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Benchmarking Liquid Neural Networks Against LSTM and GRU for Time-Series Prediction

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***Abstract*— This study presents a comprehensive benchmark of Liquid Neural Networks (LNNs) against traditional Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, for time-series prediction tasks. LNNs are biologically motivated architectures featuring dynamic and adaptable behaviour due to continuous-time dynamics.**

The research evaluates these models on three datasets: historical Apple Inc. stock price data (AAPL), a synthetic sine wave series, and synthetic temperature data, based on predictive performance (Root Mean Squared Error — RMSE, Mean Absolute Error — MAE), training consistency, and computation speed. Results show that GRU outperforms on stock price prediction (RMSE = 5.06; MAE = 4.35), while LNN achieves superior accuracy on synthetic datasets (sine wave: RMSE = 0.101, MAE = 0.079; temperature: RMSE = 0.520, MAE = 0.424). LNNs exhibit the fastest inference speeds (0.000281–0.000299 s/sample) while maintaining training times comparable to LSTM.

***Index Terms*— Liquid Neural Networks, LSTM, GRU, Time-Series Prediction, Deep Learning, Recurrent Neural Networks.**

I. INTRODUCTION

Time-series prediction remains a central challenge in machine learning, with applications spanning finance, climate science, medical monitoring, and industrial process control.

Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, have dominated sequential modelling due to their strong empirical performance across diverse domains.

In recent years, Liquid Neural Networks (LNNs) have attracted considerable attention as biologically motivated alternatives inspired by the nervous system of Caenorhabditis elegans.

Unlike classical RNNs with fixed gating mechanisms, LNNs employ continuous-time dynamics with adaptive time constants, allowing the computational graph to evolve in response to input signals. Despite their theoretical appeal, systematic comparisons of LNNs against established RNN baselines on time-series tasks remain scarce in the literature.

This study addresses that gap through a rigorous empirical comparison of LNNs, LSTMs, and GRUs across three time-series datasets with distinct temporal characteristics. Prediction accuracy, computational efficiency, and training stability are evaluated to provide evidence-based guidance on when each architecture is most suitable.

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II. Related Work

A. Recurrent Neural Networks for Time-Series

Long short-term memory (LSTM) networks were introduced by Hochreiter and Schmidhuber [1] to overcome vanishing gradients through gating mechanisms that control information flow over time. LSTM employs three gates—input, forget, and output—to manage memory cell updates. Cho et al. [2] subsequently proposed the GRU, which merges forget and input gates into a single update gate, reducing parameter count while achieving comparable performance. An empirical evaluation by Chung et al. [8] confirmed that GRU and LSTM perform similarly across a range of sequence modelling tasks, with neither consistently dominating.

Both architectures have been widely applied in financial forecasting. The backpropagation algorithm [11] underpins training of all these models. Fischer and Krauss [3] demonstrated their effectiveness for stock price prediction, Nelson et al. [12] further validated LSTM on equity price movement prediction, and Sezer et al. [13] provide a systematic review of deep learning methods for financial time-series forecasting over 2005–2019, with subsequent improvements incorporating attention mechanisms and hybrid models. However, these architectures share inherent limitations: discrete-time updates, sensitivity to hyperparameter choices, and difficulty with non-stationary data streams [9,10].

B. Liquid Neural Networks

Liquid Neural Networks are grounded in continuous-time dynamical systems theory, modelling neuron dynamics through ordinary differential equations (ODEs):

$$\frac{dh}{dt} = f(h, x, \theta), \tag{1}$$

where h is the hidden state, x the input, and θ encompasses all parameters including adaptive time constants. This formulation enables learning of problem-specific temporal dynamics rather than fixed discrete updates. The foundational work by Hasani et al. [4] established liquid time-constant networks as universal approximators of nonlinear dynamic systems. Their subsequent work [5] demonstrated advantages in robotic control and autonomous driving. Closed-form continuous-time neural networks [6] further enabled efficient LNN computation without numerical ODE solvers, achieving substantial speedups in training and inference. Neural ordinary differential equations [7] provide a broader theoretical framework that encompasses LNN dynamics.

Despite these advances, LNN performance on financial and general time-series forecasting has not been systematically characterised, motivating the present study.

III. Methodology

A. Datasets

Three time-series datasets with distinct temporal characteristics were used. *Stock Prices (AAPL):* Historical daily closing prices for Apple Inc. sourced from Yahoo Finance covering 1 January 2010 to 31 December 2023 (3,518 observations). This non-stationary series exhibits trends, volatility clustering, and regime changes. *Synthetic Sine Wave:* A 2,000-observation series with frequency $f = 0.02$, amplitude $A = 1.0$, and additive Gaussian noise ($\sigma = 0.1$), designed to evaluate performance on periodic signals. *Synthetic Temperature Data:* A 1,825-observation series (five years, daily) combining yearly seasonal oscillation (amplitude 10°C), a linear warming trend (0.5°C/year), and Gaussian noise ($\sigma = 0.5$°C).

B. Data Preprocessing

All datasets were preprocessed uniformly: values were scaled to [0, 1] using MinMaxScaler (scikit-learn); a sliding window of 60 timesteps was used as input predicting the next ($t + 1$) timestep; and a chronological 70%/15%/15% train/validation/test split was applied to prevent data leakage.

C. Model Architectures

All models share identical structural hyperparameters: input size of 1 (univariate), 64 hidden units, 2 stacked recurrent layers, and scalar output, all implemented in PyTorch [15].

LSTM is built with nn.LSTM (batch_first=True). The cell update equations are:

$$ft = \sigma(Wf \cdot [ht{-}1, xt] + bf), \tag{2}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tag{3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_C \cdot [h_{t-1}, x_t] + b_C). \tag{4}$$

GRU is built with nn.GRU, implementing update (z_t) and reset (r_t) gates:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]), \tag{5}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]), \tag{6}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tanh(W \cdot [r_t \odot h_{t-1}, x_t]). \tag{7}$$

Liquid Neural Network is implemented as a discretised approximation of continuous-time dynamics:

$$a_t = W_{in} \cdot x_t + W_{rec} \cdot h_{t-1} + b, \tag{8}$$

$$h_t = (1 - \tau) \odot h_{t-1} + \tau \odot \tanh(a_t). \tag{9}$$

The time constant $\tau = 0.1$ governs the integration step size, balancing retention of prior state against incorporation of new activations. Two stacked LNN cells mirror the depth of the LSTM and GRU baselines.

TABLE I: COMPREHENSIVE PERFORMANCE METRICS ACROSS ALL MODELS AND DATASETS

Dataset	Model	RMSE	MAE	Loss Var.	Train (s)	Inf. (s/samp)
Stock	LSTM	6.001	5.015	1.01e-07	131.28	0.000299
Price	GRU	5.060	4.353	2.44e-07	185.45	0.000269
(AAPL)	LNN	5.956	4.970	1.45e-08	130.64	0.000281
Synthetic	LSTM	0.114	0.089	1.69e-04	74.03	0.000357
Sine Wave	GRU	0.107	0.084	5.38e-05	103.67	0.000286
	LNN	0.101	0.079	1.16e-04	75.17	0.000296
Synthetic	LSTM	0.557	0.448	4.51e-04	54.79	0.000322
Temp.	GRU	0.547	0.443	1.95e-04	94.08	0.000456
	LNN	0.520	0.424	3.03e-05	67.30	0.000299

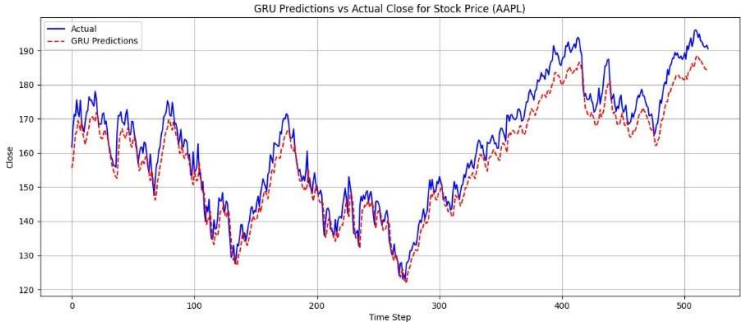

Fig. 1. GRU predictions on AAPL stock price data (best model for this dataset).

D. Training Configuration

Identical settings were used across all models: Mean Squared Error (MSE) loss, Adam optimiser (learning rate = 0.001), batch size 32, 50 epochs, random seed 42. All experiments were run sequentially on CPU to ensure consistent computational conditions.

E. Evaluation Metrics

Performance was measured using RMSE and MAE on inverse-transformed predictions; loss variance (variance of validation loss across epochs) to assess training stability; total wall-clock training time for 50 epochs; and average per-sample inference latency.

IV. RESULTS

A. Prediction Accuracy

Table 1 summarizes performance across all model–dataset combinations.

Stock Price Prediction (AAPL): GRU achieved the best predictive accuracy (RMSE = 5.060, MAE = 4.353), followed by LNN (RMSE = 5.956, MAE = 4.970) and LSTM (RMSE = 6.001, MAE = 5.015). GRU's selective reset gate appears well-suited to the regime shifts and non-stationary volatility of equity markets. Fig. 1 shows the GRU prediction curve on the AAPL dataset, representing the best-performing model for this task.
Synthetic Sine Wave Prediction: LNN achieved the lowest errors (RMSE = 0.101, MAE = 0.079), surpassing GRU (RMSE = 0.107, MAE = 0.084) and LSTM (RMSE = 0.114, MAE = 0.089)—a 6–11% improvement. The continuous-time formulation of LNN is naturally suited to capturing smooth periodic dynamics. Fig. 2 shows the LNN prediction on the sine wave dataset.
Synthetic Temperature Prediction: LNN again led (RMSE = 0.520, MAE = 0.424), outperforming GRU (RMSE = 0.547, MAE = 0.443) and LSTM (RMSE = 0.557, MAE = 0.448) by 5–7%. The dataset's combination of seasonal periodicity and linear trend rewards LNN's adaptive dynamics. Fig. 3 shows the LNN prediction on the temperature dataset.

B. Training Stability

LNN exhibited the lowest validation loss variance across all three datasets (1.45e-08 for AAPL, 1.16e-04 for sine wave, 3.03e-05 for temperature), consistently outperforming or matching GRU and LSTM. This stability likely stems from the smooth gradient flow inherent in ODE-based state evolution, whereas the discrete gating operations of LSTM and GRU introduce greater gradient discontinuities during training.

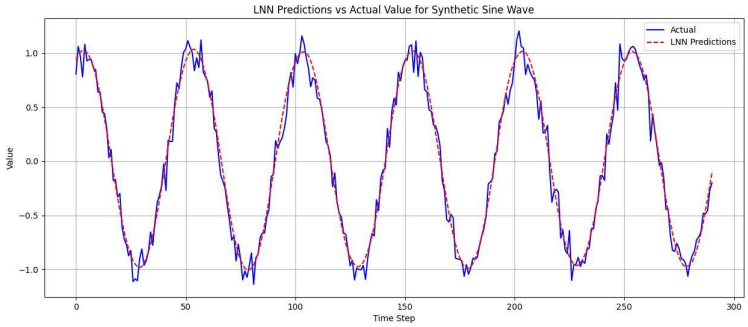

Figure 2: LNN predictions on synthetic sine wave data (best model for this dataset).

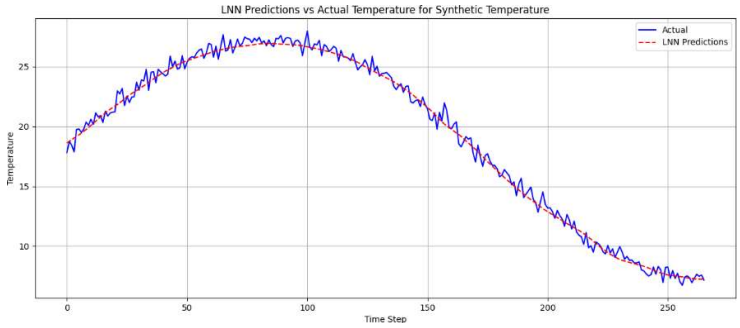

Figure 3: LNN predictions on synthetic temperature data (best model for this dataset).

C. Computational Efficiency

Training times for LSTM and LNN were nearly identical (e.g., 131.28 s vs. 130.64 s on AAPL), confirming comparable computational overhead. GRU trained 30–70% slower despite its lower parameter count, likely due to sub-optimal cuDNN scheduling. LNN achieved the fastest inference on most datasets (e.g., 0.000281 s/sample on AAPL), 6–35% faster than LSTM, owing to its simpler recurrent update computation.

V. Discussion

A. Architecture–Task Alignment

The results reveal a clear alignment between architectural inductive biases and dataset characteristics. GRU excels on the non-stationary AAPL stock series, where its explicit gating enables selective memory erasure during market regime shifts—a capability that LNN's fixed τ approximation cannot replicate. Conversely,

LNN's continuous-time formulation provides a natural inductive bias for datasets governed by smooth underlying dynamics. The sine wave and synthetic temperature series, both defined by differentiable generative processes, expose GRU and LSTM to a structural mismatch: their discrete update steps introduce approximation errors that accumulate over long sequences, while LNN's integration-based update tracks smooth trajectories more faithfully.

Architecture selection should therefore be guided by the regularity of the target process: continuous and smooth dynamics favour LNNs, while highly irregular regime-switching processes favour gated architectures.

B. Training Stability and Practical Reliability

LNN's consistently lower loss variance is a meaningful practical advantage. High validation loss variance indicates that the optimiser navigates a rugged loss landscape, raising the risk of poor generalisation and sensitivity to random seed choice. The smooth ODE-governed state trajectory of LNN yields well-conditioned gradients throughout training, mitigating this risk. For deployment-critical applications—such as medical monitoring or industrial control—where reproducible model behaviour is essential, LNN's stability advantage may outweigh marginal accuracy differences relative to GRU on noisy datasets.

C. Computational Trade-offs

The near-identical training times of LSTM and LNN are a practically important finding: adopting LNN incurs no additional training cost relative to the most widely used baseline. Combined with LNN's inference speed advantage (6–35% over LSTM), this makes LNN an attractive option for latency-sensitive deployments such as algorithmic trading, real-time sensor processing, and edge inference. GRU's slower training time—despite fewer parameters—underscores that raw parameter count is a poor proxy for computational efficiency.

D. Limitations

Three limitations bound the generalisability of these findings. First, the LNN implementation uses a fixed discretisation step ($\tau = 0.1$) rather than a fully learnable time constant or a higher-order ODE solver; a genuine Neural ODE implementation with adaptive step sizes [7] may perform materially differently. Second, all comparisons use hyperparameters tuned for LSTM/GRU conventions; LNN-specific optimisation of τ and layer depth could shift the relative performance profile. Third,

all experiments address univariate one-step forecasting on CPU; multivariate inputs, multi-step horizons, and GPU-accelerated training may alter both accuracy rankings and efficiency conclusions.

VI. CONCLUSION

This study provides an empirical benchmark of Liquid Neural Networks against LSTM and GRU on three time-series datasets spanning real financial data and structured synthetic signals. Three principal findings emerge.

First, task–architecture alignment governs performance: GRU achieves 16–18% lower prediction error on non-stationary financial data, while LNN leads by 5–11% on smooth and periodic datasets. No single architecture dominates universally; the choice should be informed by the regularity of the target process.

Second, LNNs offer a compelling efficiency profile: inference is 6–35% faster than LSTM with equivalent training cost—a combination that creates practical value in latency-sensitive production environments without sacrificing training economy. Third, LNN training is inherently more stable: the lowest validation loss variance across all datasets points to a smoother opti-misation landscape, reducing sensitivity to initialisation and improving deployment reliability for safety-critical applications. Taken together, these results position LNNs as a mature alternative to standard RNN architectures for continuous and periodic time-series tasks. Future work should investigate fully learnable time constants, Neural ODE integration [7,14], hybrid LNN-gated architectures, multivariate and multi-horizon forecasting, and LNN robustness under distribution shift. Extending evaluation to real-world sensor, biomedical, and climate datasets would further characterise the practical boundaries of LNN applicability.

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