COL774: Machine Learning
Assignment 4

Ankur Kumar (2025AIB2557)
Indian Institute of Technology Delhi

Jayesh Chaudhari (2025AIB3002)
Indian Institute of Technology Delhi

1. RNN-based Seq2Seq Model with Bahdanau Attention

1.1. Model Overview

For the maze path prediction task, we implement a sequence-to-sequence (Seq2Seq) architecture based on a Recurrent Neural Network with Bahdanau Attention. The model takes the full textual maze description (adjacency list, origin and target coordinates) as input and generates the corresponding shortest path as an output token sequence.

The model consists of:

- **Encoder:** A unidirectional RNN that processes the variable-length input sequence and produces hidden representations. The final hidden state forms the initial context for the decoder.
- **Bahdanau Attention:** At every decoding step, attention weights determine which encoder states are most relevant to the current prediction.
- **Decoder:** RNN-based auto-regressive decoder that predicts path coordinates token-by-token. Teacher forcing (ratio = 0.5) is used during training.

The model is trained using Cross-Entropy loss with padding ignored. We compute three evaluation metrics: **Token Accuracy**, **Sequence Accuracy**, and **Token-level F1**. Training was performed for 20 epochs with the following hyperparameters:

Batch Size	32
Embedding Dimension	128
Hidden Dimension	512
RNN Layers	2
Learning Rate	1e-4
Teacher Forcing Ratio	0.5
Optimizer	Adam

1.2. Dataset Split

The provided training set was further split into:

- 90% Train-Main
- 10% Train-Validation
- External Test Set

1.3. Training and Evaluation Results

Figure 1 shows loss, token accuracy, sequence accuracy, and F1 score curves across 20 epochs for train, train-val, and test splits.

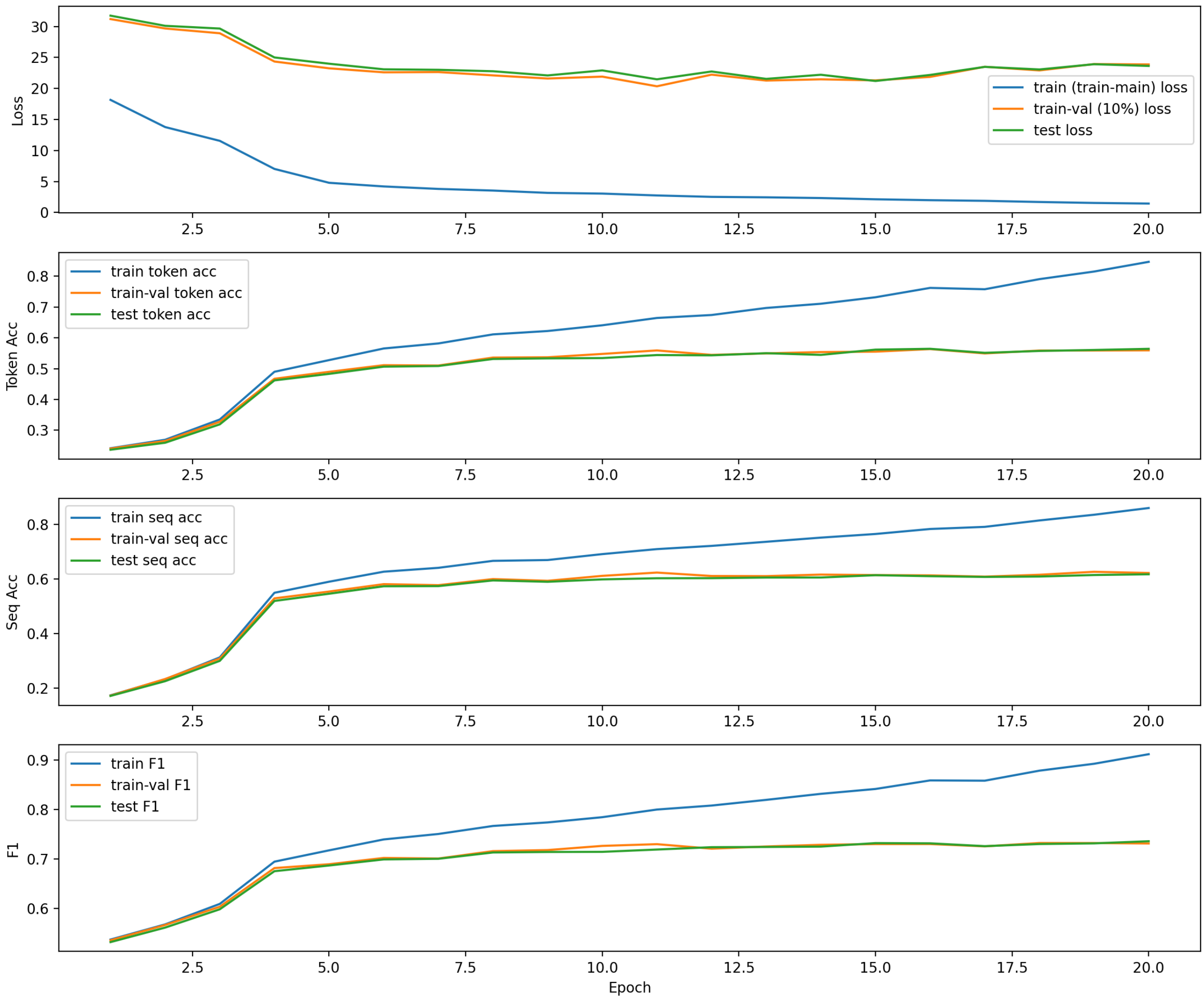

Figure 1: Training Curves for RNN Seq2Seq with Bahdanau Attention (Loss, Token Accuracy, Seq Accuracy, F1)

From the figure, we observe:

- Training loss decreases steadily while validation and test losses stabilize after epoch 10.
- Token and sequence accuracies improve consistently, with token accuracy reaching ∼0.82 and sequence accuracy ∼0.56.
- The small gap between validation and test performance suggests minimal overfitting.

1.4. Maze Visualization Results

Figure 2 shows qualitative predictions for 5 randomly selected mazes from the test set. Red markers indicate predicted traversal; circle marks the start and cross marks the target.

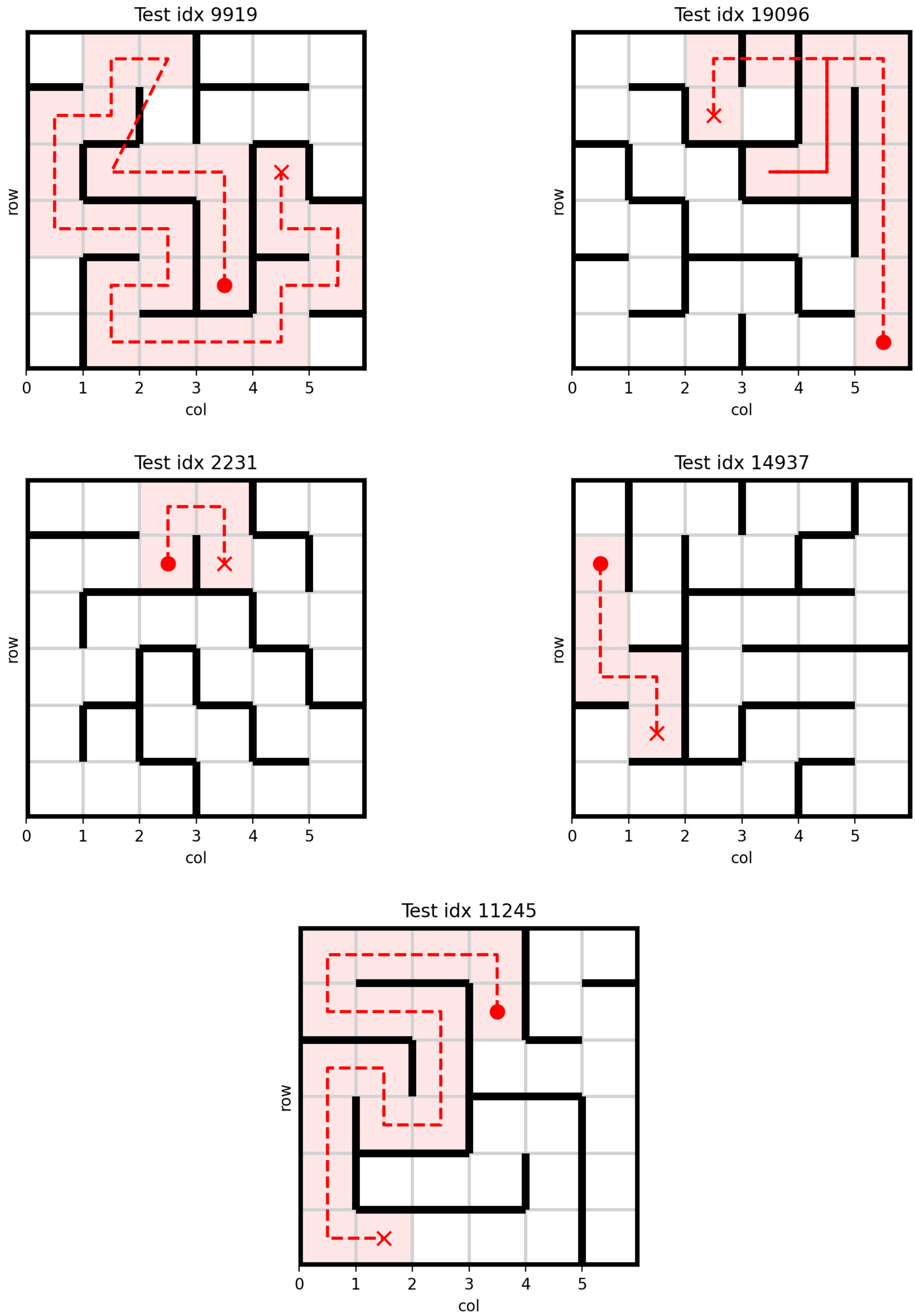

Figure 2: RNN predictions on 5 random mazes from the test set

2. Transformer-based Seq2Seq Model

2.1. Model Description

We adopt a Transformer-based encoder-decoder model with sinusoidal positional encoding and multi-head self-attention.

- $d_{model} = 128$, heads=8, layers=6
- Feed-forward dimension: 512
- Noam LR scheduler with 8000 warmup steps
- AdamW optimizer, LR initialized at 1.0
- Label smoothing: 0.1

2.2. Training Results

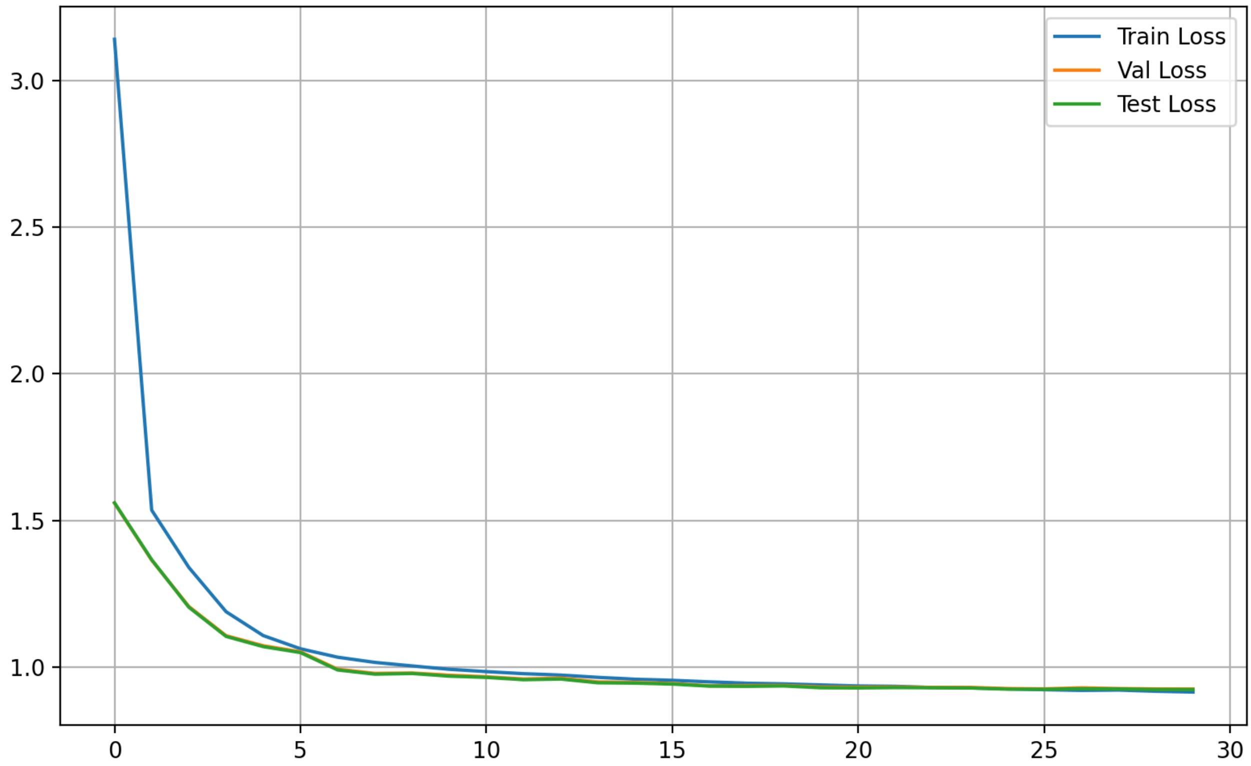

Figure 3: Loss curves for Transformer (train/val/test)

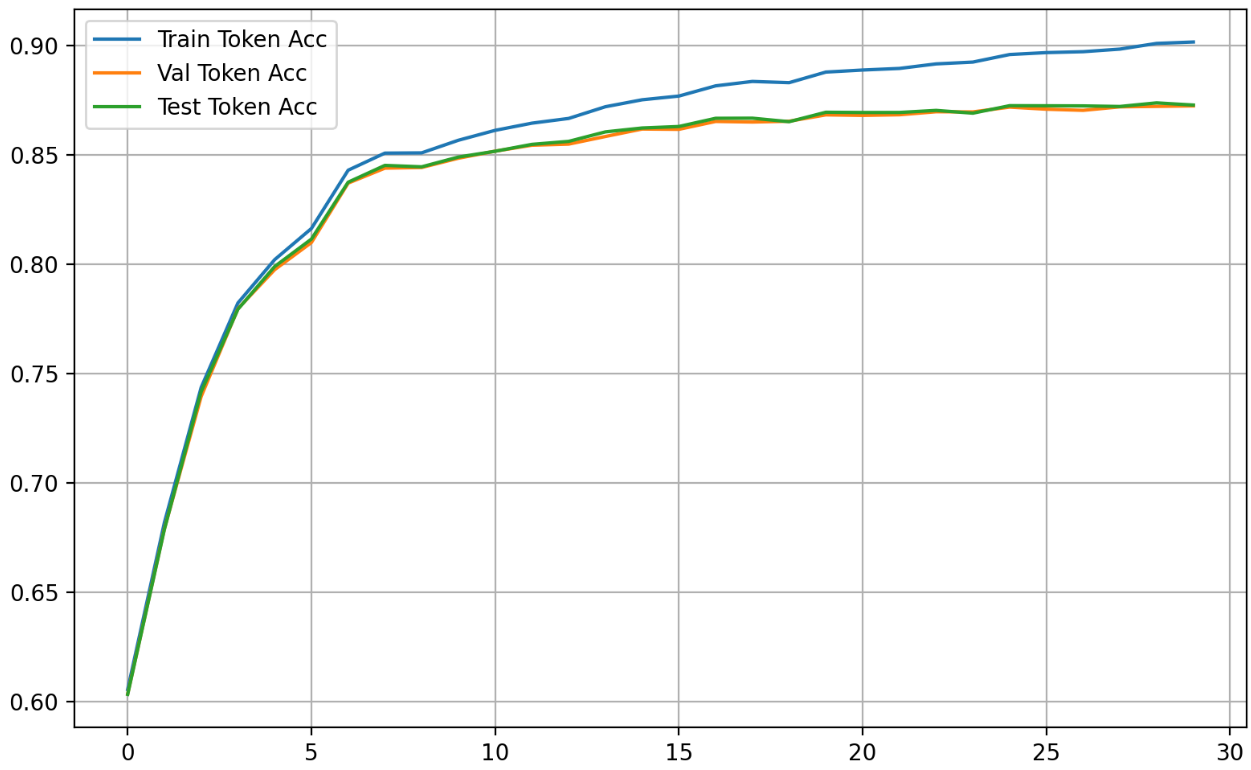

Figure 4: Token accuracy curves for Transformer

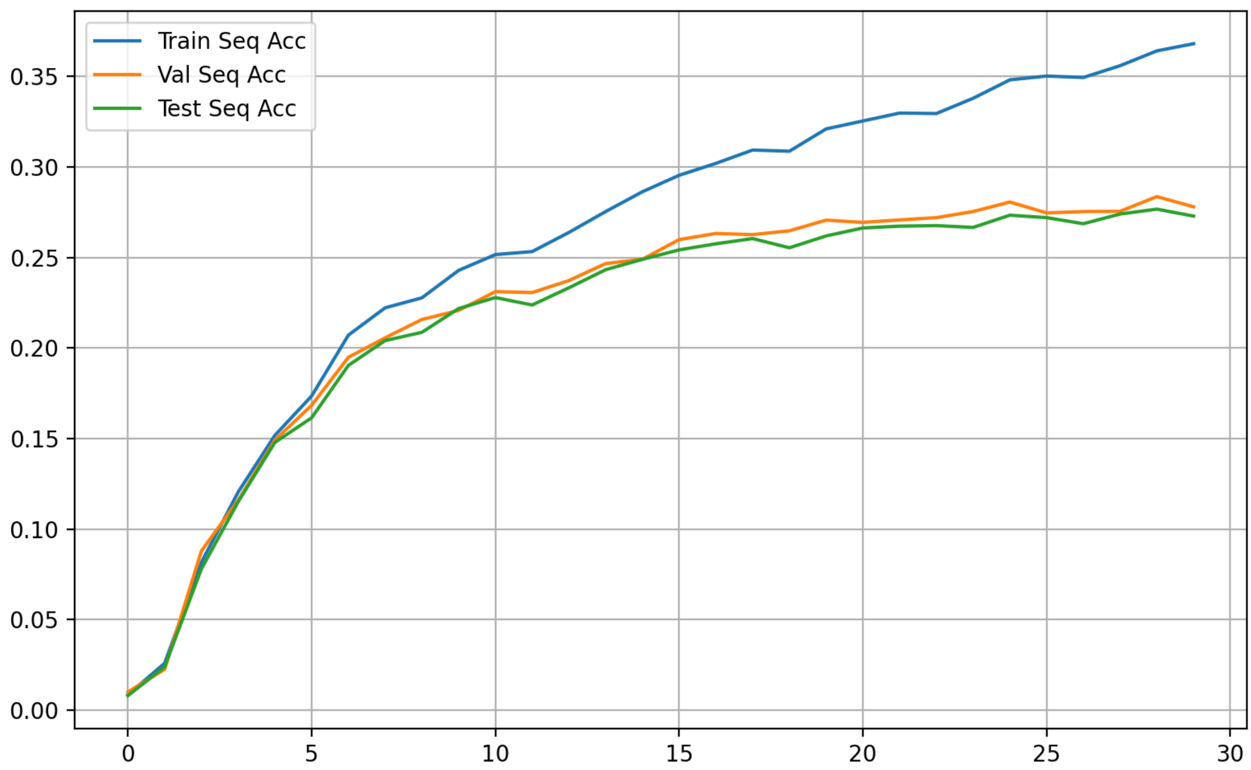

Figure 5: Token accuracy curves for Transformer

2.3. Maze Visualizations

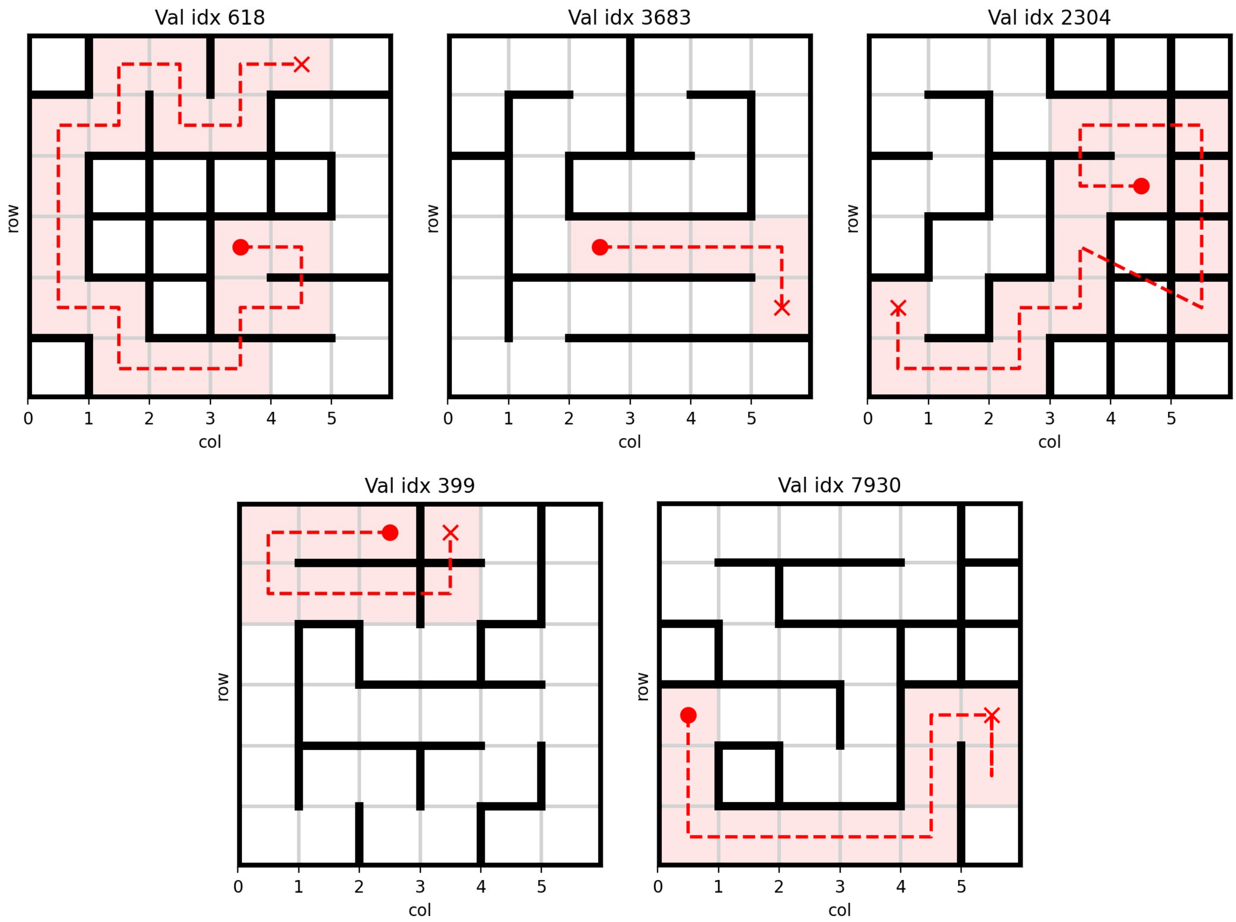

Figure 6: Predicted paths from Transformer model