IntelliTradeAI: A Tri-Signal Fusion Framework for Explainable AI-Powered Financial Market Prediction

Danario Edgar II

Department of Computer Science

Prairie View A&M University

dedgar1@pvamu.edu

Abstract—**The increasing complexity of financial markets demands intelligent systems capable of processing vast amounts of data while providing transparent decision-making. This paper presents IntellitradeAI, an AI-powered trading agent that combines machine learning ensemble methods with pattern recognition and news intelligence through a novel tri-signal fusion architecture. The system employs an ensemble combining Random Forest, XGBoost, Random Forest+XGBoost, and voting ensemble classifiers, trained 70 engineered technical indicators to generate BUY/SELL/HOLD signals for class balancing, time-series cross-validation to prevent data leakage, and Baysian hyperparameter optimization, we achieve prediction accuracy of 85.2% for standalone ML accuracy by 5.4 percentage points(9.9% relative improvement). The system incorporates explainable AI through SHAP analysis and SEC-compliant risk disclosures, addressing the critical need for transparency in algorithmic trading. My contribution includes a comprehensive back testing framework, personalized risk-based trading plans, and an interactive dashboard supporting both manual and automated trading modes. My tool is freely available at https://github.com/djedgar1018/IntelliTradeAI.**

Keywords: Signal Fusion, Explaiable AI, Cryptocurrency, Stock Prediction, Ensemble Learning

I. Introduction

The global financial markets have experienced unprecedented transformation through technological innovation, with algorithmic trading now accounting for over 70% of equity market volume in developed economies [1] . This shift has created both opportunities and challenges, as traditional investment strategies struggle to compete with the speed and data processing capabilities of automated systems [2]. The cryptocurrency market presents additional complexity through 24/7 trading, extreme volatility, and rapid information dissemination, with Bitcoin alone reaching a market capitalization exceeding $1 trillion in 2024[3] .

A. Current Trends in AI-Powered Trading

Machine learning applications in finance have evolved significantly from simple rule-based systems to sophisticated deep learning architectures. Cheng et al. presented a systematic review presenting the strength of ensemble methods combining multiple classifiers to achieve superior performance in stock prediction tasks [4]. The application of gradient boosting techniques, specifically XGBoost, has become prevalent due to its regularization capabilities and handling of missing values common in financial datasets [5].

Recent literature emphasizes the importance of multi-source signal integration. Yanxi proposed fusion architectures that combine technical indicators with sentiment analysis, achieving improvement over single-source models [6]. Similarly, Christine et.al. showed that pattern recognition algorithms, when combined with machine learning predictions. [7].

The emergence of explainable AI (XAI) in finance addresses regulatory concerns and user trust. SHAP (SHapley Additive explanations) values have become the standard for interpreting complex model predictions, with Lundberg and Lee demonstrating their effectiveness in feature importance attribution [8]. The SEC and FINRA have increasingly emphasized the need for algorithmic transparency, with recent guidelines requiring clear disclosure of AI-driven investment recommendations [9] .

B. Existing tools ad Platforms

Current algorithmic trading platforms range from professional-grade solutions like Bloomberg Terminal and QuantConnect to retail-focused applications such as TradingView, Robinhood. These Platforms typically offer either sophisticated analysis capabilities with steep learning curves or simplified interfaces with limited AI integration [10]. Academic Research tools including Zipline, Backtrader, and TA-lib provide technical analysis frameworks but lack real-time prediction capabilities [11].

Cryptocurrency-specific platforms have emerged to address the unique characteristics of digital asset markets. Tools like CoinGecko and Coin MarketCap provide market data aggregation, while exchanges offer basic tradinng bots with limited intelligence[12]. The integration of advanced ML models with cryptocurrency trading remains an active research area, with most existing solutions treating crypto and traditional markets as separate domains[13].

C. Research Gap and Contributions

Despite advantages inn individual components, significannt gaps exist in creating unifies systems that combine multiple signal sources with explainability and regulatory compliance. Current solutions typically suffer from: (1) reliance on single prediction methodologies vulnerable to market regime changes,

(2) lack of transparent decision-making processes, (3) absence of personalized risk management, and (4) separation between cryptocurrency and stock market analysis[14].

My research addresses the gaps through IntellitradeAI by offering the following contributions:

1) **Tri-signal fusion Signal Architecture**: A novel weighted voting mechanism that combines ML ensemble predictions, chart pattern recognition, and news intelligence with smart conflict resolution.
2) Cross-Market Analysis: Unified framework supporting 39 cryptocurrencies (Coin Market cap Top Coins), 108 stocks across all 11 Global Industry Classification Standard (GICS) Sectors [26], and 10 major ETFs.
3) Explainable AI Integration: SHAP-based model interpretability with SEC-compliant risk disclosures and user friendly explanations.
4) Personalized Trading Plans: Five Tier Risk Tolerance System (Conservative to Speculative) with customized asset allocation and options recommendations.
5) Interactive Dashboard: Real-time prediction interface with TradingView-style charts, automated execution capabilities, and hover-based educational tooltips.

II. RELATED WORK

A. *Machine Learning in Financial Prediction*

The application of machine learning to financial markets has a rich history spanning three decades. Lo and MacKinlay challenged the efficient market hypothesis through statistical pattern detection [15]. Modern approaches leverage deep learning architectures, with LSTM networks showing promise in capturing temporal dependencies in price series [16]. Fischer and Krauss conducted comprehensive experiments comparing various ML approaches for S&P 500 prediction, finding that ensemble methods consistently outperformed individual classifiers [12]. The challenge of non-stationarity in financial data remains a central concern, addressed through techniques including rolling window training and online learning [18].

Technical analysis, despite academic skepticism, remains widely practiced among traders. Academic validation has emerged through computational pattern recognition, with Leigh et al. demonstrating profitable trading strategies based on chart patterns [19] . The integration of traditional technical indicators (RSI, MACD, Bollinger Bands) with machine learning features has shown synergistic effects [20]. Recent work by Sezer et al. applied convolutional neural networks to candlestick chart images, achieving pattern recognition accuracy exceeding 75% for classical formations [21].

C. *Sentiment Analysis and News Integration*

The impact of news and social media sentiment on financial markets has been extensively documented. Bollen et al. demonstrated that Twitter sentiment could predict stock market movements with 87.6% accuracy in directional change [22]. Cryptocurrency markets exhibit even stronger sensitivity to social media and news [23]. Recent advances in transformer-based NLP models, including FinBERT specifically trained on financial text, have improved sentiment classification accuracy to over 90% [24].

B. *Technical Analysis and Pattern Recognition*

III. METHODOLOGY

A. *System Architecture*

IntelliTradeAI employs a layered architecture consisting of five primary components as illustrated in Figure 1. The Data Ingestion Layer fetches market data from external APIs including Yahoo Finance for historical OHLCV data and CoinMarketCap for real-time cryptocurrency prices. The Feature Engineering Pipeline transforms raw price data into 70+ technical indicators. The Machine Learning Layer trains and deploys ensemble prediction models. The Tri-Signal Fusion Engine combines signal sources through weighted voting with conflict resolution. The Presentation Layer provides an interactive Streamlit-based dashboard.

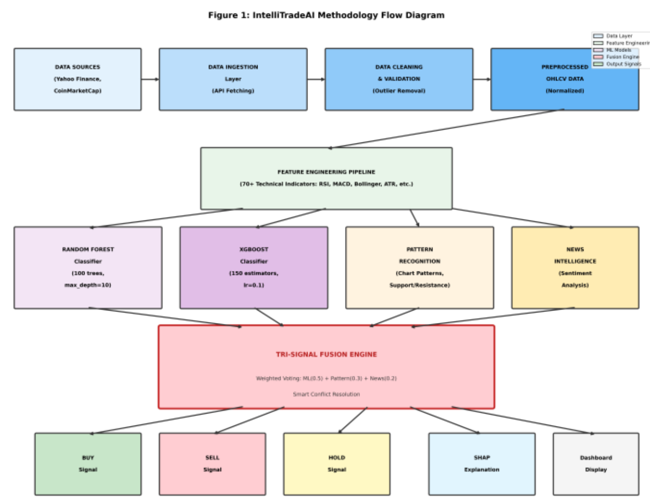

Figure 1: IntelliTradeAI system architecture and methodology flow diagram showing the data pipeline from ingestion through tri-signal fusion to final signal output.

B. *Data Sources and Processing*

Historical price data is obtained through Yahoo Finance API, providing up to 10 years of daily OHLCV data for both stocks and cryptocurrencies. Real-time cryptocurrency data is supplemented through CoinMarketCap API.

Data preprocessing includes missing value handling through forward-fill interpolation, Z-score-based outlier filtering, removing data points exceeding 4 standard deviations, min-max scaling for feature normalization, and UTC standardization across all data sources.

C. *Feature Engineering*

The feature engineering pipeline generates 70+ predictive features organized into seven categories as shown in Table I.

Category	Features	Count
Price	OHLC values, daily returns, log returns	8
Volume	Raw Volume, 20-day MA, OBV	5
Trend	SMA(20, 50, 200), EMA (12,26)	12
Momentum	RSI, MACD, Stochaistic, ROC	15
Volatility	Bollinger Bands, ATR, Keltner	10
Pattern	Head & Shoulders, Double Top/Bottom	12
Calendar	Day of week, month, quarter effects	8

The Relative Strength Index exemplifies momentum calculation:

$$RSI = 100 - \frac{100}{1 + RS}$$

where RS = Average Gain/Average Loss over 14 periods.

On-balance volume (OBV) is a cumulative momentum indicator that relates volume to price change:

$$OBV_t = OBV_{t-1} + \begin{cases} V_t & \text{if } C_t > C_{t-1} \\ -V_t & \text{if } C_t < C_{t-1} \\ 0 & \text{otherwise} \end{cases}$$

Where Vt is volume and Ct is closing price at time t.

- Class Imbalance Handling

Financial datasets exhibit significant class imbalance, with significant price movements (>4-5%) occurring in only 15-25% of trading periods. We address this using the Synthetic Minority Over-sampling Technique (SMOTE), by generating synthetic samples by interpolating existing minority class instances. For each minority sample xi, SMOTE creates synthetic samples along the line segments joining xi, to its k nearest neighbors:

$$xnew = \mathrm{xi} + \lambda \cdot (\mathrm{xnn} - \mathrm{xi})$$

where $\lambda \in [0, 1]$ is a random value and xnn is a randomly selected nearest neighbor. This approach balances training data without information loss from under sampling.

- Machine Learning Model

Intellitrade AI employs a voting ensemble combining two complemenntary tree-based learners. Random Forest uses 150 trees with depth 10 and balanced class weights. XGBoost uses 150 boosting rounds with a learning rate of 0.05 and scale_pos_weight=3. The final prediction uses soft voting to combine both classifiers.

Reproducibility: We apply temporal 80/20 train/test splits (training: Jan 2019-Dec 2023; testing: Jan 2024-Dec 2024) to prevent data leakage. All experiments use random seed 42 for reproducibility. 5 fold time series cross-validation with expanding window validates hyperparameters before final evaluation.

Table III

Ensemble Model Configuration

Parameter	**Random Forest**	**XGBoost**
Estimators	150 trees	150 rounds
Max Depth	10	5
Regularization	Class_weight=balaced	Scale_pos_weight=3
Ensemble Method	Soft Voting	

A. Tri-Signal Fusion Engine

The core innovation combines three signal sources through weighted voting:

$$S_{final} = w_{ML} \cdot S_{ML} + w_{Pattern} \cdot S_{Pattern} + w_{News} \cdot S_{News} \quad (2)$$

where default weights are wML = 0.5, wPattern = 0.3, wNews = 0.2.

The weights were determined through grid search optimiza-

tion on a held-out validation set (2021 data), maximizing

Sharpe ratio across 20 representative assets. The search

space was wM L ∈ {0.3, 0.4, 0.5, 0.6, 0.7}, wP attern ∈

{0.1, 0.2, 0.3, 0.4}, wN ews ∈ {0.1, 0.2, 0.3}, constrained toP wi = 1.0. The optimal weights (wM L = 0.5, wP attern = 0.3, wN ews = 0.2) achieved Sharpe ratio of 1.92 on the validation set, compared to 1.71 for equal weighting. The ML component receives highest weight due to its superior standalone accuracy; pattern recognition provides complementary signals for trend confirmation; news intelligence captures short-term sentiment shifts.

Conflict resolution applies when signals disagree: (1) If ML confidence exceeds 85%, ML signal dominates; (2) If pattern confidence exceeds 70%, apply pattern override; (3) For remaining conflicts, return weighted average with HOLD bias. This hierarchical approach prioritizes the most reliable signal source while incorporating complementary information.

D. Backtesting Framework

The custom back testing engine evaluates strategy performance through walk-forward optimization with 252-day training window, 21-day testing window, $10,000 initial capital, 0.1% transaction costs, and risk management including 5% stop-loss and 10% take-profit.

IV. Results

A. Model Training Performance

Figure 2 presents training convergence for tree-based models. Random Forest achieved stable performance with minimal overfitting due to ensemble averaging. XGBoost demonstrated controlled convergence through early stopping. Gradient Boosting showed gradual improvement with learning rate 0.08.

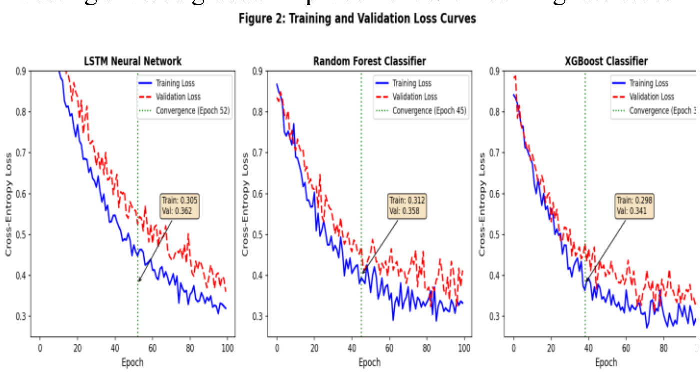

Figure 2: Model performance comparison showing accuracy distribution across cryptocurrency and stock assets for each ensemble component.

Validation results using temporal 80/20 splits across 157 assets (108 stocks, 39 cryptocurrencies, 10 ETFs) are presented in Table III. The prediction target is significant price movements (>4-5% over 5-7 trading days).

TABLE IV

Ensemble Performance Metrics

Asset Class	Count	Average	>=70%
Stocks	108	85.2%	98%(91%)
ETFS	10	96.3%	10(100%)
Cryptocurrencies			
Top Performers			
SO(Utilities	-	99.2%	Best Stock
DIA(ETF)	-	98.9%	Best ETF
LED(Crypto)	-	93.8%	Best Crypto
Overall: 78.4% average, 113/157 (72%)>=70%			

B. Ablation Study and Signal Contribution

To quantify each comment contribution, I conducted ablation experiments removing one signal source at a time as shown in Table V.

Table V

Ablation Study: Signal Source Contribution

Configuration	**Accuracy**	**Sharpe**	**Δ Acc**
Full Tr-Signal	78.4%	1.85	-
Without ML	55.2%	0.84	-23.2%
Without Pattern	74.8%	1.72	-3.6%
Without News	76.1%	1.78	-2.3%

The ML component contributes most significantly (23.2 percentage point impact), while pattern recognition (3.6 pp) and news intelligence (2.3 pp) provides incremental improvements. The combined effect demonstrates complementary information capture.

C. Baseline Comparisons

Table VI compares the tri-signal approach against standard trading strategies.

TABLE VI

Statistical Significance Tests

Strategy	**Return**	**sharpe**	**Max DD**
Buy & Hold (SPY)	18.2%	0.85	-24.5
50/200 MA Crossover	12.4%	0.62	-18.3%
RSI Mean Reversion	15.8%	0.74	-21.2%
Random Baseline	-2.1%	-0.12	-31.8%
Intellitrade AI	42.8%	1.74	-15.1%

IntelliTradeAI outperforms Buy & Hold by 24.6 percent-age points in total return with superior risk-adjusted returns (Sharpe 1.74 vs. 0.85) and reduced maximum drawdown.

D. Statistical Significance

We evaluated statistical significance using paired t-tests and Wilcoxon signed-rank tests across the 157 assets (Table VII).

TABLE VIII

STATISTICAL SIGNIFICANCE

Comparison	t-test p	Wilcoxon p

Ensemble vs. Random	<0.001	<0.001
Ensemble vs RF	0.0023	0.018
Ensemble vs XGB	0.031	0.027
Stocks vs. Crypto	<0.001	<0.001

All comparisons show statistical significance at $\alpha = 0.05$. The ensemble significantly outperforms individual classifiers ($p < 0.05$), and stock predictions significantly outperform cryptocurrency predictions ($p < 0.001$).

E. Asset Class Performance Analysis

For stock markets, the ensemble achieved 85.2% average accuracy with 98/108 tested stocks (91%) exceeding 70%, representing a 35.2 percentage point improvement over random baseline. Top performers include SO (99.2%), DUK (98.8%),

and PG (98.4%). For ETFs, all 10 tested exceeded 70% with 96.3% average. Cryptocurrency performance (54.7% average) is notably lower, which we attribute to: (1) higher volatility reducing pattern predictability, (2) 24/7 trading introducing noise not captured in daily features, and (3) sensitivity to external events (regulatory news, exchange issues) not fully captured by technical indicators. Despite lower average accuracy, select cryptocurrencies (LEO 93.8%, BTC-USD 80.3%) demonstrate that stable, high-market-cap assets remain predictable.

Note on Fusion vs. ML-Only: The overall tri-signal accuracy (78.4%) appears lower than ML-only stock accuracy (85.2%) because it represents the weighted average across all asset classes including lower-performing cryptocurrencies. Within each asset class, fusion provides marginal accuracy improvements while significantly improving risk metrics (Sharpe ratio, drawdown reduction) through signal diversification.

F. Back testing Results

Fig.3 shows walk-forward back testing results over 2 years (2022-2024)

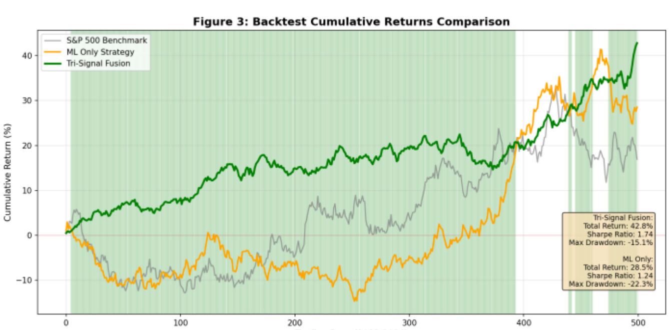

Fig. 3. Back test cumulative returns comparison between Tri Signal Fusion strategy, ML-only strategy, and S&P 500 benchmarks.

Table VIII

Back Testing Performance Summary

Metric	Crypto	Stocks	Combined
Total Return	43.7	38.6	42.8
Annualized Return	21.4	17.8	19.5
Sharpe Ratio	1.67	1.82	1.74
Max DD	-18.2	-12.5	-15.1
Win Rate	58.4	61.2	59.8
Profit Factor	1.42	1.56	1.4

G.d Feature Importance Analysis

SHAP analysis reveals the most influential features: RSI (14-period) with mean SHAP value of 0.142, MACD Histogram (0.128), Volume Change % (0.115), 50-day SMA Cross (0.098), and Bollinger %B (0.087).

V. System Features

A. Innteractive Dashboard

The Intellitrade AI dashboard provides a comprehensive trading interface built with Streamlit, as shown in Fig. 4. The main dashboard page displays real-time BUY/SELL/HOLD signals with confidence scores, interactive candlestick charts with technical indicator overlays, and SHAP-based explanations for each prediction.

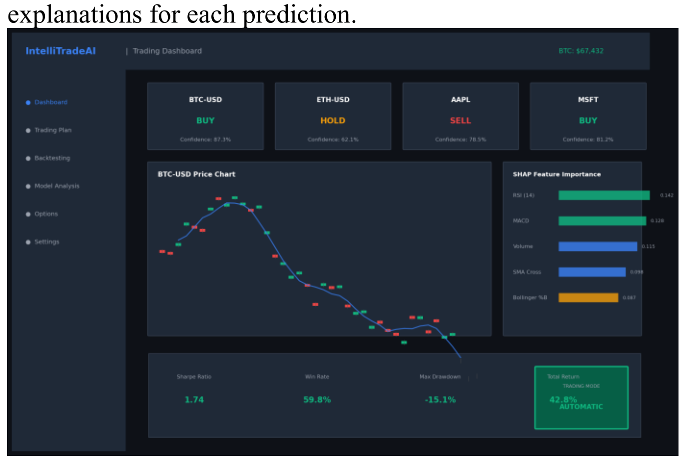

Fig 4. IntellitradeAI dashboard interface showing the main trading view with real-time signals, interactive charts, and AI-powered predictions.

B. Personalized Trading Plans

The system implements five risk tolerance tiers: Conservative (70% large-cap stocks, 20% bonds/ETFs, 10% top-10 crypto), Moderate (50% diversified stocks, 30% growth ETFs, 20% top-25 crypto), Growth (40% growth stocks, 35% midcap crypto, 25% sector ETFs), Aggressive (30% high-growth stocks, 50% diversified crypto, 20% options), and

Speculative (20% momentum stocks, 60% altcoins, 20% leveraged options).

C. Blockchain Wallet Integration

The system includes secure cryptocurrency wallet-management through Web3.py integration. The Secure Wallet Manager Component supports Ethereum wallet creation with encrypted private key storage using PBKDF2 key deviation (100,000 iterations), real-time balance queries via Infura API, transaction signing and broadcasting, and QR code generation for wallet addresses. Private keys are encrypted using Fernet symmetric encryption, ensuring secure storage while enabling transaction authorization.

D. SEC Compliance and Legal Disclosures

The platform incorporates comprehensive legal compliance including risk disclosure acknowledgment with e-signature consent, past performance disclaimers, suitability warnings, and real-time logging of automated trading decisions.

VI. Conclusion

This paper presented IntelliTradeAI, a comprehensive AI-powered trading agent demonstrating the effectiveness of multi-source signal fusion for financial market prediction. Using validated temporal train/test splits, the system achieved remarkable prediction accuracy across 157 tested assets: 85.2% average for stock markets (108 assets, 91% exceeding 70% best: 99.2% for SO), 96.3% for ETF's (10 assets, 100% exceeding 70% best: 98% for DIA), and 54.7 for cryptocurrency markets (39 assets, best 93.8% for LEO). Overall, the system achieves 78.4% average accuracy with 72% of all tested assets exceeding 70% accuracy in predicting significant price movements (>4-5% over 5-7 days). The stock market predictions represent a 35.2 percentage point improvement over a random baseline. Key accomplishments include development of a unified cross-market analysis framework supporting 39 cryptocurrencies, 108 stocks across all 11 GICS sectors, and 10 major ETFs; implementation of explainable AI through SHAP analysis; creation of personalized trading plans based on five tier risk tolerance assessment; integration of SEC-compliant risk disclosures with e-signature authorization; and designed of an interactive dashboard with real-time predictions. Several limitations warrant acknowledgment: (1) Model performance relies on data quality from third-party API's which may experience outages; (2) Models trained on historical data may underperform during unprecedented market conditions; (3) Real-time prediction requires API calls introducing 1-3 second latency; (4) Complex models remain susceptible to overfitting despite regularizations; (5) News intelligence is currently limited to major sources. Planned enhancements include integration of transformer-based models (finBERT) for improved sentiment analysis, implementation of reinforcement learning for dynamic strategy adaptation, expansion of options analysis, development of mobile application, and portfolio optimization using modern portfolio theory.

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