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Seasonality In Stock Market Prediction: Insights From Statistical, Machine Learning, And Deep Learning Models

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Abstract: The forecasting of stock market trends has advanced with a sequence of paradigms from statistical schemes, machine learning algorithms, and deep learning architectures; nonetheless, issues remain with the effective representation of seasonal patterns and external influences. This research examines the ways in which current schemes handle cycles of a periodic kind—directly with the help of decomposition or indirectly with the use of deep architectures—and the importance of external factors like sentiment analysis, macroeconomic indicators, and time-based indicators. The notable finding is the disconnected form of these schemes, wherein the seasonal factors and external influences are often examined independently. The discussion integrates these findings and highlights the need for unified schemes wherein seasonality-aware modeling may combine with nonlinear learning schemes and structured external inputs. As a next step, a seasonal-aware framework with external integration is outlined.

***Keywords* -** Stock market prediction, Seasonality, Time series forecasting, Exogenous features, Sentiment analysis, Deep learning.

I. INTRODUCTION

Due to its constant turbulence, noise, and volatility, predicting movements in the stock market is still one of the most difficult and complex problems to solve. Investors, policymakers, and other researchers have worked hard to build models that deal with the complexities of financial time series and provide accurate and precise forecasts. Out of the many factors that affect stock market behavior, seasonality is one of the most important and striking factors that captures temporal repetition and patterns such as quarterly earnings cycles, Month-end effects, fiscal year endings, and even other cycles caused by events like the festive season and budget announcements. If such models, has seasonality and other temporal patterns woven into them to capture the structure of time series, then, most like models generated will have recursive patterns and thus weathered systematic forecasting errors.

Traditional models such as ARIMA, SARIMA, and Holt-Winters models were specifically developed to model and predict trends and seasonality and were until recently the leading models in time-series prediction. However, they depend on linear assumptions and have not done well with financial markets being nonlinear and dynamic. In contrast to these, machine and deep learning models, specifically recurrent neural networks such as LSTM and GRU, have shown overwhelmingly strength in coping with nonlinear relations and long sequences. However, the majority of these models model seasonality implicitly and not explicitly, and that makes them overfit or underestimate when market cycles play a critical role. The gap between traditional seasonal modeling and modern prediction models is the combination of approaches from these two fields.

Recent works have also advocated exogenous variables and temporal markers for enhancing predictive potential. There is unique supplemental information that overlaps with seasonal trends, such as weather forecasts, announcements on budget plans, emotions in news and social media, and macro signals; however, the literature has used these features in an ad-hoc manner, failing to view them through the lens of a systematic seasonal forecasting framework. As a result, the combined effects of seasonality, deep learning models, and exogenous variables is poorly understood, which remains an open problem.

This paper attempts to resolve the gaps by providing a systematic literature review of stock-exchange prediction approaches that incorporate seasonality, such as conventional statistical models, machine learning, deep learning, or hybrid models. The current literature review categorizes the existing literature by the conceptual taxonomy, in terms of how they treat seasonality, what aspects are employed, and what type of model is used, as opposed to standard literature reviews which simply review and abstract the contributions for readers. In this way, the paper not only reviews current contributions, but signals out some brief future research lines that provide a bridge into more complex hybrid models drawing on decomposition, deep learning, and external features.The structure of the article is as follows: Section 2 will consist of a literature review; Section 3 will comprise a critical comparative review and comparison; Section 4 will consist of a discussion; and Section 5 will conclude with key findings and recommendations for future research.

II. Literature Survey

2.1 Foundations of Seasonality in Time Series Forecasting

Seasonality, which is a key feature of financial time series, contains repetitive patterns due to structural factors (e.g., earnings cycles, fiscal policy changes, dividends) and behavioral factors (e.g., day-of-the-week effects, January effects). Estimating cycles aids in forecasting by incorporating a time structure into erotic stock prices. X-11 and Classical, and in particular STL components, are all used frequently, while Fourier and wavelet transformations are useful for identifying periodic structures that are global and localized.

Explicitly modeling seasonality significantly adds to the interpretability of the data and avoids the spurious attribution of liquidity effects during the end of a quarter as some form of external shocks. By surfacing cyclical components in this manner, traditional and deep learning models can now shift their focus to nonlinear residuals and thereby avoid overfitting and improve stability. Failing to include seasonality introduces the risk of unreliable forecasting and out-of-the-model trading decisions, making seasonality a vital feature for reliable financial forecasting.

2.2 Statistical Approach

2.2.1 Traditional Statistical Models

Traditionally, statistical techniques like ARIMA and its seasonal version, SARIMA, were favored by economists as they were simple to understand and interpret [1],[2]. Furthermore, the models perform adequately well for both linear trends and seasonal components for consistent and stable situations. Likewise, Holt-Winters exponential smoothing also performed well for financial indices forecasting in the trend and seasonal context [3]. The GARCH class of models, including ARCH, GARCH, and TARCH, were utilized primarily for volatility clustering: a consistent cyclical pattern of financial returns [4].

While these models offer transparency and natural in-seasonality handling, they can be limited by the linearity assumption, as demonstrated in Sirisha et al. [21] which compared ARIMA, SARIMA and LSTM for retail profit data, suggesting LSTM outperformed all empirical statistical baselines when compared in terms of accuracy, though limited datasets and exogenous features were shortcomings present throughout. Similarly, Kulshreshtha et al. [26], showed a combined collection of ARIMA and LSTM outperformed Facebook Prophet, although Prophet itself remains firm for benchmark accuracy for seasonal data.

2.2.2 Machine Learning Models

Support Vector Machines (SVMs), Random Forests (RFs), and Gradient Boosting Machines (GBMs), which are machine learning classifiers that have been utilized for stock predictions, typically by accomodating the problem as a classification (up/down movement) or regression (predicting prices) sample [5], [6] for example. However, they require engineered features (e.g., lagged prices, day-of-week, month-of-year), as they do not have seasonal treatment mechanisms built-in.. Research points out the superiority of ML models over statistical ones when feature engineering is well conducted [6]. Nevertheless, over-reliance on univariate datasets as well as limited hyperparameter tuning usually limits their generalizability. In addition, incorporation of exogenous factors (macro variables, sentiment, meteorological) is not well explored for purely ML settings [12].

2.2.3 Deep Learning Models

The best transformative advances for predictive finance came from deep learning architectures. Stock indexes, commodity prices, and prediction of sectors all employ Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) [7], [8]. Their strengths include the capability for long-term dependence and nonlinear dynamics. However, vanilla LSTMs automatically learn seasonality but may overfit [9].

Several studies suggest Hybrid decomposition–LSTM pipelines. Niu et al. [22] presented a VMD-LSTM model, wherein time series were decomposed through Variational Mode Decomposition (VMD) and each resultant subseries predicted by LSTM, and this worked better for various indices. Lv et al. [23] came up with the CEEMDAN-ARMA-LSTM (CAL) model, wherein CEEMDAN decomposition distinguishes components, ARMA takes care of linearity, and LSTM covers nonlinearities, demonstrating notable accuracies compared to baselines. Likewise, Yujun et al. [24] came up with the hybrid LSTM-VMD, which vindicated the robustness for indices such as S&P500 and DAX but suffered from over-reliance on univariate price data. Agarwal et al. [25] followed up with an SVMD-LSTM model, which surpassed all baselines (EMD-LSTM, VMD-LSTM, SVR, MLP).

Rezaei et al. [27] put forward CEEMD-CNN-LSTM and EMD-CNN-LSTM, combining frequency decomposition with CNN feature extraction and LSTM forecasting, which beats traditional baselines. Li et al. [28] presented the HDFM model, which incorporates CEEMDAN, VMD, clustering, and GRU for managing noise and non-stationarity. Al et al. [29] compared traditional models (ARIMA, SARIMA, GARCH) with several DL versions (BiLSTM, ConvLSTM, Multivariate LSTM), revealing the superiority of DL. Botunac et al. [30] combined LSTM with trading strategies and technical indicators (TEMA, MACD, MOM), finding better trading results. Song et al. [31] put forward BO-LSTM (Bayesian Optimized LSTM), which optimizes LSTM hyperparameters using Bayesian networks, and which attains better prediction ability for volatile stocks. Later, attention mechanisms and transformer architectures were employed [7], [10] and offer the potential for learning global dependencies and implicit seasonality. Their applications for finance environments, though, come anew and do not include a comparative study with the seasonality-aware decomposed methods [14], [20].

2.2.4 Hybrid and Advanced Methods

Hybrid structures of decomposition techniques (STL, EMD, VMD, CEEMDAN) and ML/DL models are prevalent since they can recover piecewise seasonality and noise before nonlinear learning. Some of the hybrids are ARIMA-LSTM hybrids [26], STL + ensemble learning [4], and decomposition + CNN-LSTM models [27]. These techniques are always superior to one-model baselines across a number of datasets.

Despite their promise, challenges remain: many models rely purely on past price data, with no consideration of external factors like sentiment, macroeconomic indicators, and weather [8], [12]. Moreover, advanced architecture, such as the transformer, attention-augmented LSTM, and Bayesian-optimized-enhanced models [7], [31] has not been fully investigated in conjunction with decomposition techniques. This represents a significant opportunity for research at the intersection of deco- mposition techniques, external information, and next-generation deep learning architecture.

III. Critical Analysis and Comparative Study

In the literature review, we examine an evolution of stock market forecasting procedures from statistical models, to the current hybrid models. Although each approach to models has seen varying success, they are often contingent upon how the models treat seasonality, if exogenous inputs are incorporated into the models, and the trade-off between complicity and interpretability. The literature review section of the dissertation provides a comparative overview presented in three sections: (i) tabular comparison of studies, (ii) a critical evaluation of the strengths and weaknesses of the methods,. and (iii) Key insights & research gaps.

3.1 Comparison of Representative Approaches in Stock Market Prediction

The table below (Table 3.1) offers a structured summary of the studies that have been examined through associated traits, including seasonality response, type of inputs utilized, dataset used, and results generated.

Method / Study	Seasonality Treatment	Input Type	Dataset(s)	Reported Results
STL + LSTM [1]	Explicit (STL decomposition into seasonal/trend/residual)	Seasonal / trend / residual series	Chinese & US indices (various)	Higher accuracy than raw-LSTM; noise reduction and better generalization
CEEMDAN + ARMA + LSTM (Hybrid) [2]	Explicit (CEEMDAN frequency decomposition + ARMA for linear parts)	IMF components (linear + nonlinear)	Multiple indices (e.g., DAX, HSI, S&P500, SSE)	Significant MAE/RMSE reductions vs LSTM/ARIMA; strong across indices
Frequency decomposition + DL [3]	Explicit (EMD/CEEMD + frequency components)	Frequency components fed to DL (LSTM/CNN)	Multiple stock sets	Improved accuracy over single-model DL approaches
STL + Stacking Ensemble [4]	Explicit (STL preprocess)	Decomposed inputs into ensemble learners	Mixed indices / stocks	Robust ensemble performance; better than single models but pipeline complex
Feature selection survey [5]	N/A (survey) — discusses engineered seasonal features	Price, technical, derived features	Broad (survey across many markets)	Highlights importance of engineered temporal features for ML models
LSTM Survey [6]	Implicit (LSTM learns patterns)	Price/time-series (sometimes augmented)	Broad (survey)	LSTMs strong overall; recommends decomposition & exogenous inputs
LSTM + Self-Attention [7]	Partial (attention emphasizes temporal importance)	Price sequences	NASDAQ / multiple equities	Better temporal dependency capture; accuracy gain over plain LSTM
NLP / Sentiment Survey [8]	N/A (survey) — discusses event-driven seasonality	News, tweets, sentiment + price	Broad (survey)	Sentiment helps capture event/season-driven moves; integration uneven
Ensemble (Price + News) [9]	Implicit (seasonality through features)	Price + textual sentiment	Various equities/index datasets	Ensemble of RNN/LSTM/GRU with text improves forecasts vs price-only
CNN-LSTM [10]	Implicit (CNN extracts local/periodic patterns)	Price + indicators	Shanghai A-share / other indices	Improved accuracy over plain LSTM; seasonality still not explicit
Hybrid comparative study (RNN-based hybrids) [11]	Mixed (some hybrids use decomposition)	Varied: price, indicators	Multiple indices	Hybrids (CNN-LSTM, GRU combos) often outperform single models

Aggregate ML/DL comparison [12]	Varies by method	Price / technical / engineered features	Mixed index datasets	Comparative view: DL > ML > statistical when large data & features used
LSTM vs TCN Review [14]	Implicit (model-specific)	Price/time series	Survey across datasets	TCN can match/beat LSTM for long-range dependency capture
Decomposition + Linear/Neural comparison [15]	Explicit (decomposition methods used)	Price + decomposed components	Selected index datasets	Decomposition + neural often outperforms pure linear or pure neural models
Prophet (trend + seasonality) [17]	Explicit (additive trend & seasonality modeling)	Price / aggregated time series	Broader time series (examples incl. finance)	Good at multiple seasonalities; interpretable baseline
Wavelet + DL hybrids [18]	Explicit (wavelet frequency decomposition)	Wavelet coefficients + price	Financial series	Good at capturing localized cyclic behavior; hybrid improves accuracy
EMD/CEEMDAN applications [19]	Explicit (intrinsic mode extraction)	IMF components	Multiple financial series	Decomposition handles non-stationarity; when combined with DL yields strong results
Transformers / Attention Survey [20]	Implicit/Partial (attention captures global patterns)	Raw sequences (sometimes multivariate)	Time-series benchmarks	Transformers effective for long-horizon dependencies; finance adoption growing
Sirisha (2022) [21]	SARIMA/ARIMA explicit; LSTM implicit	Univariate retail profit series	Retail profit dataset	LSTM outperformed ARIMA/SARIMA but study limited by single univariate data & no exogenous inputs
VMD-LSTM [22]	Explicit (VMD decomposes into modes)	Subseries (IMFs) forecasted with LSTM	HSI, SPX, FTSE, IXIC	VMD-LSTM > LSTM/ELM/CNN & other hybrids on RMSE/MAE/MAPE
CEEMDAN-ARMA-LSTM (CAL) [23]	Explicit (CEEMDAN → ADF → ARMA/LSTM per component)	IMF partitions (linear/nonlinear)	DAX, HSI, S&P500, SSE	Large MAE reductions vs LSTM/ARIMA; strong cross-index performance
LSTM-VMD [24]	Explicit (VMD)	Decomposed IMFs → LSTM per IMF	S&P500, HSI, SZ, ASX, DAX, VIX	High R^2 in many cases; weaker performance on some indices (e.g., S&P500)
SVMD-LSTM [25]	Explicit (SVMD decomposition)	Decomposed IMFs → LSTM	HSI, SENSEX, S&P500, WTI	Outperformed many baselines across RMSE/MAE/MAPE/R^2/CID
ARIMA + LSTM [26]	Explicit (ARIMA captures linear seasonality) + LSTM residual	Univariate S&P500 (intraday/hourly)	S&P500 (Yahoo)	Hybrid > Prophet & single models (RMSE 1.74 vs Prophet 27.59)

CEEMD-CNN-LSTM / EMD-CNN-LSTM [27]	Explicit (CEEMD/EMD)	IMF → CNN feature extractor → LSTM	S&P500, Dow Jones, DAX, Nikkei225	CEEMD-CNN-LSTM outperformed LSTM, CEEMD-LSTM, CNN-LSTM on RMSE/MAE/MAPE
HDFM [28]	Explicit (CEEMDAN + VMD + clustering)	Clustered IMFs → GRU forecasting	SSEC, SZI, SPX	Surpassed 8 benchmarks; ablation shows benefit of combined decomposition + clustering
Al (2024) [29]	Statistical explicit (ARMA/ARIMA/SARIMA/GARCH) vs DL implicit	Uni/multivariate price/time features	PSX-100 (2009–2021)	2-layer multivariate Bi-LSTM best (RMSE 0.071) over classical models
Botunac (2024) [30]	No formal seasonality decomposition (technical indicators only)	Price + technicals (TEMA, MACD, MOM) + LSTM forecast	SPY, DIA indices & stocks (AAPL, MSFT, TSLA)	LSTM-augmented strategies improved trading returns and forecasting error metrics
BO-LSTM [31]	Implicit (LSTM), with Bayesian hyperparameter optimization	Price series (gold stocks)	Gold stock datasets	BO-LSTM outperforms vanilla LSTM by better hyperparameter tuning; increased robustness

Table 3.1: Comparative Study of Stock Market Prediction Methods with Seasonality Treatment

3.2 Strengths and Weaknesses of Different Model Families

The ensuing table (Table 3.2) illustrates the strengths and weaknesses of each category of model, from statistical methods, to current hybrid frameworks, in order to assert their relevance under differing market conditions..

Approach Type	Strengths	Weaknesses
Statistical (ARIMA, SARIMA, Holt-Winters, GARCH, Prophet	•Well-established, interpretable • Strong at modeling explicit seasonality (lags, differencing, seasonal smoothing) • Require less data, fast to train	• Struggle with nonlinear/volatile patterns • Limited handling of multivariate & exogenous features • Accuracy drops in highly dynamic stock markets
Machine Learning (RF, SVM, GBM, XGBoost, SVR	• Handle nonlinearities better than statistical methods • Can integrate engineered seasonal & technical features • Flexible with feature types (technical, sentiment, macro)	• No inherent seasonality modeling (depends on feature engineering) • Risk of overfitting with noisy financial data • Require careful feature selection & preprocessing

Deep Learning (LSTM, Bi-LSTM, CNN-LSTM, Attention-based, Trans-formers, BO-LSTM)	• Strong predictive power for nonlinear & long-sequence dependencies • Capture complex hidden temporal structures • Handle large-scale, multivariate, high-dimensional data	• Seasonality learned only implicitly (hidden states) • Opaque / less interpretable ("black box") • Prone to overfitting & unstable without decomposition or exogenous features
Hybrid (STL+LSTM, ARIMA+LSTM, CEEM-DAN+ARMA+LSTM, VMD-LSTM, SVMD-LSTM, Wavelet-LSTM, Decomposition + GRU, Ensemble Stacking)	• Combine explicit seasonality modeling (statistical/decomposition) with DL power • Reduce noise via decomposition (STL, VMD, CEEMDAN) • Often achieve superior accuracy and robustness • Balance interpretability + predictive strength	• Complex architectures, harder to implement & optimize • Higher computational cost • Many rely only on price/time series (ignoring exogenous sen-timent/macro factors) • Limited benchmarking across diverse markets

Table 3.2: Strengths and Weaknesses of Different Approaches for Stock Market Prediction

3.3 Key Insights & Research Gaps

This table (Table 3.3) summarizes the primary implications from the comparative review, as well as indicating gaps in the literature, which highlight a need for a cohesive seasonality-enabled forecasting framework.

Observation	Research Gap
Statistical models capture seasonality well but fail on nonlinear, volatile markets.	Need methods that go beyond linear assumptions while preserving explicit seasonal structure.
ML/DL models provide strong predictive power but treat seasonality only implicitly.	Explicit decomposition or feature integration is required to stabilize predictions.
Hybrids show promise by combining decomposition + DL.	Still underexplored: few frameworks systematically integrate seasonality + DL + exogenous features (sentiment, macroeconomic, weather).
Existing studies often focus on single datasets/indices.	Lack of generalizable frameworks tested across diverse global markets.

Table 3.3: Key Insights and Research Gaps in Stock Market Prediction

IV. Discussion

The majority of past research in stock market forecasting prioritizes historical prices and technical measures, but exogenous and temporal considerations are essential to define cyclical and seasonal patterns. Sentiment inputs like news headlines, budget announcements, central bank actions, and geopolitical events have been found to enhance predictions by picking up on sudden departures from normal cycles, but they are typically handled in an ad-hoc way without integration to seasonal decomposition. In a similar manner, exogenous factors such as weather, macroeconomic factors (GDP, inflation, interest rates), and industry-specific drivers such as energy demand, often engage with periodic market trends but are typically input directly into ML/DL models in their raw form, constraining their interpretability and applicability. Seasonal markers, such as month-end, quarter-end, and fiscal-year frequencies coinciding with portfolio rebalancing, taxation, and earnings announcements, are underutilized, generally represented as categorical features instead of being incorporated systematically into seasonal frameworks. This disjointed treatment leads to the requirement for a reconciled framework, which brings seasonality modeling, deep learning, and structured exogenous integration together in an explicit way. To remedy this, we suggest a hybrid structure in which STL decomposition isolates price data into trend, seasonal, and residual parts, LSTM/Attention-based models identify nonlinear relationships from residuals, and sentiment, macroeconomic, environmental, and temporal signifiers are incorporated as aligned auxiliary inputs. A hybrid fusion layer subsequently blends output from seasonality-driven elements and nonlinear predictors to generate final predictions that blend interpretability with predictive power. The envisioned contributions of the proposed framework are four: (i) it offers the first systematic unification of seasonality, deep learning, and exogenous/temporal features in one pipeline, (ii) it enhances accuracy by denoising using explicit decomposition while preserving nonlinear dynamics, (iii) it boosts interpretability by connecting exogenous drivers and seasonal components, and (iv) it provides generality and flexibility across a variety of markets and industries and is thus an extendable solution to seasonality-aware stock prediction.

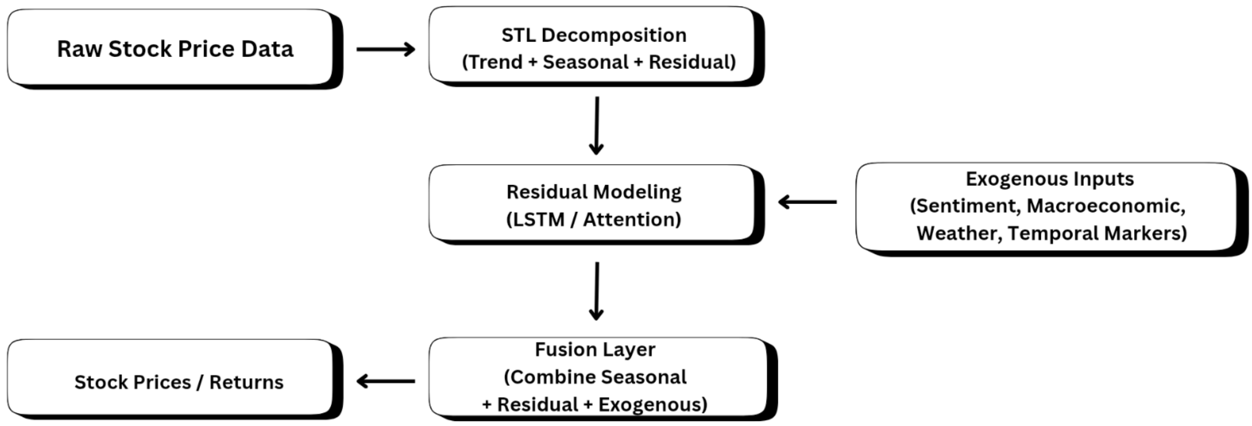

Figure 1: Proposed Unified Framework:
Seasonality + Exogenous + Deep Learning

As displayed in the preceding Figure 1, we propose the unified framework for the seasonality-aware stock market prediction area. The schema begins with the raw stock price data, where an STL decomposition results in a trend component, seasonality component, and residual component. While the seasonality component detected repetitive patterns, the residual series is trained with complex non-linear LSTM/Attention-based networks. Meanwhile, the models will also include external and temporal contents or features such as macroeconomic factors, sentiments, weather statistics, and the fiscal calendar. Finally, the exogenous, seasonality, and residual elements are merged using a fusion layer resulting in the final stock price prediction.

V. Conclusion & Future Direction

With particular emphasis to seasonality as well as the effects of exogenous and temporal variables, this paper provides a critical assessment of stock market prediction approaches. Statistical models that are good at identifying regular cycles, including ARIMA, SARIMA, and Holt-Winters, are less equipped to handle nonlinearities and abrupt shocks. Although they frequently overlook seasonal trends, machine learning and deep learning models such as LSTM and attention networks successfully include subtle dynamics. Despite their very limited and uneven deployment, hybrid models have seemed to be potential alternatives to those now in use. Regarding a comprehensive systematic framework that incorporates seasonal decompositions, residual learning, and the methodical application of exogenous variables, one noteworthy gap in the literature has been highlighted.

In the future, there are avenues to achieve an overall hybrid architecture, which mathematically specifies how to decompose statistically (e.g., STL, wavelets), and to integrate deep learning methods to add both seasonal structure and non-linear structure. It will also be essential to systematically incorporate macroeconomic environmental features, sentiment features, and temporal coverage in order to go beyond very basic surface level accommodation. Further, it will be helpful to be able to enhance interpretability through the decomposing seasonal, exogenous, and residual components into something that will also build trust and understanding. Finally, cross-validation and validation in other markets and incorporation in decision-support systems will strengthen robustness and practical knowledge. Addressing any and all of these will significantly enhance both accuracy and practical application of stock market prediction systems.

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