Predicting Asset Returns with Deep Learning

FORECASTING ASSET RETURNS USING DEEP LEARNING ALGORITHMS

Puzzle of Financial Forecasting

01

Asset return prediction involves assembling complex pieces—risk, uncertainty, temporal patterns, and technical indicators—into a coherent picture using deep learning.

Deep Learning as the Solver

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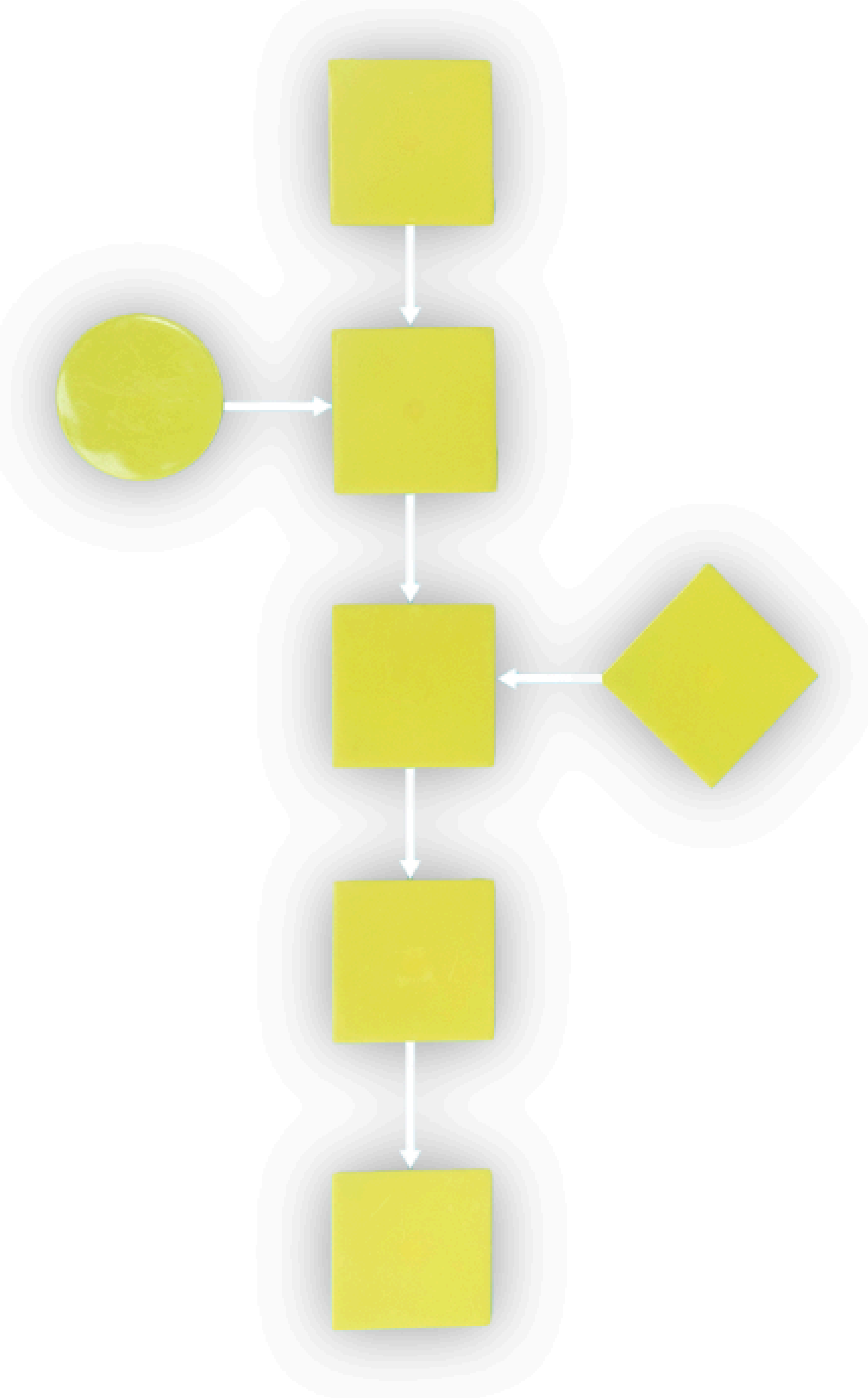
Techniques like LSTM networks and transformer architectures help decode intricate financial time series by capturing sequential dependencies and transforming data into informative formats.

Literature Review: Deep Learning in Financial Time Series

Evaluating LSTM and Transformer Models in Financial Forecasting



LSTM networks capture long-term dependencies and outperform traditional forecasting methods in specific financial cases

Mesquita (2020) showed LSTM's effectiveness in rejecting the Random Walk Hypothesis for Brazilian stocks

Gezici (2024) compared transformer-based models: ViT, DeiT, and ConvMixer, finding ConvMixer best at predicting asset price direction

Shimabukuro (2024) contrasted classical econometric models with LSTM, highlighting deep learning's advantage in modeling complex, non-linear financial patterns

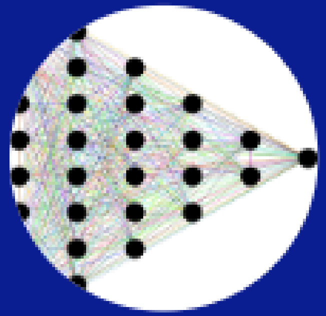
Despite advantages, challenges like overfitting remain significant in deep learning financial forecasting

Overcoming Challenges in Financial Prediction

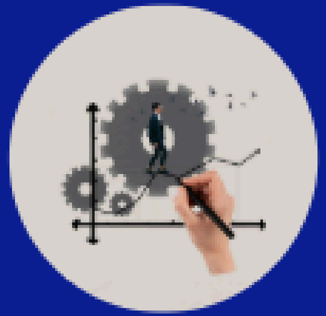
Advancing Robust Machine Learning Models for Market Insights

Machine learning faces high data volume needs, market noise, and overfitting risks in financial prediction

Advanced deep learning models like **LSTMs** and **transformers** capture complex, non-linear financial time series patterns



This study analyzes multiple neural network architectures for predicting financial returns



Performance evaluation identifies the most effective approaches for real-market financial applications

Goal: Develop robust predictive tools to improve accuracy and reliability in financial forecasting

Evaluating Deep Learning Models for Financial Prediction

Five Hypotheses and the Core Research Problem

01

Hypotheses on model performance

- **H1:** LSTM architectures outperform traditional feedforward networks in predicting financial series.
- **H2:** Transformer-based models better capture market noise and generalize across assets.
- **H3:** Deep learning models show less overfitting than traditional machine learning with large datasets.
- **H4:** Multilayer Perceptrons (MLP) are less effective at capturing temporal dependencies.

02

Central research problem

Which deep learning architectures generalize best for financial return prediction?

Data Description and Preprocessing

Dataset Overview and Variable Summary from Brazil's B3 Exchange (2021-2024)

Year	Data Points	Trading Date	Ticker	Opening Price	High Price	Low Price	Closing Price	Trading Volume
2021	Approx. 250,000	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2022	Approx. 250,000	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2023	Approx. 250,000	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2024	Approx. 100,000	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Deep Learning Model Architectures for Asset Return Prediction

Explore four tailored architectures capturing temporal and pattern-based insights in financial sequences

LSTM

Recurrent networks with gated memory cells designed to capture long-term temporal dependencies in sequential data.

CNN 1D

Convolutional layers extracting local temporal patterns by sliding filters over sequences.

Transformers

Attention-based models efficiently capturing relationships across distant time steps in sequences.

MLP

Multilayer Perceptron serving as a baseline model, processing input densely without temporal memory.

Training and Evaluation Methodology

Optimizers, Loss Functions, and Metrics for Robust Model Performance

Models trained using **Adam** and **Adagrad** optimizers to enhance convergence

Minimized **Mean Squared Error (MSE)** loss to improve prediction accuracy

Used batch size of **32** with **early stopping** to prevent overfitting

Evaluated models with **Root Mean Squared Error (RMSE)**, **Mean Absolute Error (MAE)**, and **Mean Absolute Percentage Error (MAPE)**

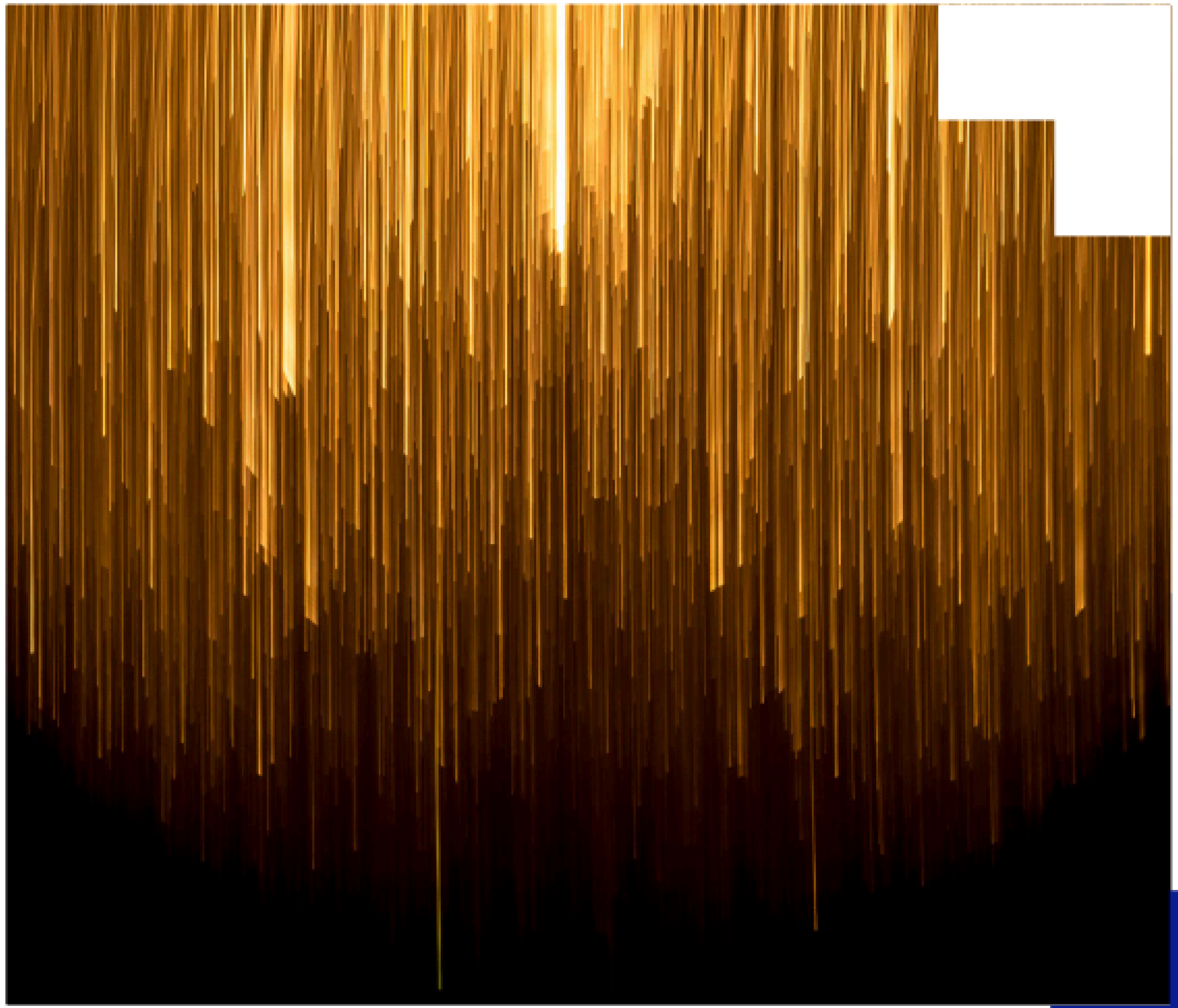
Included coefficient of determination (**R^2**) to assess prediction fit and generalization

Comprehensive metrics ensure robust assessment of accuracy and generalization across test data

Results: Model Performance Comparison

Evaluating Model Performance and Hypotheses

Key insights on deep learning models for financial series prediction



H1 was not fully supported as LSTM struggled with generalization

H2 partially valid; transformers performed well but sometimes gave static predictions

H3 refuted due to overfitting observed even in deep models including MLP

H4 confirmed; MLP was less effective at capturing temporal patterns

H5 supported; increasing complexity beyond a point led to overfitting despite regularization

Financial series prediction remains challenging due to volatility and noise

Decoding Financial Return Prediction Challenges

Insights on deep learning limitations and future research paths

- Deep learning models like **LSTM** and **transformers** show potential but face limits from market volatility and noise
- Performance is constrained by risks of **overfitting** and unpredictable financial time series behavior
- No current model delivers a definitive predictive solution for financial returns
- Future research should focus on **advanced data preprocessing**, **hybrid model architectures**, and stronger **regularization techniques**
- Ongoing advances in **computational power** and **algorithm design** are essential to progress in this domain