Comparative Analysis of Ensemble LSTM and Random Forest for Stock Trend Prediction: A Many-to-One Transfer Learning Approach

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Abstract. Discovering patterns in the diverse financial time series is an extremely challenging task. The Efficient Market Hypothesis holds that such efforts are futile, but the latest advancements in the field of deep learning have reignited this debate. This paper explores a "many-to-one" transfer learning strategy. This paper uses a dataset to compare the robust tree-based logic of the Random Forest (RF) regressor with the time-sensitive network of the Long Short-Term Memory (LSTM) network. The empirical findings on the data of 2024 indicate that there is a strong difference, yet Ensemble LSTM has done well in pattern recognition, which the direction accuracy rate of 54.35%, the RF model surprisingly has a better level of strategy return of 40.11%, as compared to the benchmark of 37.06%. The ultimate conclusions reveal that it is possible that the tree-based models have aggressive robustness in returning high volatility profit opportunities.

Keywords: Stock prediction, LSTM, Random forest, Transfer learning, Financial time series

1 Introduction

Again, in line with the efficient market hypothesis, the variation of stock prices is just a random walk phenomenon, and there is even the fact that there is always the possibility of performing better than the market [1]. This cynicism has been a source of division among the financial and academic circles. However, the rapid increase in the frequency of data and computing speeds has moved the debate to the how, rather than if, and has established machine learning as a key instrument in the decoding of finer, non-linear responses hidden within market noise [2].

One of the factors in this field that continues to pose a dilemma though is which modeling architecture to use. Classical machine learning models including Random Forest (RF) and Support Vector Machines have been historically preferred because of the ability to interpret their results and their resistance to overfitting. These essentially discrete-time models which not only assume that the market data is represented by discrete images, but also deliver good performance in feature-based classification, but have frequently been demonstrated to be unable to capture the sequential relationships, the story, behind price trends. On the other hand, the emergence of

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Deep Learning has placed Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks in the limelight. The ability to unlock the time dynamics of the market by having a memory of previous events, these architectures, in theory, hold a more finer power of prediction [3].

The existing research advances are not able to find out whether good predictive performance will result in the adequate financial reporting. The current paper attempts to address this gap by providing a detailed comparative analysis. To predict the future trend of one entity (AAPL), this paper utilizes the methodology of many-to-one transfer learning whereby it trains the model using the collective historical data of large technology companies (FAANG). This paper is meant to not only examine a long short term memory network with regards to their direction accuracy, but also examine their real profitability in real trading simulations.

2 Related Work

The history of financial forecasting has been characterized by the hegemony of computing intelligence to the sophisticated linear statistical models.

2.1 Machine Learning in Finance

Ensemble techniques, such as the Random Forest, were regarded as the best before the annihilation of deep learning. The operations of these models consist of building a very large number of decision trees, which should successfully lower the variation that is isolated to a single predictor. Key parameters found in other models such as tree-based models are very efficient at dealing with high-dimensional financial data and do not tend to demand a substantial amount of parameter tuning (see recent literature). They excel at their so-called feature engineering, or the process of deriving practical meaning out of technical indicators such as Moving Averages, RSI, and the like instead of being trained on raw time series [4].

2.2 The Shift to Deep Learning

Following the identification of constraints of snapshot learning, scientists started shifting to sequence-based models. Particularly LSTM networks which are set up to address the vanishing gradient issue have performed astonishingly in this field [5]. The study by Istiake Sunny et al. revealed that the LSTM and Bi-LSTM models were able to beat traditional ARIMA models in terms of their predictive ability of volatile stocks such as Tesla [6]. On the same note, Shahi et al. emphasized that LSTMs were able to reduce short-term noise and confined to underlying patterns by maintaining a long-term memory [7]. One common problem observed in these studies, though, is that neural network training is highly unstable and different problems can be obtained depending on random initializations.

2.3 Ensemble Strategies

To overcome such instability, recent research proposes that it is time to stop depending on one model. Ensemble methods are known to increase robustness; these techniques are methods that amalgamate predictions of two or more independent models. The work is based on this foundation, where an Ensemble LSTM strategy is applied, averaging the results of five independent networks to provide the results as statistically significant and not as the artifact of a successful initialisation [8].

3 Methodology

This paper developed a transfer learning model to be able to capture the universal laws of market movement and not the specifics of one stock.

3.1 Data Engineering and Transfer Learning

The paper has consolidated past daily data of the FAANG group (Facebook, Amazon, Apple, Netflix, Google) as of 2016 to 2024. The variation in price levels is a crucial issue with multi-stock training because, a $3000 stock will not respond numerically the same as a $150 stock. To address this, this paper invented relative features instead of absolute prices.

This paper uses Relative SMA, clinton (2007) states that the ratio of Close Price and 7-day Simple Moving Averages as well as the 21-day Simple Moving Averages are calculated. This paper also uses Volatility normalization (on the basis of volatility and volume changes in percentages). This paper also introduces Technical Indicators (combining RSI and MACD to represent the momentum). By allowing such normalization, the model can also learn morphological patterns (such as price is 5% above the mean) which can be transferred across assets.

3.2 Model Architectures

The two architectures used in the current paper to indicate the two opposite market prediction philosophies are:

The first architecture is a Random Forest Regressor. This model has 100 estimators set and considers the market as one subject to independent decision points. It uses the statistical likelihood of the technical indicators that are used to predict the return of the following day without any concern with the sequential nature of inputs. The second architecture is Ensemble LSTM. This paper developed a time-series specific architecture that the window size of T=10 days. Its main part is an LSTM layer of 50 units, and then a Dropout layer rate=0.3 to train it to generalize. This paper realized that deep learning is stochastic in nature and it thus trained 5 independent instances of this model. The overall output of this ensemble is averaged to give the final prediction and it includes a stable and reliable signal.

4 Experimental Results and Discussion

It was necessary to assess whether the true utility of these architectures was worthwhile, so This paper has gone by theoretical training data, and has done a rigorous back-testing simulation. Here, a strongly held-out dataset of the period between January 2024 and the present was used in this stage because that period was selected to simulate the uncertainty inherent in real-life trading in which the future is completely unknown.

4.1 Performance Evaluation and Stability Analysis

Table 1 is a summary of the main metrics, although the numbers are usually misleading since it fails to capture what happens throughout training. A closer look at how the model is behaving can be found in Figure 1 which provides a health check of an Ensemble LSTM in all its aspects. In Fig. 1a, this paper can see that the model is able to reach a stable convergence, however, the validation loss follows the training loss without the usual divergence in financial deep learning which is a sign of overfitting. The error distribution in Fig. 1b confirms this stability as well. The resid way is close to the normal distribution, which meets the requirement that the model has done its job and all that remains is unbiased white noise.

Table 1. Performance Comparison on Test Set

Model	Directional Accuracy	Strategy Return	Benchmark Return
Random Forest	53.88%	40.11%	34.88%
Ensemble LSTM	54.35%	37.06%	37.06%*

*Remark: The difference of benchmark returns is slightly greater since data is aligned sequentially in sequence generation.

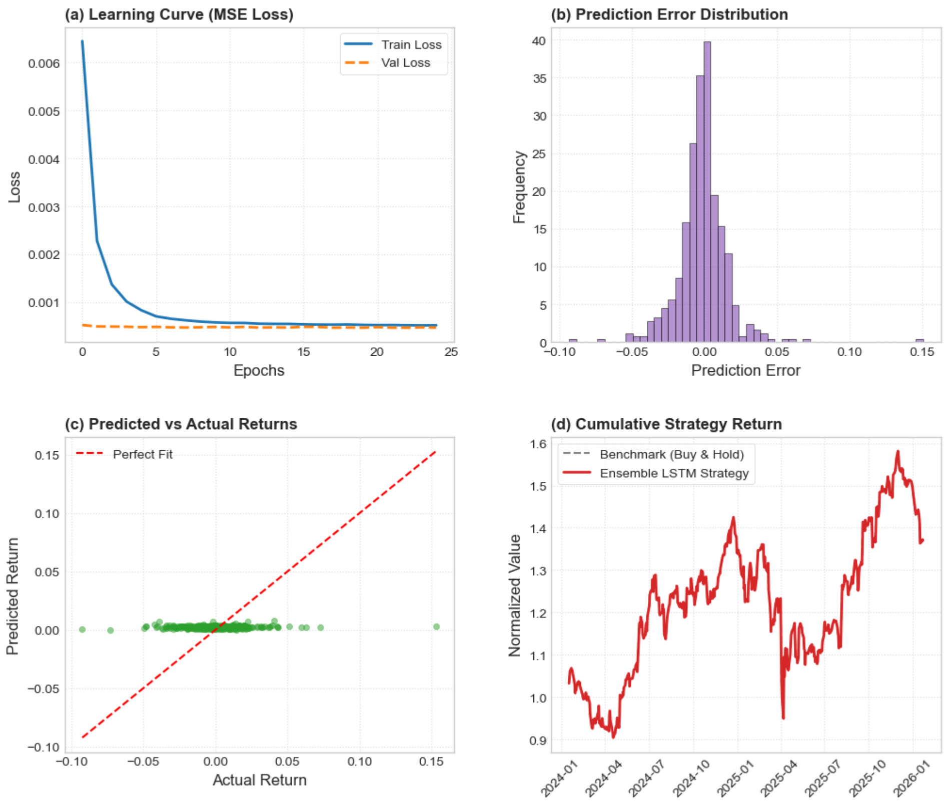

Fig. 1. Extensive performance assessment of the Ensemble LSTM model on the test set (AAPL, 2024). (a) training and validation loss curves where convergence is stable, (b) histogram of error values that model is robust, (c) scatter plot of predicted and actual returns and (d) cumulative strategy returns versus Buy and Hold benchmark. (Picture credit: Original)

4.2 The Accuracy-Profitability Paradox

There is a widely held guided assumption within the quantitative finance that the more predictive power a model the better the financial returns of that model will be. Currently, one cannot assert whether this correlation is still maintained in empirical studies. The findings include a very interesting counter-story. The Ensemble LSTM which is advantaged by its capability to memorize long term temporal relations made a better directional accuracy of 54.35%. It coincides with the available literature that has suggested deep learning architectures as having a single capability unique among all neural network architectures to identify subtle and non-linear patterns in time series data [9]. The LSTM also identified the current trend direction more often compared to the traditional one because of the ability to block out the short-term market noise.

The financial truth, however, gives a different account. On implementation of these predictions as a trading model, the Random Forest model, although with a marginally-lower accuracy of 53.88% had a cumulative return of 40.11%. This not only showed higher performance compared to the LSTM strategy (37.06%), but also compared to the performance of the market. This mismatch compels people to challenge the notion that it is the most significant measure of profitability that people do the right things more frequently.

4.3 Interpretation

The aim of this research was to learn why a weaker model might still give high returns and how a model of inaccurate enough nature might give a high profit. It appears that the solution is in the structure of the mistakes and the market factors in 2024. The tree-based models have diverse thresholds despite the fact that the Long Short-Term Memory model (LSTMs) is programmed to reduce the total error - which normally results to cautious and smooth forecasting [10].

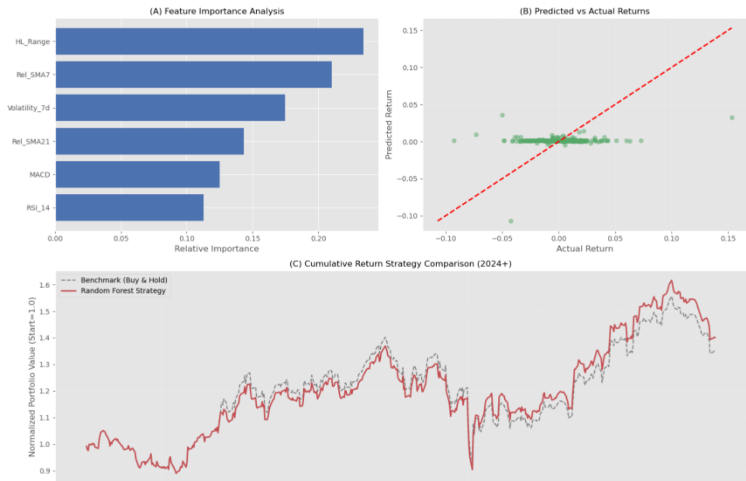

Fig. 2. Random Forest random forest importance analysis. (a) Help identify the key factors that drive price or revenue forecasts and select the most predictive technical indicators (b) Intuitively display the degree of deviation between the predicted values and the actual values. (c) Evaluate whether the active strategy can outperform the passive holding. (Picture credit: Original)

A hint to this behavior can be listed in the feature importance analysis in Figure 2. It determines Volatility 7d (7 Day Volatility) and Rel SMA (Relative Moving Average) as the most important predictor of the Move Forest. This implies that the model is not just a trend-following; it is aggressively deciding who to follow that exhibits high volatility. This is a hunting behavior, as in a market where prices move sharply and decisively, that enabled the Maximum Buildings of the Random Forest to score a handful of large-size returns. The LSTM on the other hand was consistent but perhaps over cautious to really take advantage of the outlier events. As shown in the picture, the relative significance of Volatility 7d and Rel SMA is high, which indicates that the model is highly dependent on the market momentum and deviation, to create profitable trading entries.

5 Conclusion

This paper set out on a comparative trip of the case of traditional machine learning, and the deep machine learning in prediction of stock trends. The results provide an insightful finality that an excellent predictive ability does not necessarily mean that returns would be high.

Ensemble LSTM was the more scientifically accurate mechanism, because it provides accurate and stable direction predictions by being able to model the dependence of time. It is an excellent signal generator of risk-averse type. Conversely, the Random Forest model exhibited a practical strength, that is, using the feature thresholds to capture the large market movements to enable optimum returns in the simulation.

This implies that the future of quantitative finance is not in the selection between the two, but in hybridization, to practitioners and researchers. A mixture of the wisdom of LSTMs over time and the opportunistic behavior of the Random Forests would potentially provide a very viable strategy that would be both accurate and highly profitable.

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