A Comparative Analysis of Deep Learning & Numerical Methods for Estimating Influenza Cases

Project Presentation - CS-5513: Numerical Computation

Presentation by:
Mohammed Rakib & S M Rafiuddin

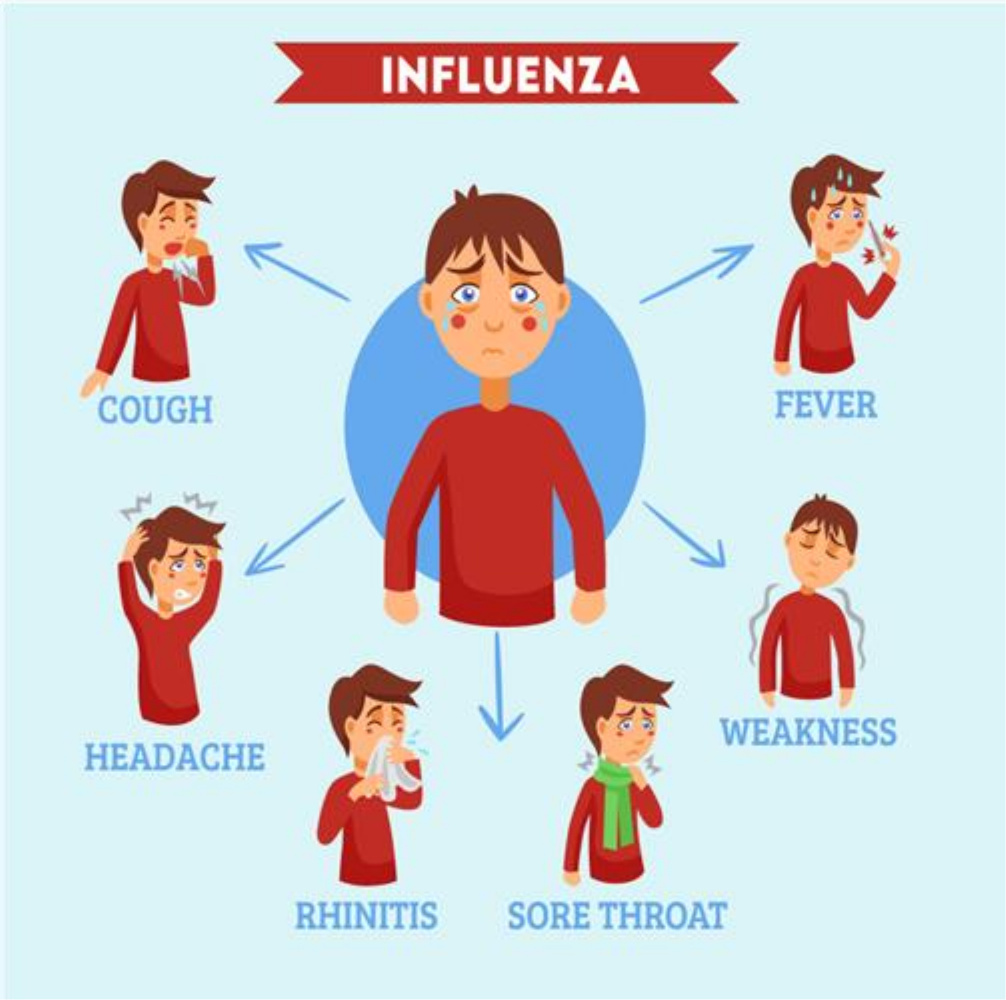
Date: May 3rd, 2024

Table of Contents

Introduction

- **What is influenza?**
  - **A highly infectious respiratory illness characterized by seasonal outbreaks and pandemics**

- **Objective:**
  - **To explore and compare two distinct approaches in predicting the no. of influenza cases**



Introduction

- **Numerical Methods:**
  - Midpoint Method
  - Modified Euler Method
  - RK4 Method

- **ML & DL Methods:**
  - 1D-CNN
  - LSTM
  - FTA-LSTM
  - Random Forest

Motivation for Comparative Analysis

- Understanding Methodological Differences:
  - Mechanistic Insights vs. Pattern Recognition
- Evaluating Performance:
  - Accuracy in Peak Forecasting
  - Overall Forecast Accuracy
- Insightfulness and Interpretability:
  - Overall Understanding

Dataset

Analysis of H1N1 Outbreak in Sao Paulo, Brazil.

- **Infected individual at the beginning of the outbreak in 2009.**
- **The prevalence of H1N1 influenza weekly cases from 2009 to 2010.**

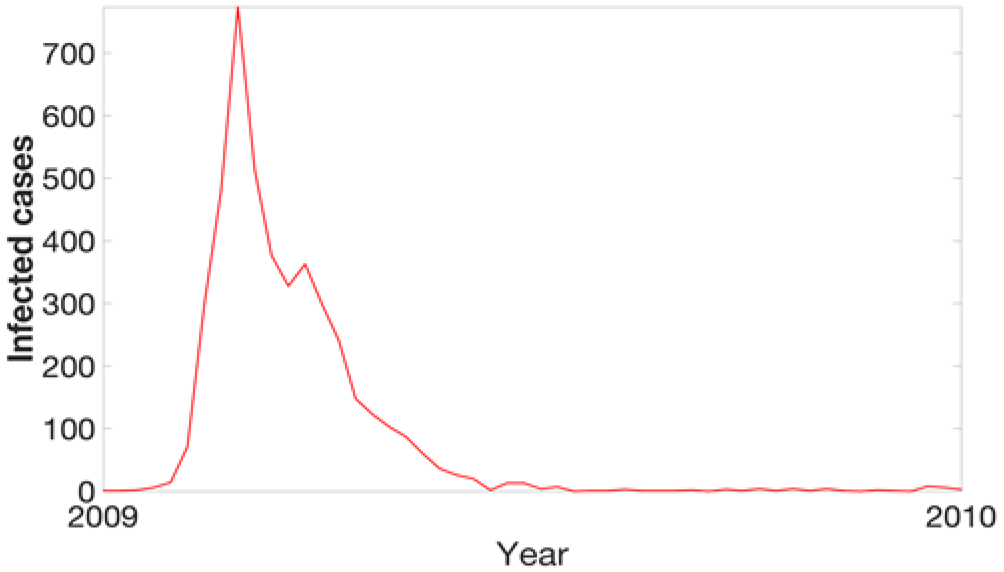


Fig. 01: **H1N1 outbreak using the SVIR model, supported by numerical computations and real-world data from Sao Paulo, Brazil.**

Dataset

- Consists of 394 entries.
- Approximately 7.5 years if each entry corresponds to a week.
- Two columns, which seem to indicate the year-week combination (e.g., 200923) and the number of cases reported during that week.

200923	1
200924	1
200925	2
200926	6
200927	14
200928	71
200929	297
200930	480
200931	774
200932	514
200933	377
200934	328

Fig. 02: Snapshot of the dataset consists of Weeks and Infected Cases

Methodology: SVIR Model

The SVIR model is an epidemiological model used to describe the spread of infectious diseases within a population.

$$\frac{dS}{dt} = mN - \beta\frac{SI}{N} + \gamma R - vS - \mu S,$$
$$\frac{dV}{dt} = vS - \xi\frac{VI}{N} - \mu V,$$
$$\frac{dI}{dt} = \beta\frac{SI}{N} + \xi\frac{VI}{N} - rI - \mu I,$$
$$\frac{dR}{dt} = rI - \gamma R - \mu R,$$

Here,
S = Susceptible Individuals
V = Vaccinated Individuals
I = Infected Individuals
R = Recovered Individuals

Methodology: SVIR Model

Model Parameters	Value
Natural recovery rate	r = 1.17
Total population	N = 42075716
Immunity loss rate	γ = 0.003 (Assumption)
Death rate	μ = 0.00025
Birth rate	m = 0.0006298
Infection rate	β = 2.8 (Assumption)
Vaccination rate	v = 0.108 (Assumption)
Infection rate among vaccinated	xi = 0.3

Methodology: 1D-CNN

1D CNN:

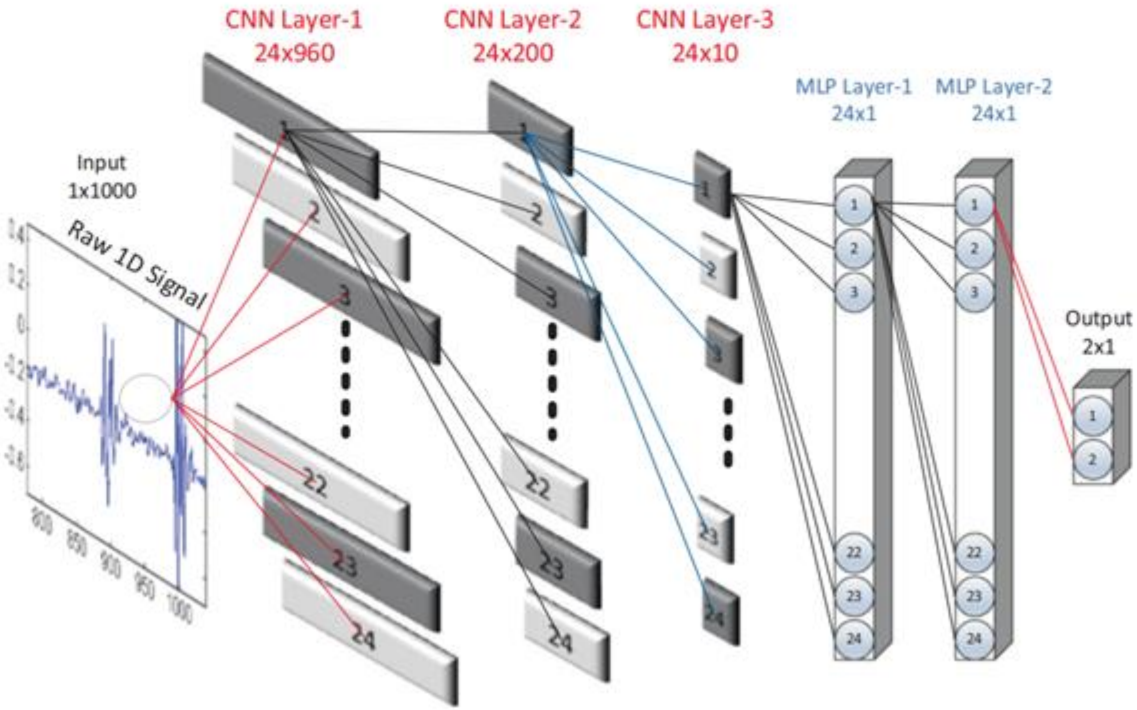
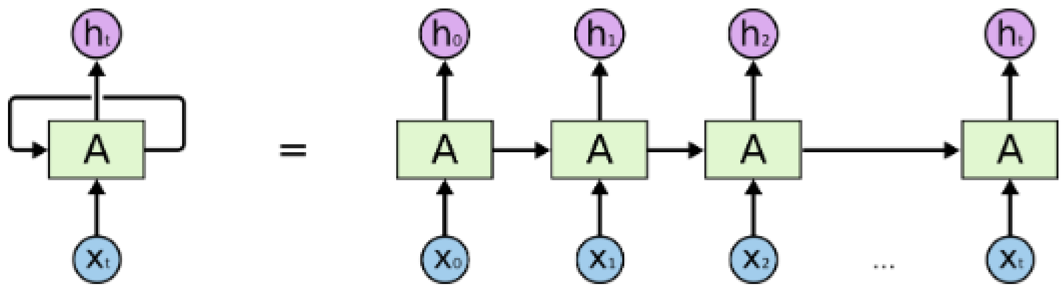


Fig. 3: 1D CNN for Time Series Data

Methodology: LSTM

Long Short-Term Memory

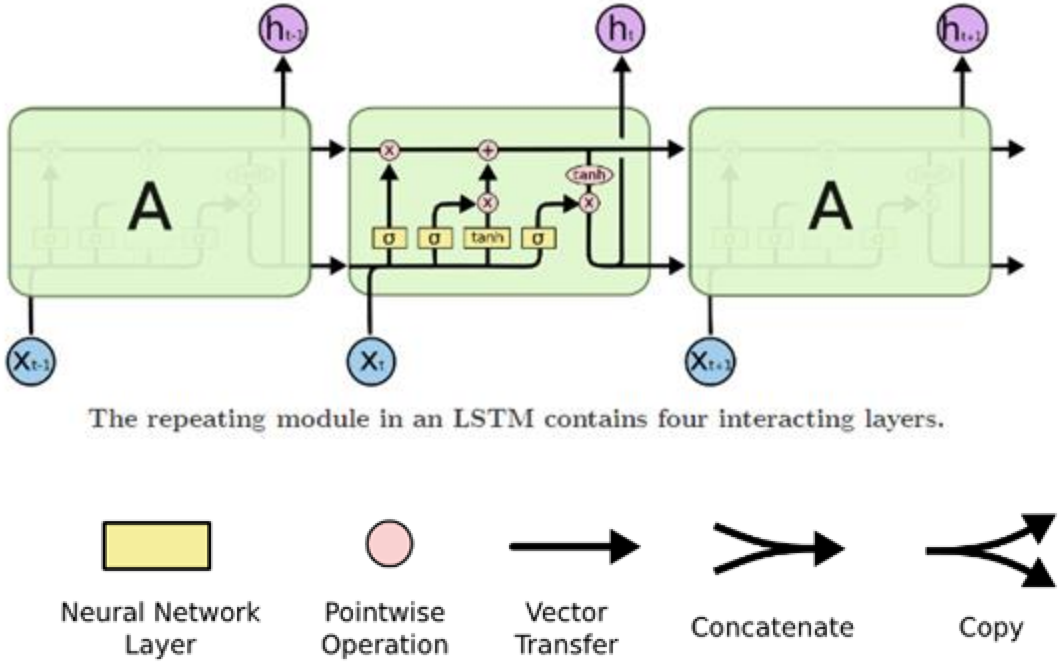


An unrolled recurrent neural network.

Fig. 4: Basic Unit of LSTM

Methodology: LSTM

Long Short-Term Memory



The repeating module in an LSTM contains four interacting layers.

Fig. 05: Structure of LSYTM Model

Methodology: FTA-LSTM

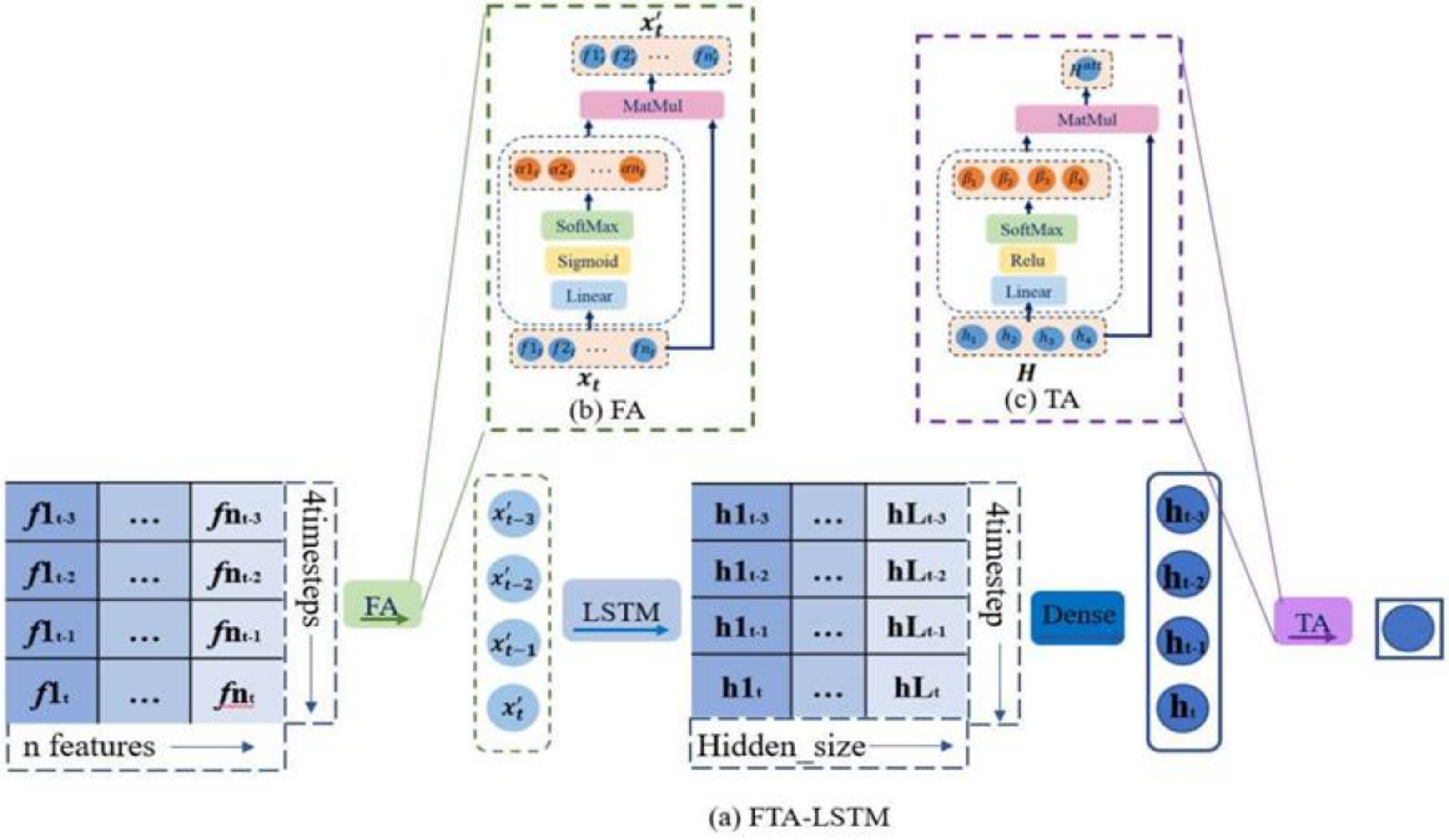


Fig. 06: Structure of FTA-LSTM

Methodology: Random Forest

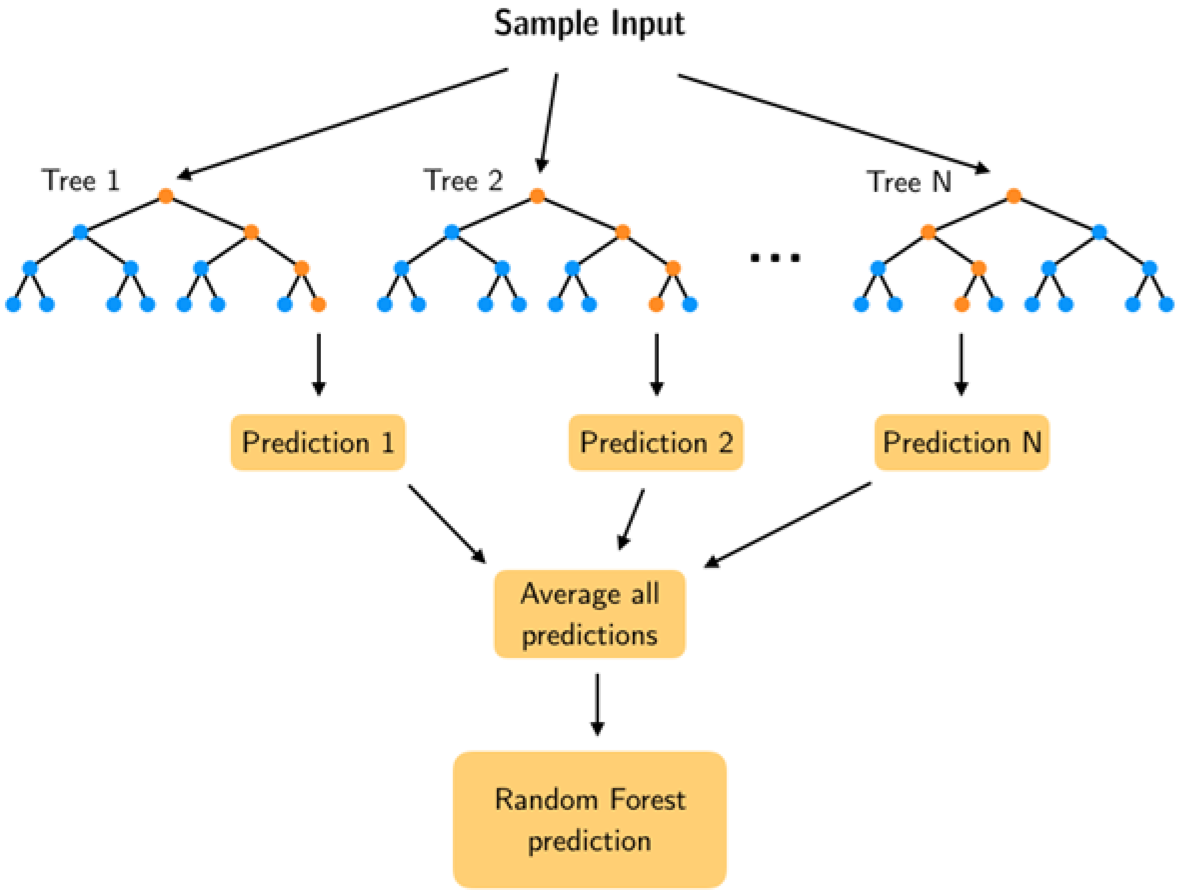


Fig. 07: Structure of Random Forrest Model

Result: Evaluation Metric

- **Mean Absolute Error quantifies the average magnitude of the errors in a set of predictions, without considering their direction (i.e., no positive or negative sign distinction).**

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

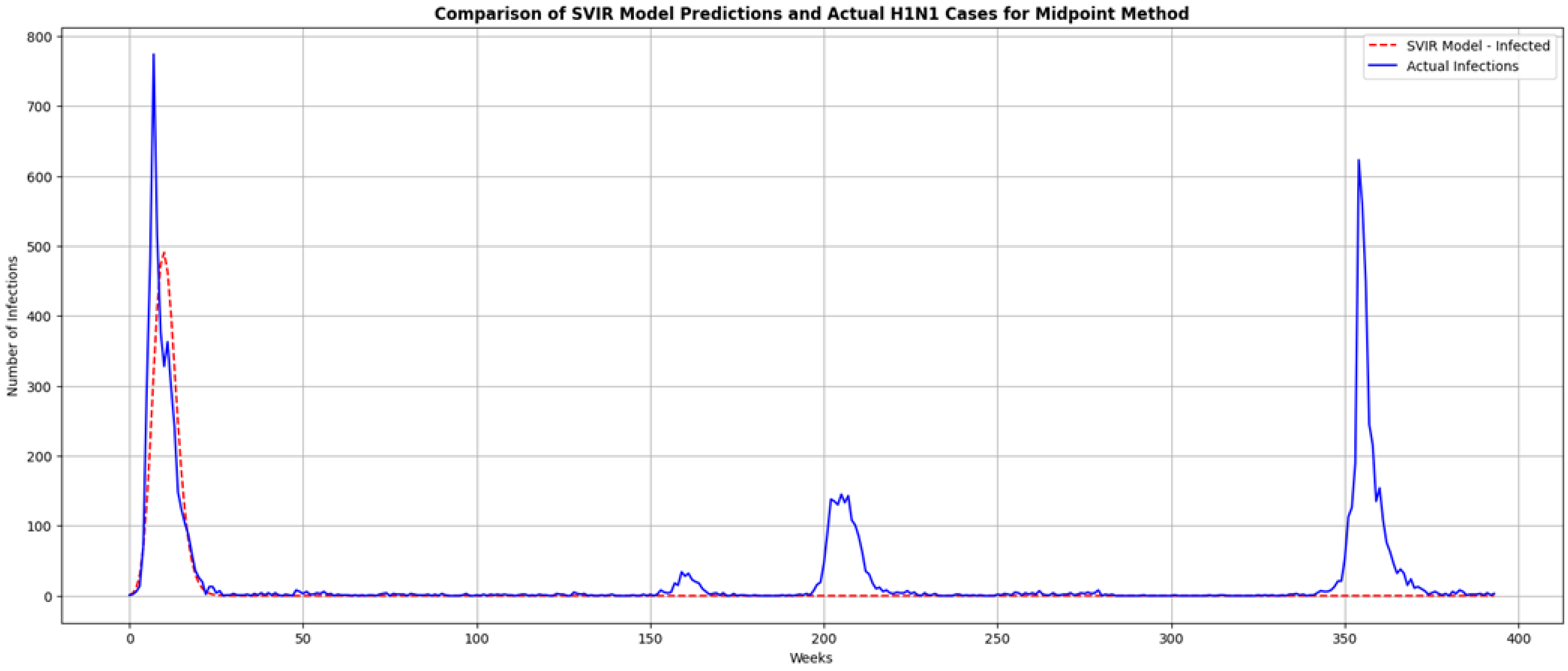
where,

n: *number of observation*

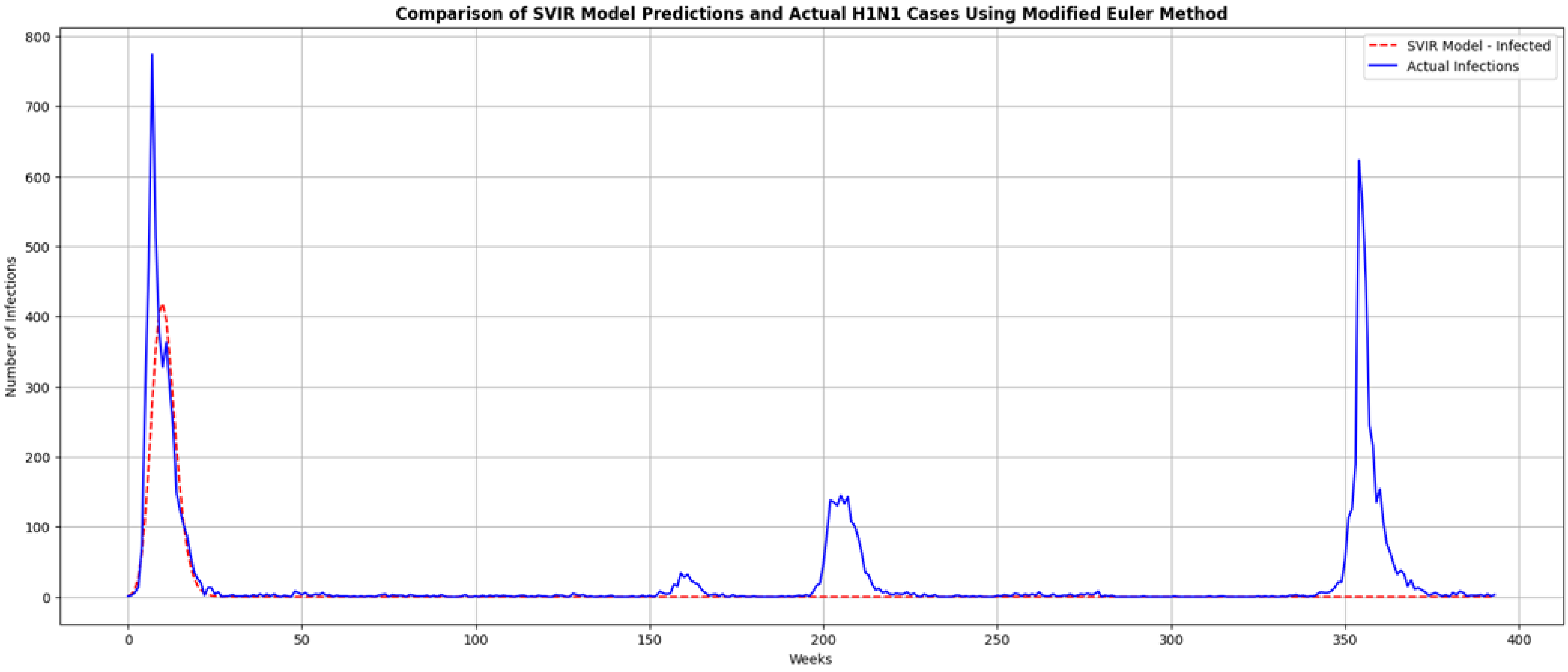
y_i: *the actual value of the* i^{th} *observation*

$\hat{y}_i$: *the predicted value of the* i^{th} *observation*

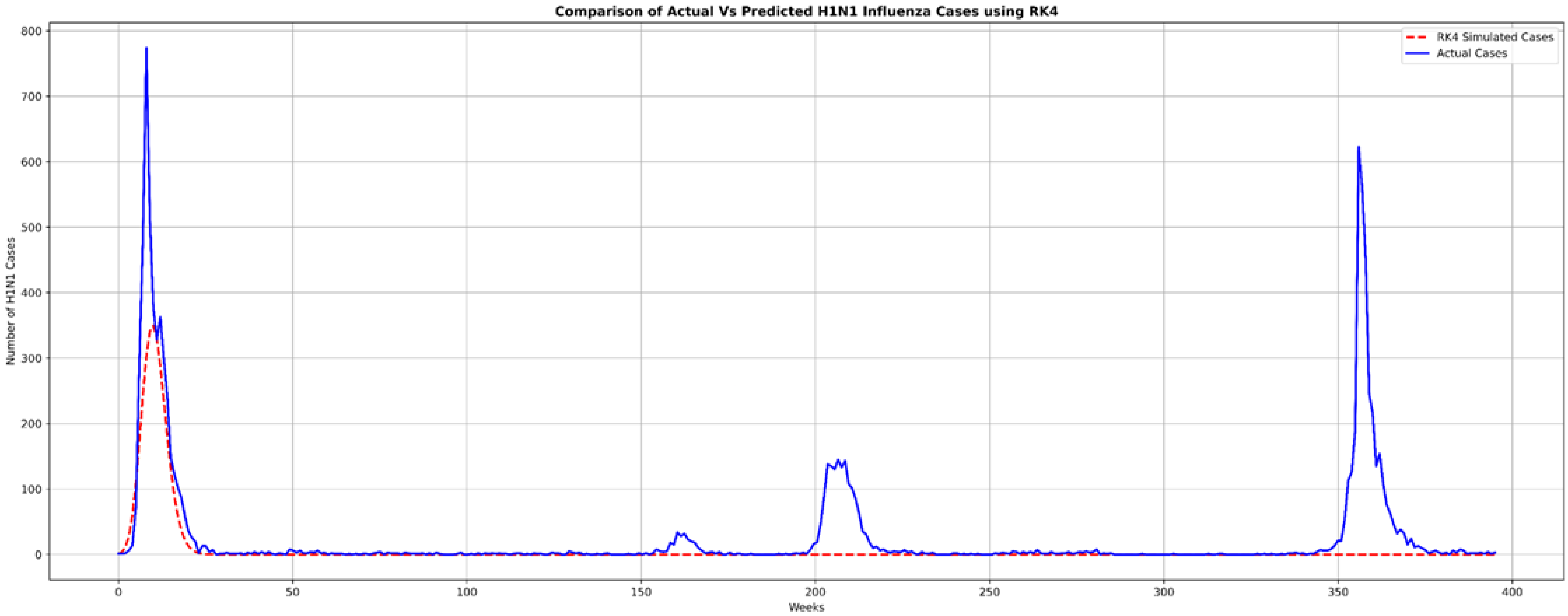
Result: Midpoint Method



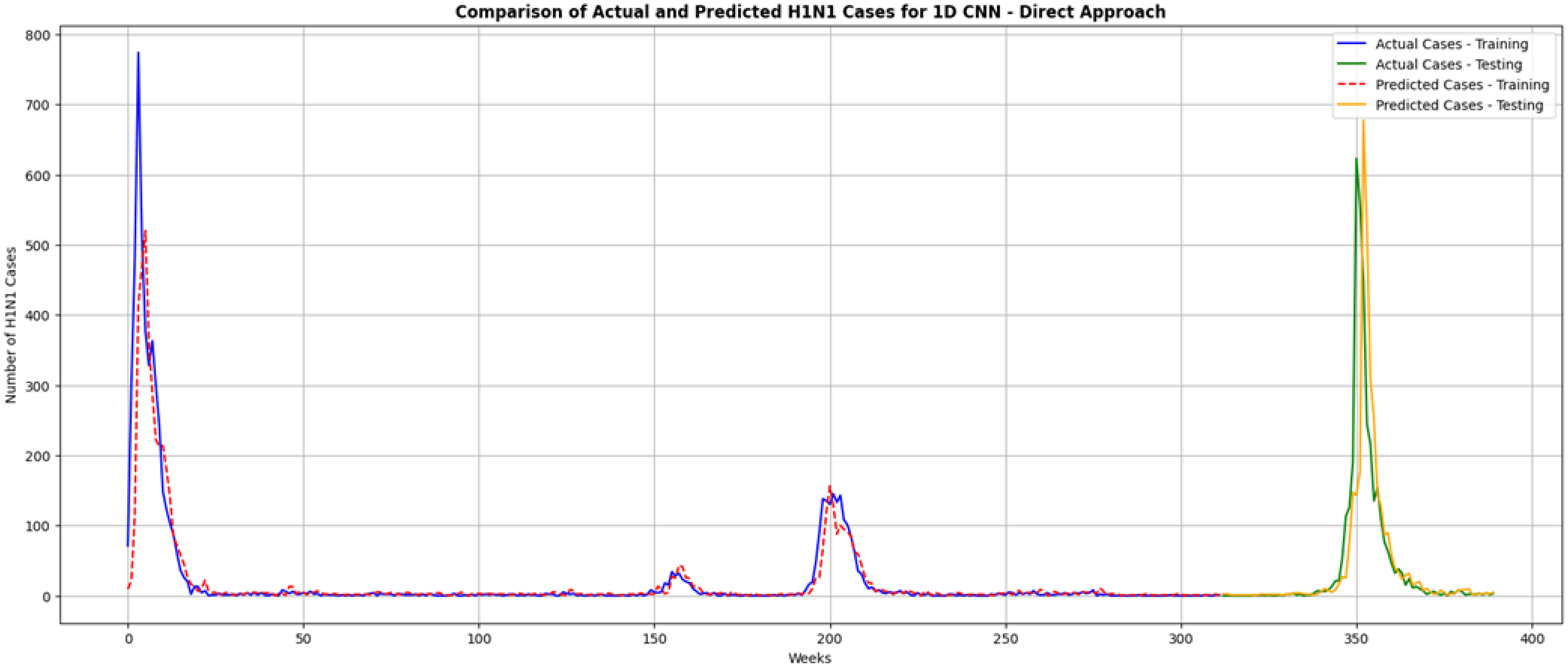
Result: Modified Euler Method



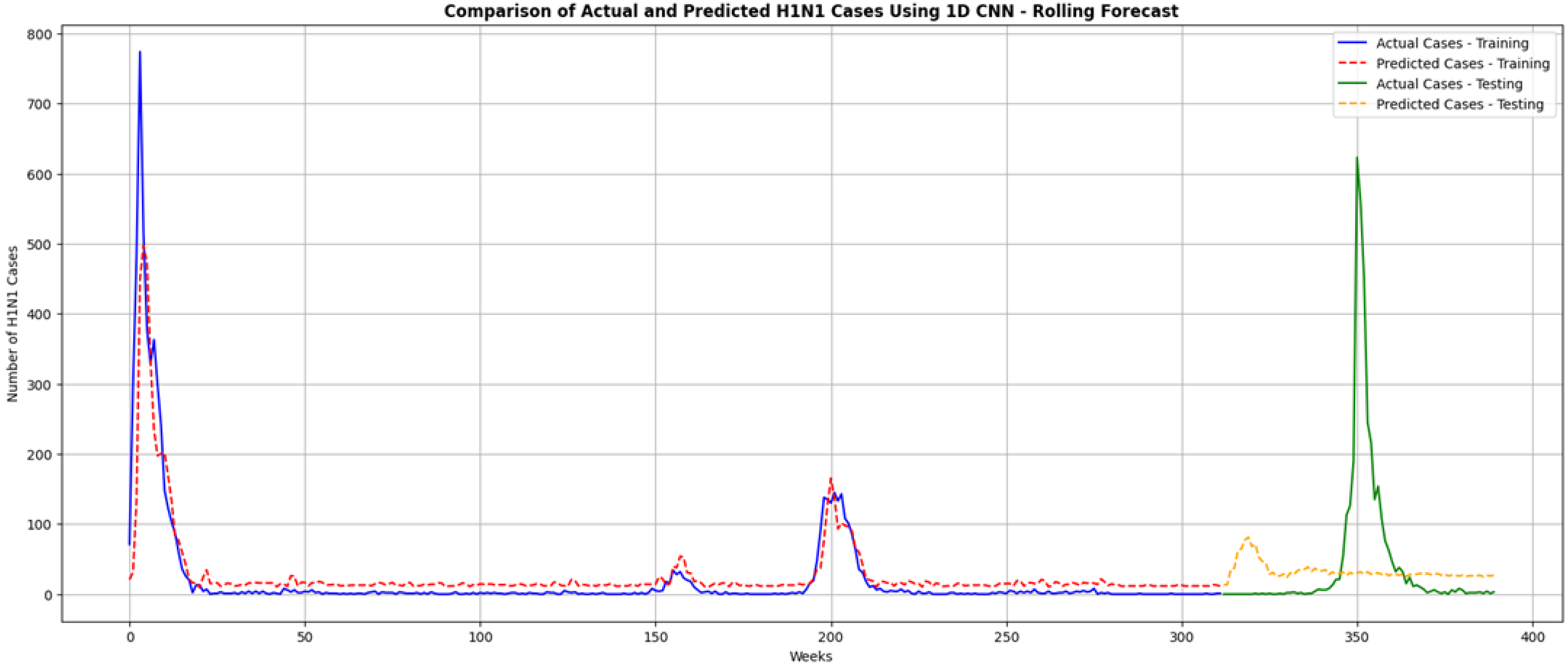
Result: Range-Kutta Order 4



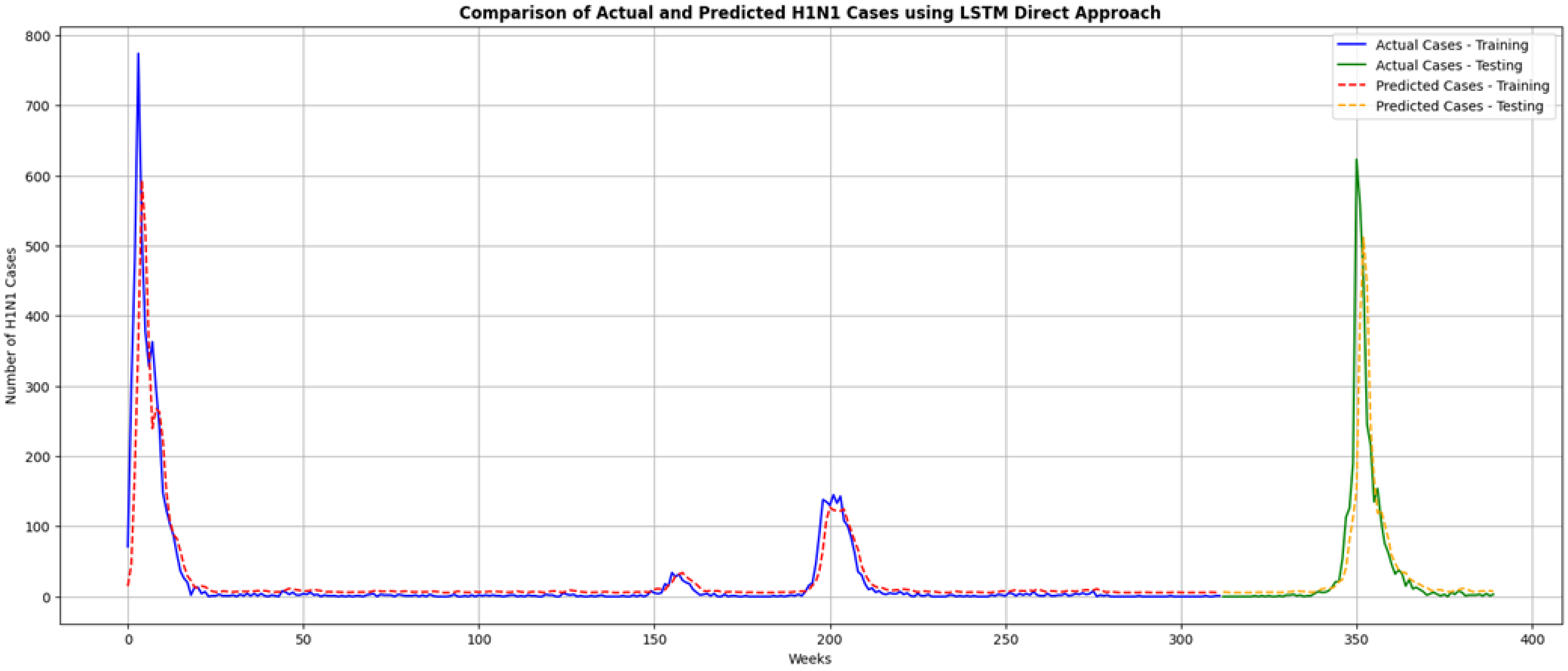
Result: 1D CNN – Direct Forecast



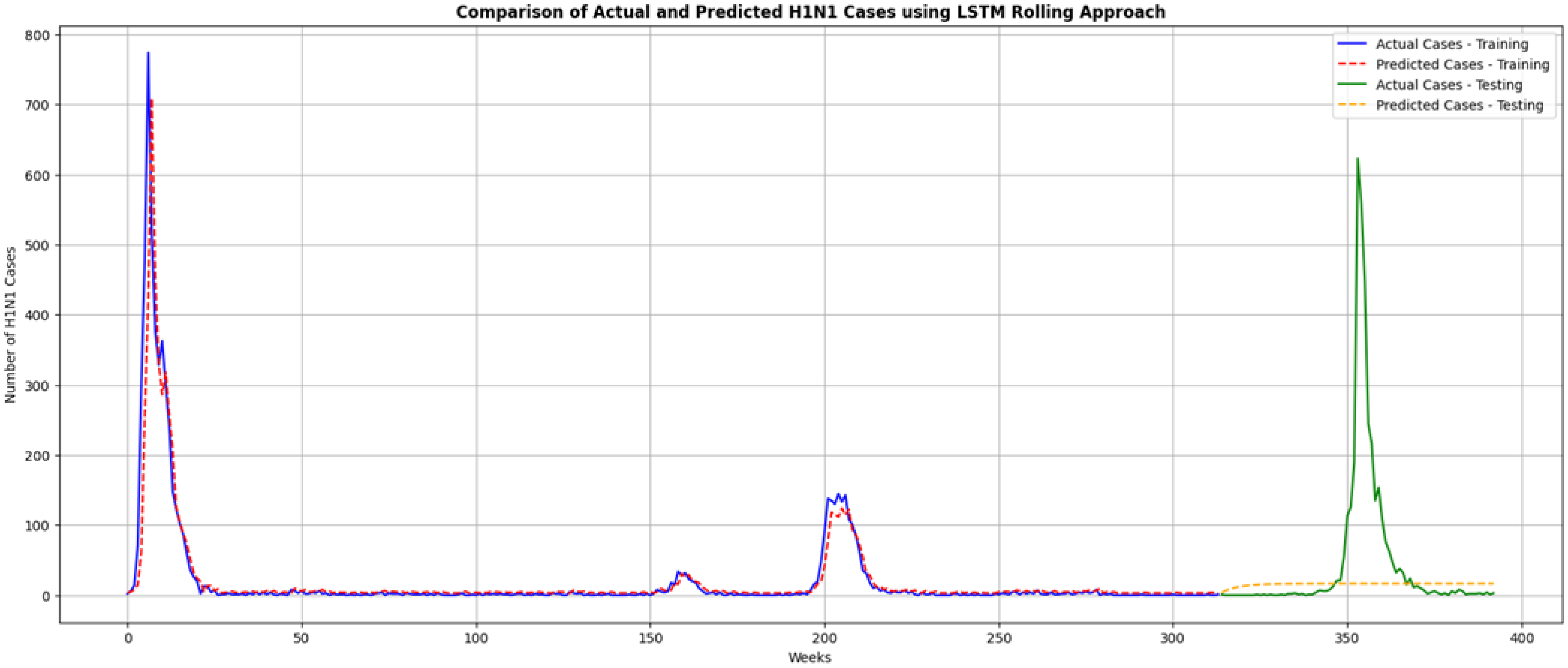
Result: 1D CNN – Rolling Forecast



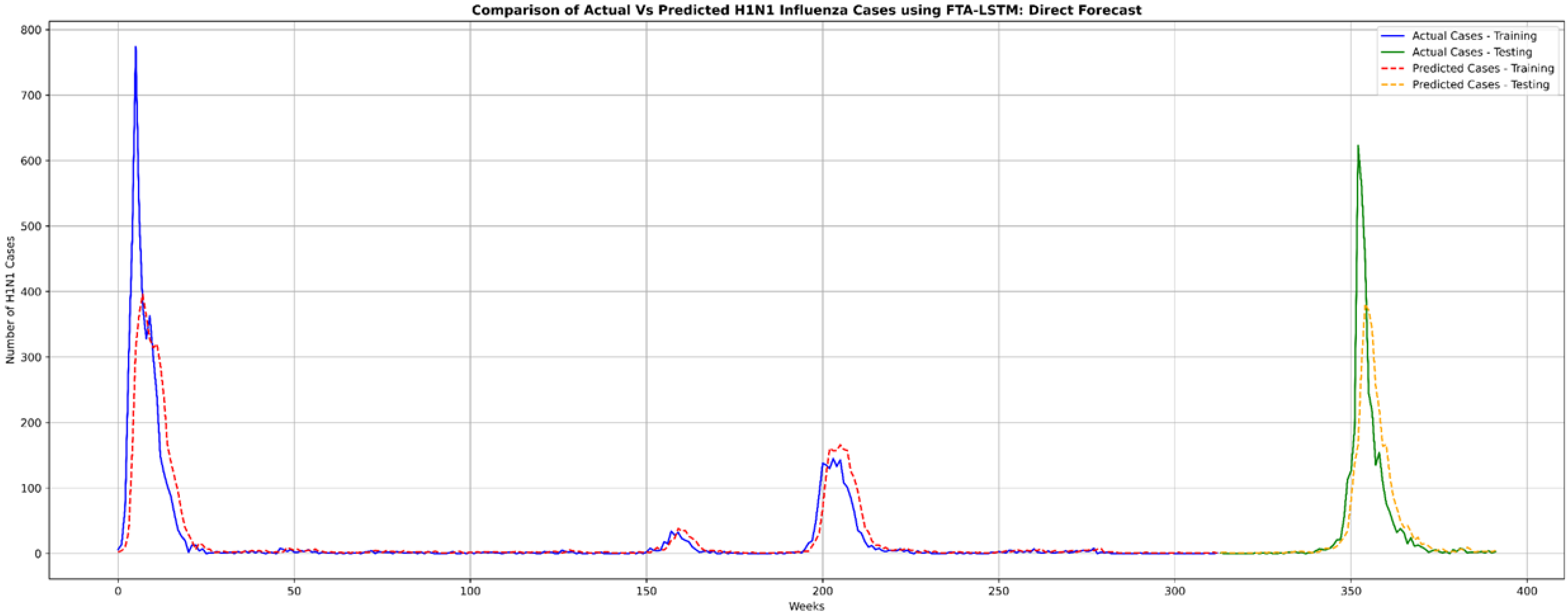
Result: LSTM - Direct Forecast



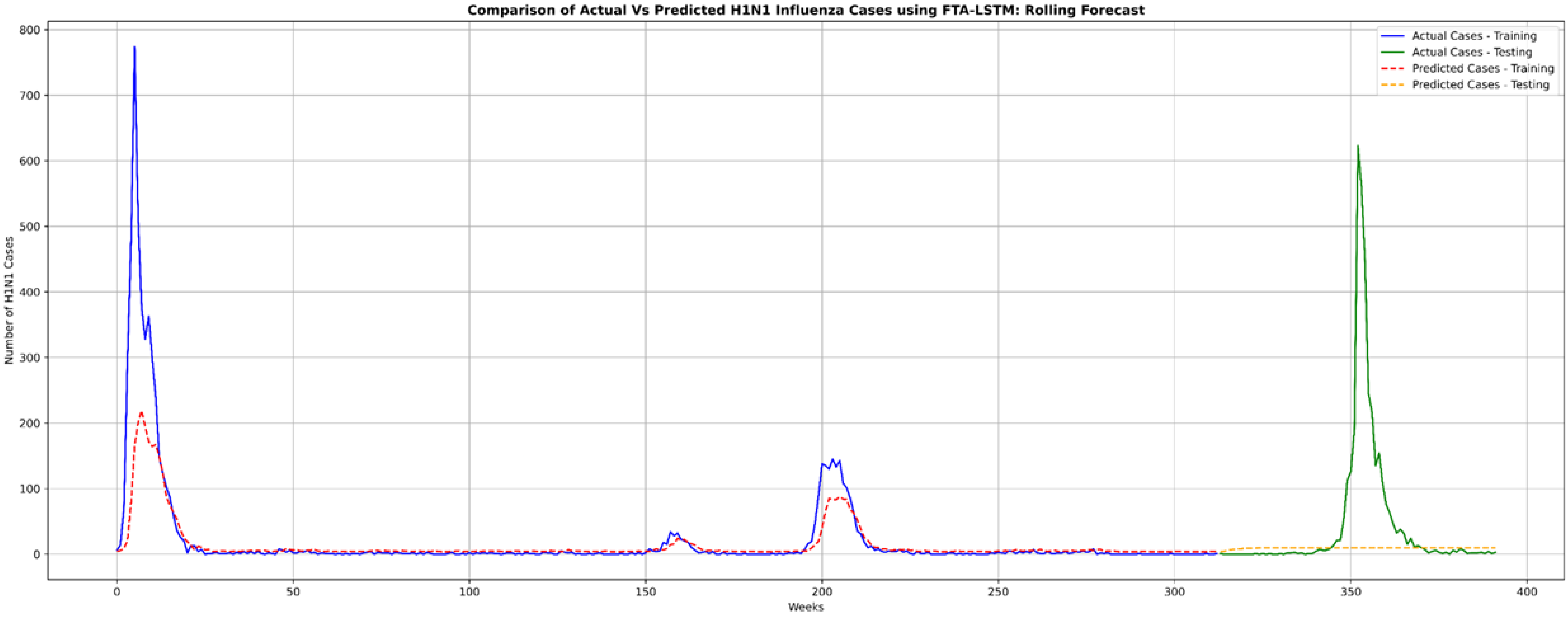
Result: LSTM – Rolling Forecast



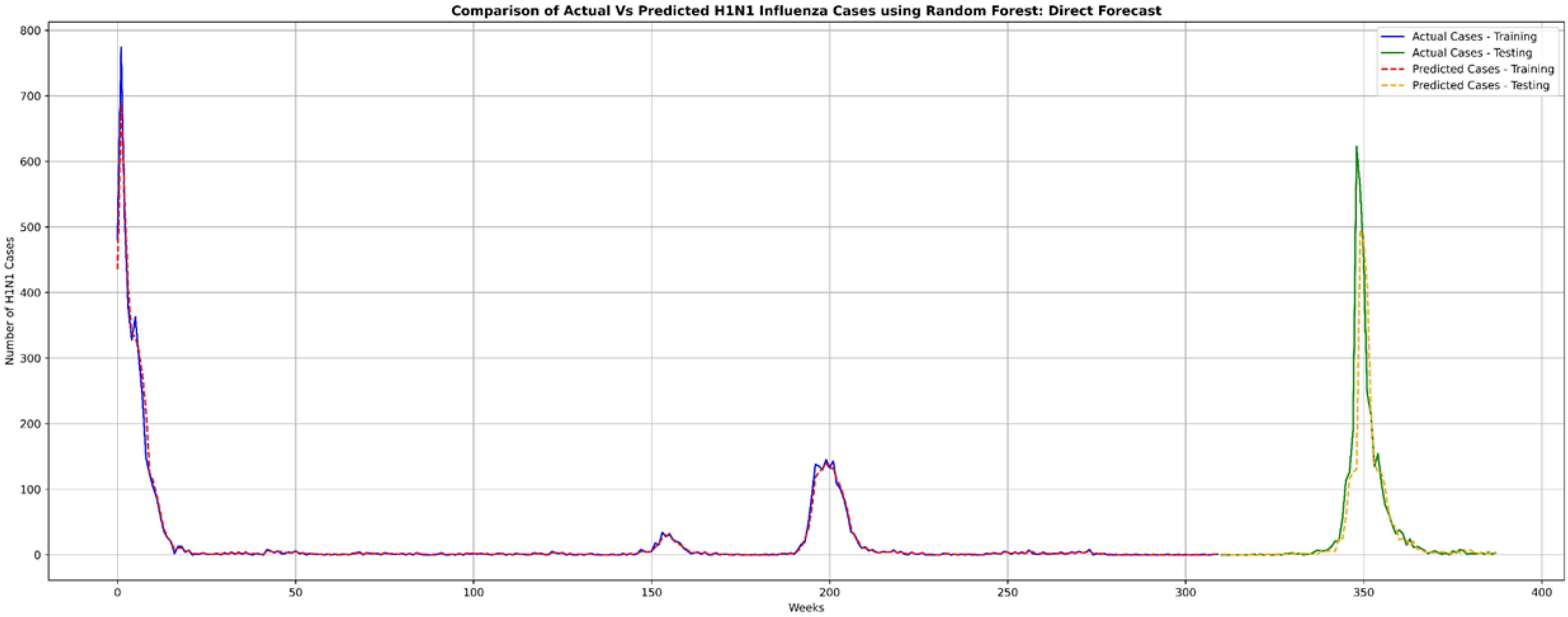
Result: FTA-LSTM – Direct Forecast



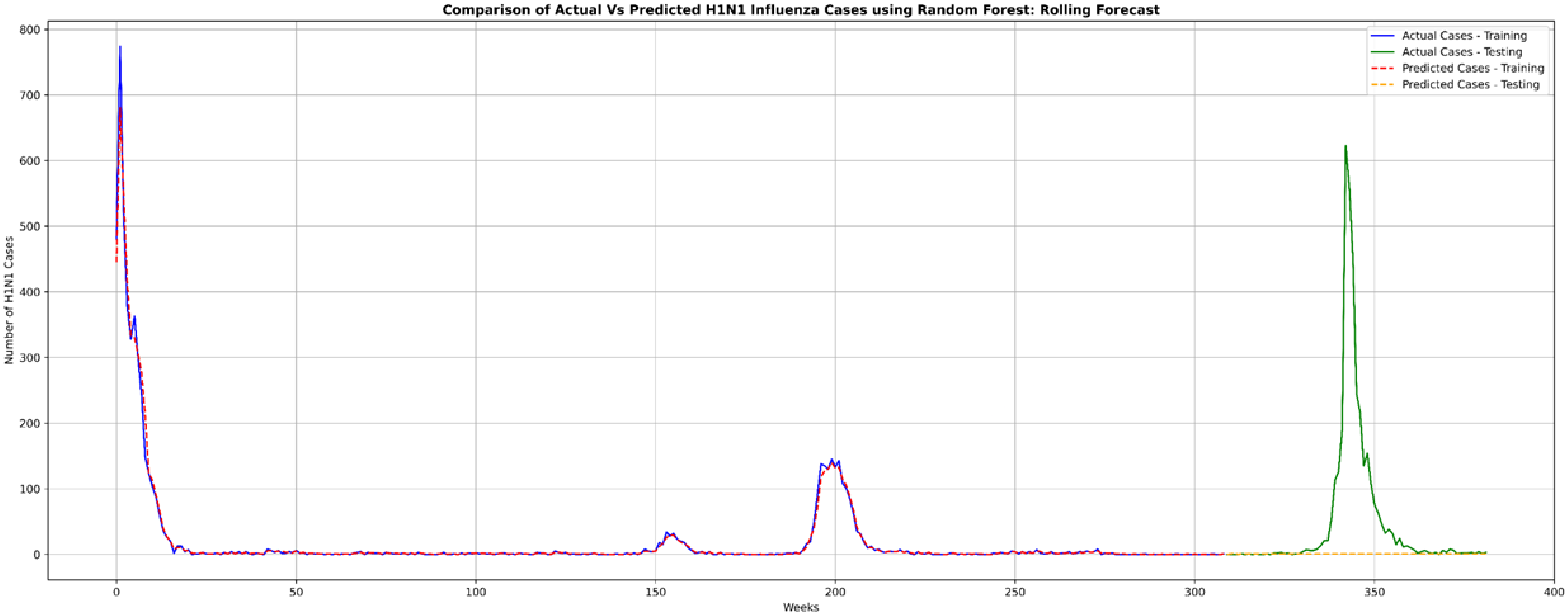
Result: FTA-LSTM - Rolling Forecast



Result: Random Forest – Direct Forecast



Result: Random Forecast - Rolling Forecast



Result: Main Table Comparison

Approach	Model	Training MAE	Testing MAE
Numerical Methods	Midpoint	12.25	44.35
	Modified Euler	11.56	44.31
	RK4	11.67	44.35
ML & DL Methods	1D CNN - Direct	10.06	25.05
	LSTM - Direct	11.35	20.49
	FTA-LSTM - Direct	10.26	24.16
	Random Forest - Direct	***2.09***	***14.67***
	1D CNN - Rolling	11.19	46.88
	LSTM - Rolling	6.97	44.42
	FTA-LSTM - Rolling	12.76	44.39
	Random Forest - Rolling	***2.11***	***47.28***

Result: Window Size Comparison

Approach	Models	MAE		
		w=1	w=4	w=8
Direct Forecast	1D CNN	16.63	25.05	26.70
	LSTM	26.39	19.96	23.53
	FTA-LSTM	***16.48***	34.66	40.27
	Random Forest	20.35	***16.35***	***19.16***
Rolling Forecast	1D CNN	46.50	46.88	46.35
	LSTM	45.08	***45.22***	***44.81***
	FTA-LSTM	46.56	47.74	47.82
	Random Forest	***44.20***	46.22	48.33

Numerical SVIR VS DL Approach

Aspect	Numerical SVIR Approach	Deep Learning Approach
Foundation	**Compartmental** models based on differential equations describing population flows	**Data-driven** models that learn from large datasets without predefined structures
Interpretability	**High**; parameters have clear epidemiological meanings	**Low**; often seen as a "black box" due to complex model architectures
Data Requirements	Requires **known parameters** and **initial conditions** from epidemiological data	Requires **large datasets** and **can integrate diverse data types** (text, numbers, images)
Computational Demand	**Lower**; simpler calculations but may require fine-tuning	**Higher**; needs substantial computational power for training, less for inference
Scalability	**Scalable** with complexity dependent on model design	**Highly scalable** with data volume and complexity but computationally intensive
Flexibility	**Less flexible**; relies on accurate disease dynamics modeling	**More flexible**; capable of identifying patterns and adapting to new data
Use Case	Well-suited for **diseases with well-understood dynamics** and **available epidemiological data**	Ideal for situations where **extracting patterns from large-scale data** can inform outcomes

Application

- Public Health Monitoring.
- Finance and Stock Market Forecasting.
- Soil Moisture Forecasting.
- Multi-Domain Adaptation e.g. Supply Chain Inventory Management.

Conclusion

- We perform a thorough analysis & comparison of deep-learning based approaches with numerical SVIR model approximations.

- Our findings indicate that Random Forest outperforms other models for influenza forecasting.

- Direct Forecast Approach expectedly works better compared to Rolling Forecast Approach

Thank You!

Questions?