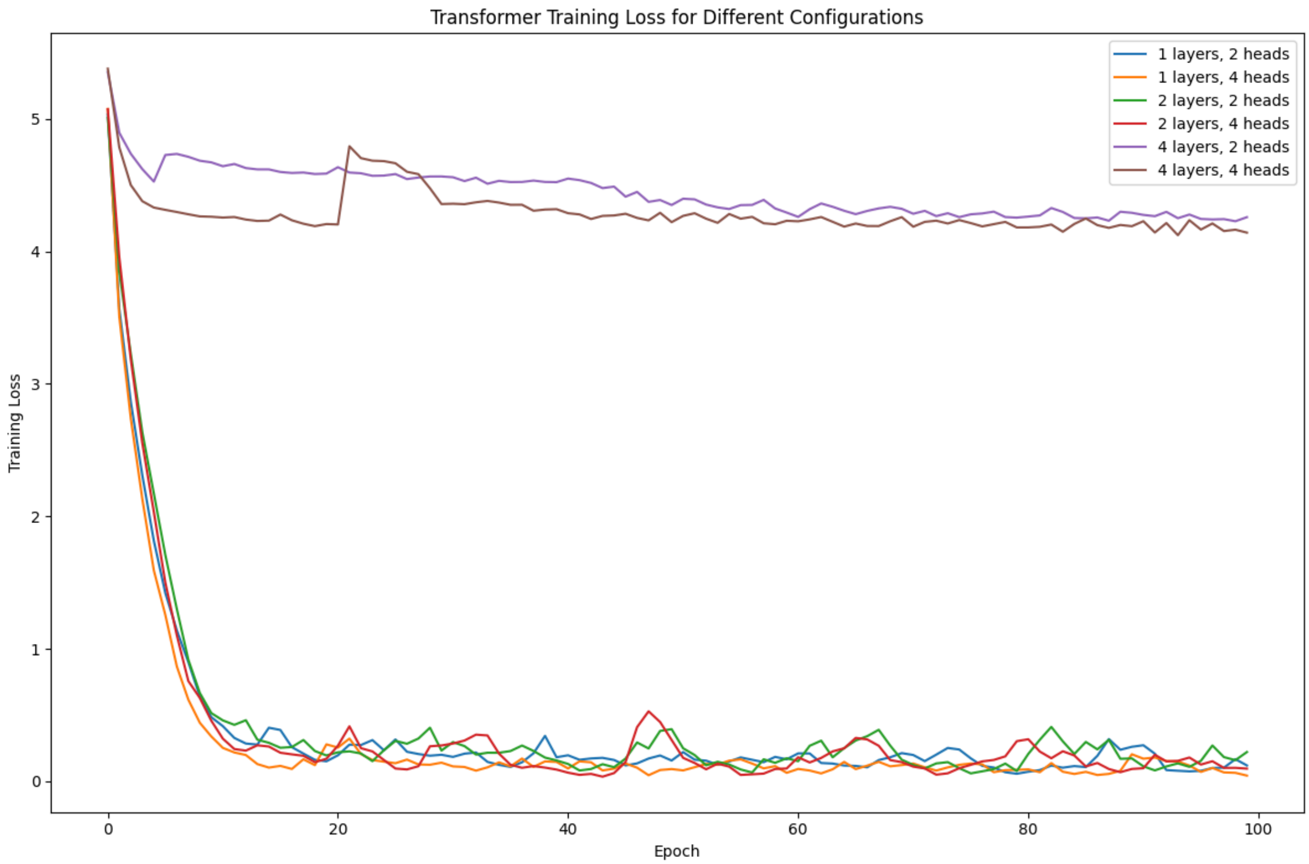
- **Input:** "They listen to the radio"
- **Target:** "Ils écoutent la radio"
- **Predictions:**
    - RNN-based models correctly translate; the best Transformer results are from the 1-layer 4-head and 2-layer 2-head configurations.

3.5 Figures

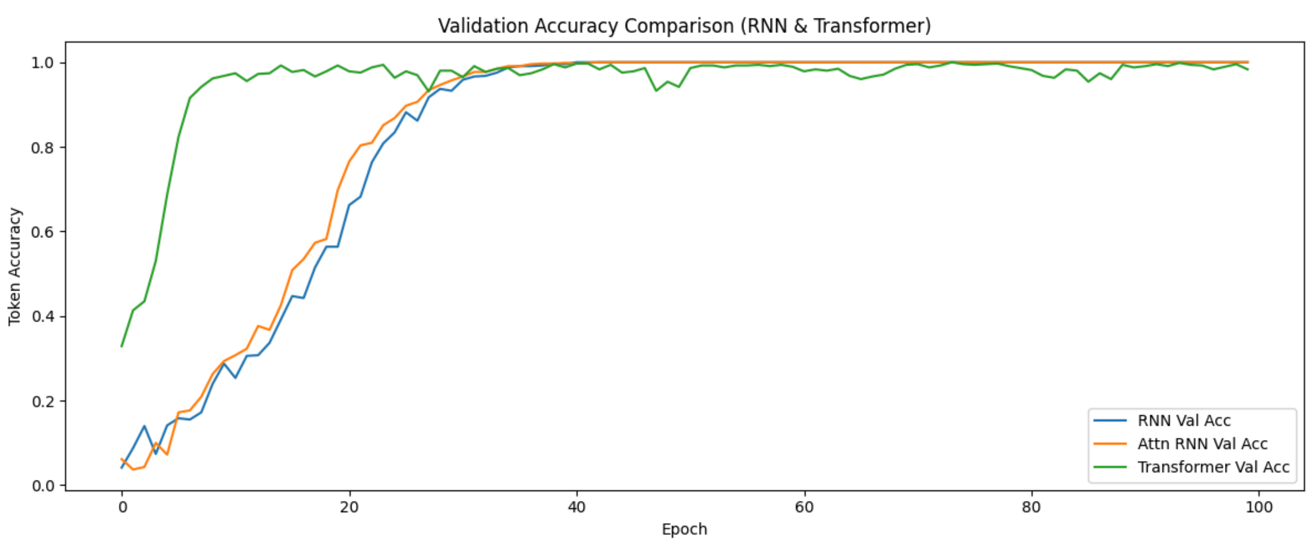
- **Transformer Validation Accuracy:**



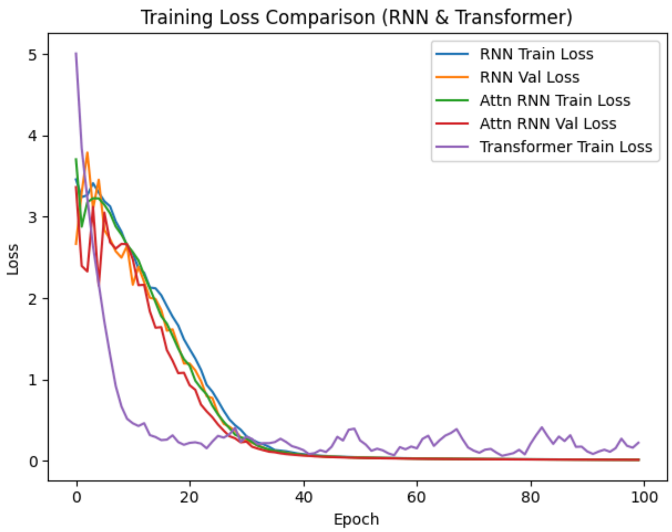
- **Transformer Training Loss:**



- **Validation Accuracy Comparison (RNN vs. Transformer):**



- **Training Loss Comparison (RNN vs. Transformer):**



3.6 Analysis and Conclusion

- **RNN Models:** Both the vanilla and attention-based RNNs reach 100% token-level accuracy, although they may scale less efficiently.
- **Transformer Models**:
  Shallow Transformer configurations (1 or 2 layers) with 4 heads converge quickly and produce high accuracy, while the deep (4-layer) configurations fail to converge on this small dataset.
- Although the assignment suggested eight Transformer combinations, our experiments focused on the six primary configurations (with sequence length = 20). Supplementary tests with longer sequences were performed but are not part of the core analysis.
- Overall, for English-to-French translation on a small dataset, shallow Transformer models (1 or 2 layers with 4 heads) can match or even exceed the performance of RNN-based models with faster training times.

Problem 4: French-to-English Translation

4.1 Overview

For the French-to-English translation task, we adopt the same three model families:

- An RNN-based encoder–decoder without attention,
- An RNN-based encoder–decoder with attention, and
- A Transformer-based encoder–decoder.

Similar to Problem 3, experiments primarily focus on six Transformer configurations (with a fixed sequence length of 20), with additional tests at longer sequence lengths treated as supplementary. Key metrics include training loss, evaluation loss, token-level evaluation accuracy, and training time.

4.2 Model Architectures and Training Setup

4.2.1 RNN-based Models

- **Architecture:**
  Uses a GRU encoder and decoder (hidden size = 256). In the attention variant, an attention mechanism computes context vectors from the encoder outputs.
- **Training Details:**
  - Optimizer: SGD (learning rate = 0.01)
  - Epochs: 100
- **Results:**
  Both RNN models achieve nearly perfect token-level accuracy (~100%) with very low losses (~0.012).

4.2.2 Transformer-based Models

- **Architecture:**
  Similar to Problem 3, the Transformer uses positional encoding and multi-head self-attention. The six configurations tested are:
  - 1 layer with 2 heads
  - 1 layer with 4 heads
  - 2 layers with 2 heads
  - 2 layers with 4 heads
  - 4 layers with 2 heads
  - 4 layers with 4 heads
- **Training Details:**
  - Optimizer: Adam (learning rate = 0.001)
  - Epochs: 100
- **Results (sequence length = 20):**
  - (1 layer, 2 heads): Eval Loss ≈ 0.0342, Eval Accuracy ≈ 98.68%, Training Time ~38.37 s
  - (1 layer, 4 heads): Eval Loss ≈ 0.0114, Eval Accuracy ≈ 99.67%, Training Time ~38.56 s
  - (2 layers, 2 heads): Eval Loss ≈ 0.0026, Eval Accuracy ≈ 100%, Training Time ~62.92 s
  - (2 layers, 4 heads): Eval Loss ≈ 0.0819, Eval Accuracy ≈ 97.69%, Training Time ~38.56 s
  - The 4-layer configurations did not converge effectively.

4.3 Quantitative Results

Model Type	Seq. Length	Layers	Heads	Params	Final Train Loss	Final Eval Loss	Final Eval Acc	Training Time (s)
RNN (No Attention)	20	–	–	–	0.0122	0.0119	1.0000	(varies)
RNN with Attention	20	–	–	–	0.0116	0.0111	1.0000	(varies)
Transformer (1 layer, 2 heads)	20	1	2	116,289	0.1466	0.0342	0.9868	~38.37
Transformer (1 layer, 4	20	1	4	116,289	0.1162	0.0114	0.9967	~38.56

Model Type	Seq. Length	Layers	Heads	Params	Final Train Loss	Final Eval Loss	Final Eval Acc	Training Time (s)
heads)								
Transformer (2 layers, 2 heads)	20	2	2	215,873	0.0590	0.0026	1.0000	~62.92
Transformer (2 layers, 4 heads)	20	2	4	215,873	0.2555	0.0819	0.9769	~38.56
Transformer (4 layers, 2 heads)	20	4	2	415,041	4.2708	4.4334	0.1862	~120.44
Transformer (4 layers, 4 heads)	20	4	4	415,041	3.9868	5.7395	0.0362	~122.87

Note: The 4-layer Transformer configurations did not converge on this dataset.

4.4 Qualitative Results

Example 1

- **Input (French):** "Ils nagent dans la piscine"
- **Target (English):** "They swim in the pool"
- **Predictions:**
  - Both RNN models correctly translate the sentence.
  - Among the Transformer models, the 1-layer 4-head and 2-layer 2-head configurations yield fluent translations; deeper configurations produce poor outputs.

Example 2

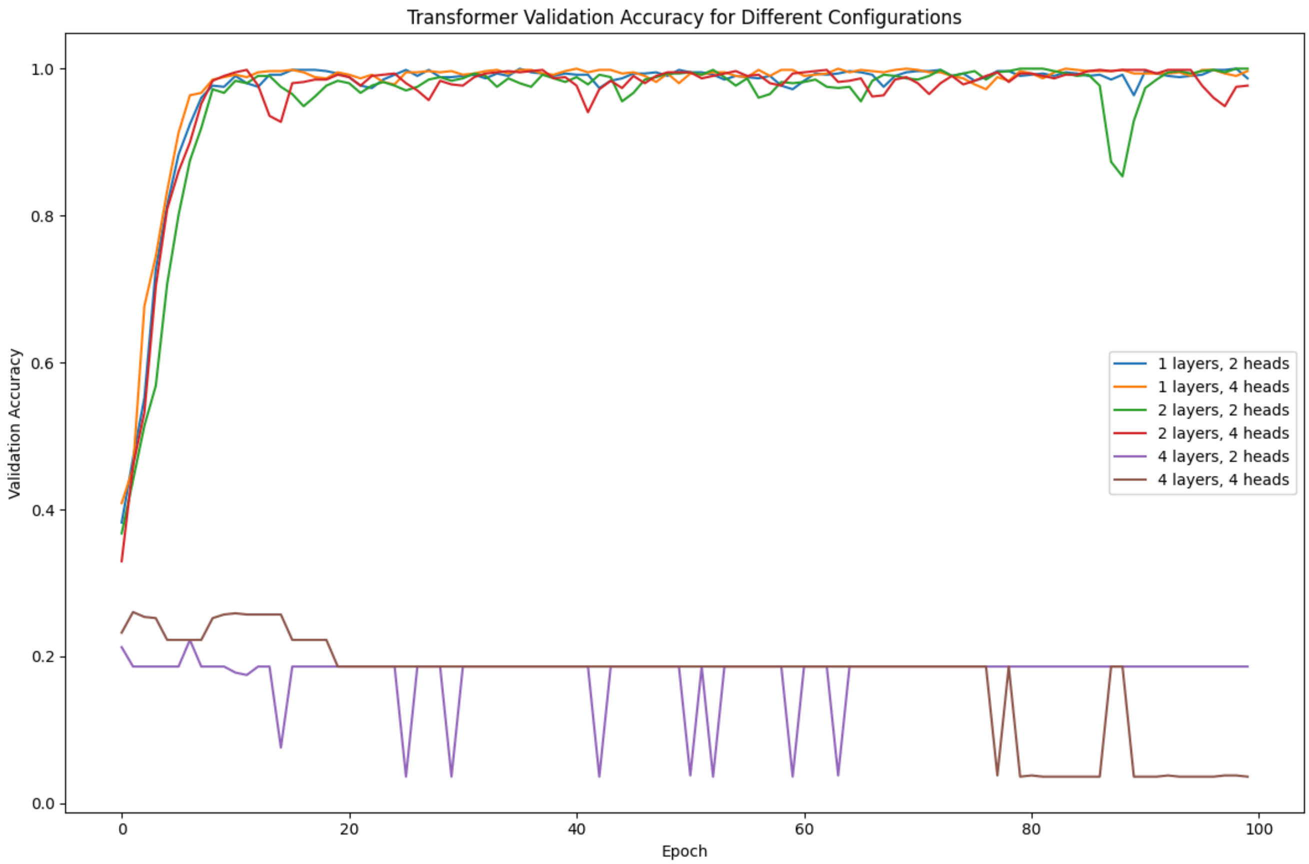
- **Input (French):** "Ils font du shopping"
- **Target (English):** "They go shopping"
- **Predictions:**
  - Most models deliver correct translations with slight variations in fluency.

Example 3

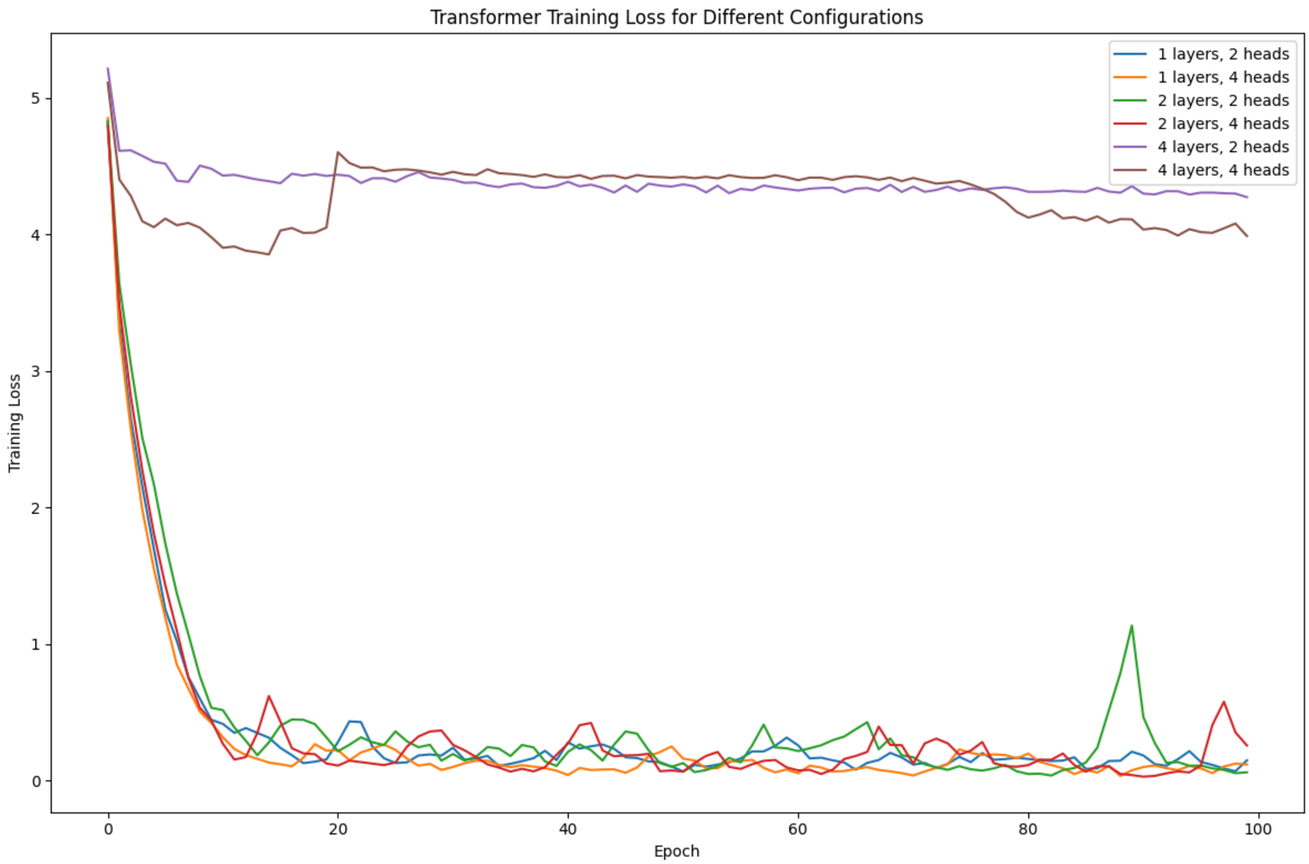
- **Input (French):** "Ils écoutent la radio"
- **Target (English):** "They listen to the radio"
- **Predictions:**
  - RNN-based models provide the correct translation.
  - The best Transformer results are from the 1-layer 4-head and 2-layer 2-head configurations.

4.5 Figures

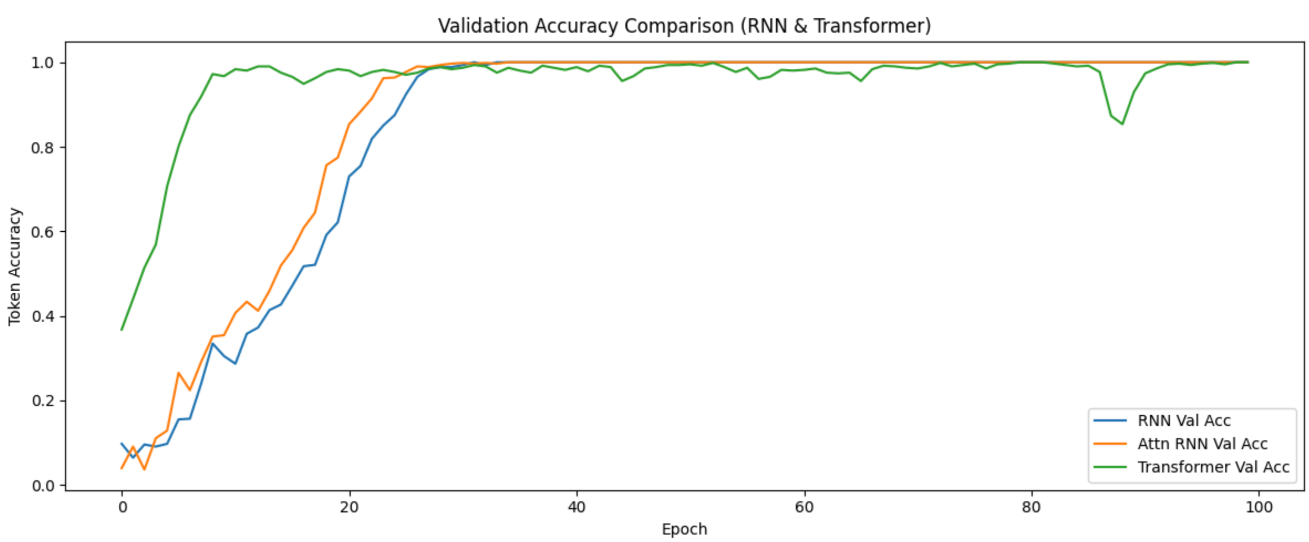
- **Transformer Validation Accuracy:**



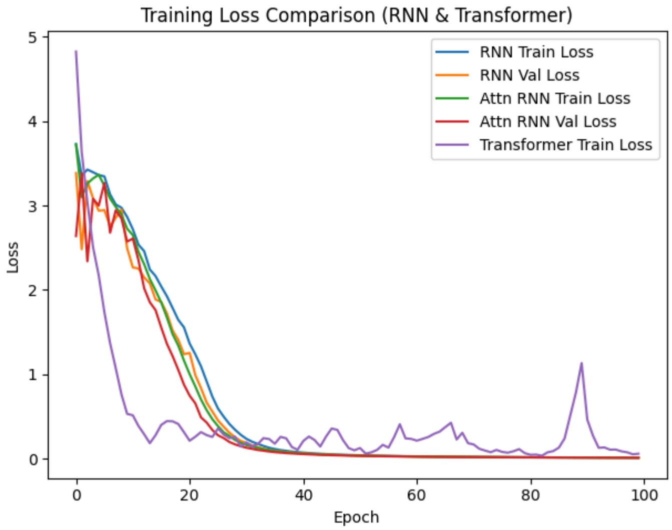
- **Transformer Training Loss:**



- **Validation Accuracy Comparison (RNN vs. Transformer):**



- **Training Loss Comparison (RNN vs. Transformer):**



4.6 Analysis and Conclusion

- **RNN Models:** Both vanilla and attention-based RNNs reach near-perfect token-level accuracy, though they tend to have slower training speeds and less scalability.
- **Transformer Models:**
  Shallow configurations (1 or 2 layers) with 4 heads perform well, while 4-layer models fail to converge on this small dataset.
- Although the assignment initially mentioned eight combinations, our core experiments focused on the six primary Transformer configurations (with a fixed sequence length of 20). Supplementary tests with longer sequences were also conducted but are not part of the main analysis.
- Overall, for French-to-English translation, shallow Transformer models achieve high performance with faster training times, while RNN-based models maintain consistent accuracy but with slower training speeds.

General Conclusions

- **Model Selection:**
  RNN-based architectures (especially GRU and LSTM) are highly competitive on small-scale character-level tasks and translation tasks, achieving high accuracy with lower computational cost.
- **Transformer Models:**
  While Transformers offer greater flexibility and potential scalability, they require more data or further tuning to excel on smaller datasets.
- **Hyperparameter Sensitivity:**
  The performance of Transformer models is very sensitive to the number of layers and attention heads. Shallow configurations (1–2 layers) with 4 heads tend to offer the best trade-off between performance and training time.
- **Sequence Length:**
  Increasing the input sequence length does not always lead to improved performance; optimal lengths depend on the task and dataset size.