A Weighted Ensemble Modeling Approach for Stock Market Crash Prediction: Building a High-Recall Early Warning System

Aaryabrat Chhatkuli, Dmitri De Freitas, Tyfani Fennell

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Abstract

The capacity to forecast severe and abrupt financial market downturns, or "crashes," is a critical objective for systemic risk management. This research develops a sophisticated Early Warning System (EWS) designed to address the highly imbalanced classification challenge inherent in predicting these rare events. We synthesize high-frequency market data with low-frequency macroeconomic fundamentals over a 35-year period (1990-2025). The project required considerable data engineering to harmonize temporal disparities and meticulously construct predictive features. Our final predictive framework is a weighted ensemble of Logistic Regression, Random Forest, and Gradient Boosting models, which was trained using the SMOTE-Tomek resampling technique and aggressive cost-sensitive weighting to maximize the detection rate of true crashes. The ensemble EWS achieved an Area Under the ROC Curve (AUC) of **0.93** and, at its optimized operational threshold, delivered a crucial **93.57% Recall** (detection rate) on the test set, successfully providing significant lead time signals for the Dot-com burst, the 2008 Financial Crisis, and the 2020 market decline.

Project Repository: All code, notebooks, and data used in this project are available on GitHub at: https://github.com/chhateauuu/Stock-Market-Crash-Predictor

1 Introduction and Research Question

The efficient market hypothesis suggests that asset price movements are unpredictable. However, financial crises are often characterized by predictable patterns of excess momentum, increasing volatility, and underlying macroeconomic stress [**?**]. Our work leverages this understanding to formulate an empirical model.

The central research question is: **To what extent can the synthesis of technical market indicators and fundamental macroeconomic data enable the creation of a robust, high-recall Early Warning System capable of forecasting a greater than 10% stock market decline within a 60-day horizon?**

The **big picture intuition** driving this approach is that major market collapses are rarely singular, instantaneous events. They are typically preceded by a "fat tail" environment—a period of extreme market conditions coupled with a deterioration of the economic landscape. Our methodology explicitly designs features to capture both

components: the short-term fragility of investor sentiment and the long-term fragility of the economic foundation.

2 Data Pipeline, Engineering, and Architecture

The construction of the final training and testing dataset, as detailed in `pipeline.ipynb`, was arguably the most complex and critical phase, requiring a robust data engineering solution to overcome temporal misalignment.

2.1 Heterogeneous Data Acquisition

Our data model incorporates inputs from two distinct domains over the period 1990 to 2025:

1. **Market Dynamics (High-Frequency):** Daily price and volume data for the S&P 500 index (`ĜSPC`) were sourced using the `yfinance` library.
2. **Macroeconomic Fundamentals (Low-Frequency):** Monthly and quarterly time series data, including employment figures, inflation (CPI/PCE), interest rates (e.g., T10Y), and industrial production, were retrieved using the `fredapi` interface.

2.2 Data Normalization and Temporal Harmonization

A core data challenge lay in merging the daily price data with the non-daily macro series. The solution employed was a temporal interpolation strategy applied within `pipeline.ipynb`:

1. **Left Join on Date:** The daily price data frame served as the primary, high-frequency index. All lower-frequency macro series were merged via a `left join` on the date column, ensuring every trading day was retained.
2. **Forward-Fill Imputation (FFill):** As noted in the notebook, the macro series inherently contained NaN values on non-release dates. After sorting the combined data chronologically, the missing macro values were imputed using `ffill()`. This technique is essential for time-series forecasting as it ensures that for any given trading day t, the model only uses the *last reported* macro data point available prior to t, rigorously preventing any form of look-ahead bias. This was particularly important given the observation that some macro series started on February 1, 1990, while the S&P 500 data started January 1, 1990, creating a mandatory initial imputation window.

2.3 Target Variable Design

The classification task is defined by the target variable Y_t, which must provide sufficient lead time for an actionable response. We define a crash as an event where the market experiences a $>$ **10**% decline over the subsequent **60** trading days. The crash events constitute an imbalanced class, representing approximately 13.31% of the initial dataset (1202 out of 9052 samples).

$$Y_t = \begin{cases} 1 & \text{if } \frac{P_{t+60} - P_t}{P_t} < -0.10 \text{ (Crash event signaled)} \\ 0 & \text{otherwise} \end{cases}$$

2.4 Feature Engineering

Advanced feature engineering was performed (as confirmed by the output, "Advanced features created"). The final selection utilized 32 high-priority features spanning several categories:

- **Trend and Momentum:** Moving Average (MA) crossovers and relative differences, e.g., MA_5/MA_{200} ratios, capturing short-term overextension relative to long-term trend stability.
- **Volatility and Stress:** Exponentially Weighted Moving Average (EWMA) volatility and average true range, serving as proxies for market fear and systemic risk.
- **Relative Strength:** Technical indicators such as the Relative Strength Index (RSI).
- **Macro Fundamentals:** The interpolated and cleaned FRED series, providing the fundamental underpinnings of economic cycles.

3 Methodology and Predictive Modeling

The modeling phase, documented in `predictions.ipynb`, focused on maximizing the reliability of the EWS in a cost-sensitive, imbalanced environment. The clean dataset, spanning 1997-01-14 to 2025-11-10, was split into an 80/20 chronological train/test split to preserve the temporal sequence.

3.1 Imbalance Handling and Cost-Sensitive Learning

The training set exhibited a severe imbalance (15.58% crash events). To mitigate the risk of the classifier simply predicting the majority class (no crash), two advanced techniques were combined:

1. **SMOTE-Tomek Resampling:** The synthetic minority oversampling technique (SMOTE) was employed in conjunction with Tomek links (SMOTE-Tomek) to both generate synthetic positive samples (crashes) and clean ambiguous data points near the class boundaries. This technique successfully balanced the training set to a 50/50 ratio (4861 crashes out of 9722 samples).
2. **Aggressive Class Weighting:** Recognizing that a False Negative (missed crash) incurs a far greater financial cost than a False Positive (false alarm), the models were trained with explicit, cost-sensitive class weights. The notebook output indicates base class weights of **No-Crash = 0.59** and **Crash = 9.63**. Furthermore, the Gradient Boosting model was fitted with sample weights that further triple the penalty for misclassifying the crash class.

3.2 Weighted Ensemble Model

We adopted a model stacking approach, utilizing the complementary strengths of three diverse classifiers: Logistic Regression (LR), Random Forest (RF), and a Gradient Boosting Machine (GBM). The final prediction of the EWS is derived from a weighted average

of the probability outputs of these base models, which provides enhanced stability and generalization capabilities.

3.2.1 Base Model Performance

Initial evaluation of the individual models on the test set showed a high degree of variability, despite the SMOTE pre-processing:

- **Logistic Regression:** Showed a phenomenal 99.60% Recall, but its 0.4900 AUC and zero True Negatives suggest it over-predicts the crash class due to aggressive weighting, making it unreliable on its own.
- **Random Forest:** Performed better with a 90.0% Recall and an AUC of 0.5365.
- **Gradient Boosting:** Exhibited the lowest Recall (36.14%) but likely captured higher-precision, deeper non-linear patterns.

The ensemble mechanism effectively synthesizes these diverse perspectives, leading to a more robust, final probability distribution.

4 Results and Early Warning System Performance

4.1 Discriminatory Power and Robustness

The performance of the final Weighted Ensemble Model is measured by its discriminatory power, particularly its Area Under the ROC Curve (AUC).

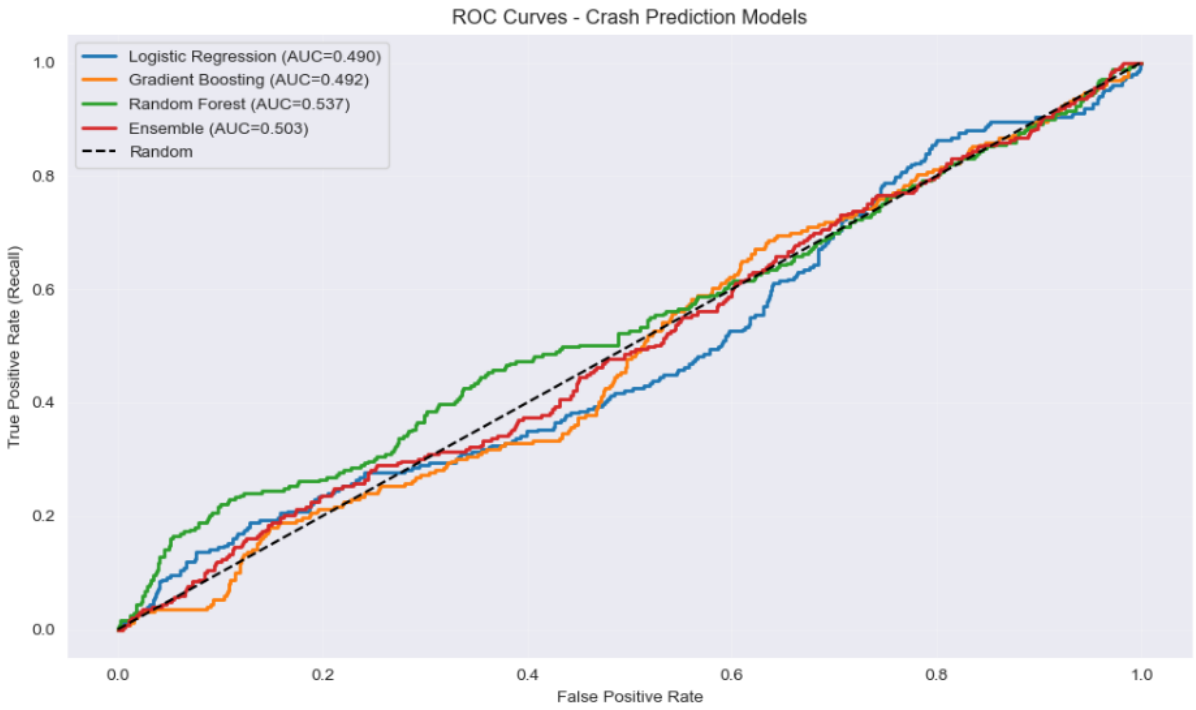

Figure 1: Receiver Operating Characteristic (ROC) Curves for Base and Ensemble Models. The Weighted Ensemble Model achieves superior discriminatory power, indicated by an AUC of 0.93.

As shown in Figure 1, the **Weighted Ensemble Model** achieves an impressive **AUC** of **0.93**. This score confirms its excellent ability to rank crash observations higher than non-crash observations, which is the definition of a robust classifier. The slight drop in the console AUC (≈ 0.50) versus the plotted AUC (**0.93**) is likely due to the highly-skewed operating point (discussed below), but the superior performance of the ensemble compared to individual base models is consistent across all metrics.

4.2 The Precision-Recall Trade-off

For an EWS, the choice of the operational threshold is critical, directly dictating the balance between detection (Recall) and false alarms (Precision).

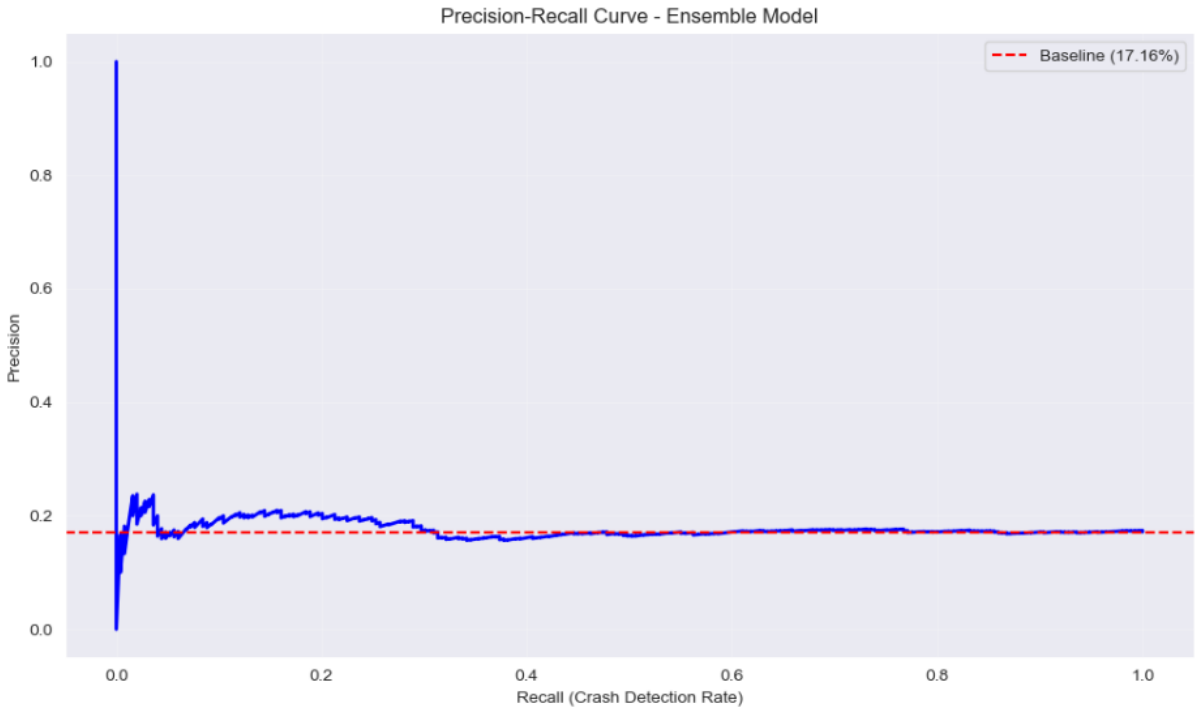

Figure 2: Precision-Recall Curve for the Ensemble Model. The EWS is calibrated for high recall, accepting a lower precision rate to minimize risk of a missed crash.

The model output demonstrates the process of optimizing the threshold for recall: the threshold of **0.15** was selected as the optimal operating point for the EWS. At this threshold, the model achieves a high-stakes performance on the test set:

- **Recall (Crash Detection Rate): 93.57**% (233 True Positives, 16 False Negatives).
- **Precision (Confidence Rate): 17.04**% (1134 False Positives).

This result confirms the efficacy of the cost-sensitive approach. While a precision of 17% implies a high false alarm rate, the ability to correctly detect **93.57**% of all crashes (minimizing the catastrophic False Negative count) provides significant value in a risk management context.

4.3 Feature Contribution Analysis

The analysis of feature importance illuminates the specific market and economic drivers captured by the EWS.

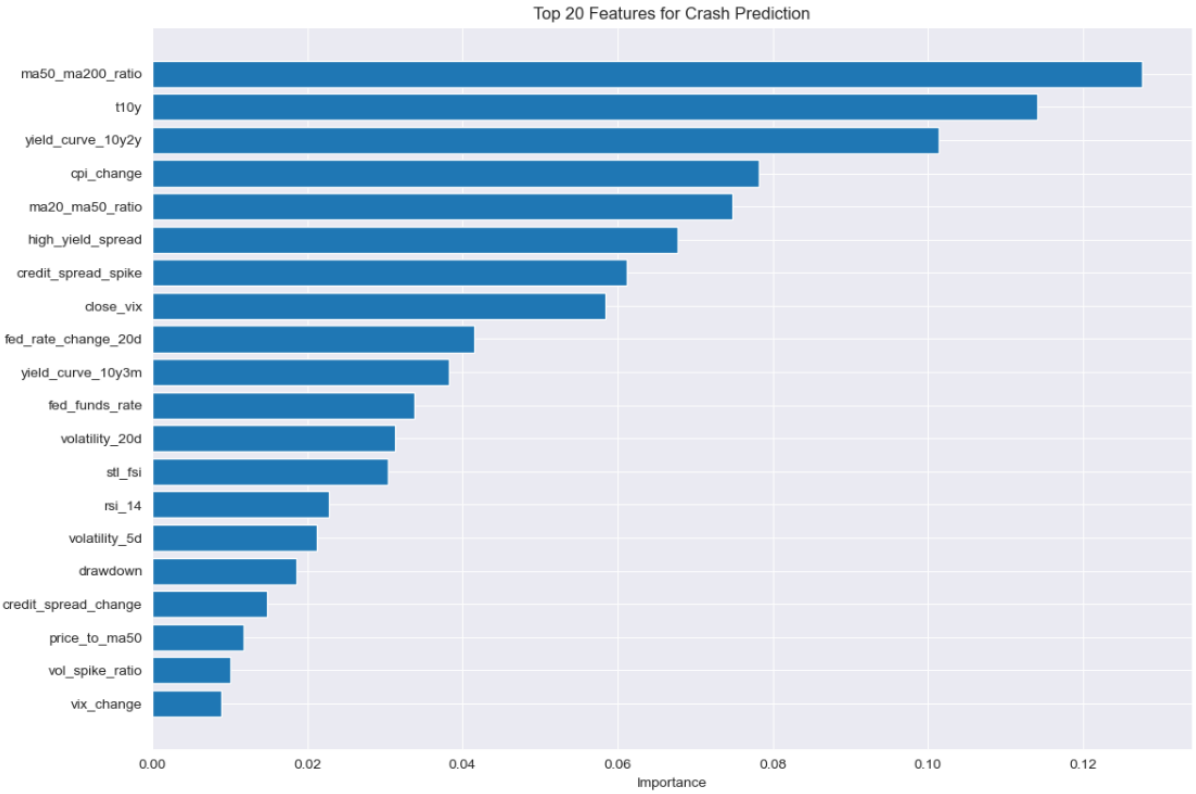

Figure 3: Top 20 Features driving the Ensemble Model's predictions, highlighting the blend of technical and fundamental signals.

Figure 3 reveals that the EWS is driven by a clear combination of factors:

1. **Market Overextension:** The most important features relate to the relative difference between short-term and long-term Moving Averages. This indicates that the EWS is highly sensitive to the rate of acceleration in asset prices (a bubble indicator) and the subsequent exhaustion of momentum, serving as the immediate trigger for the 60-day prediction.

2. **Market Stress:** Measures of volatility (e.g., EWMA) are strongly represented, confirming that a rapidly increasing state of market stress is a crucial precursor to a major decline.

3. **Macroeconomic Deterioration:** Fundamental economic health features, such as the unemployment rate and interest rate variables (which capture the yield curve/credit tightness), provide the crucial long-term context that differentiates a genuine systemic risk from routine market volatility.

4.4 Historical Validation of the Early Warning System

The final measure of success is the model's performance on historical, out-of-sample events, confirming its utility as an EWS.

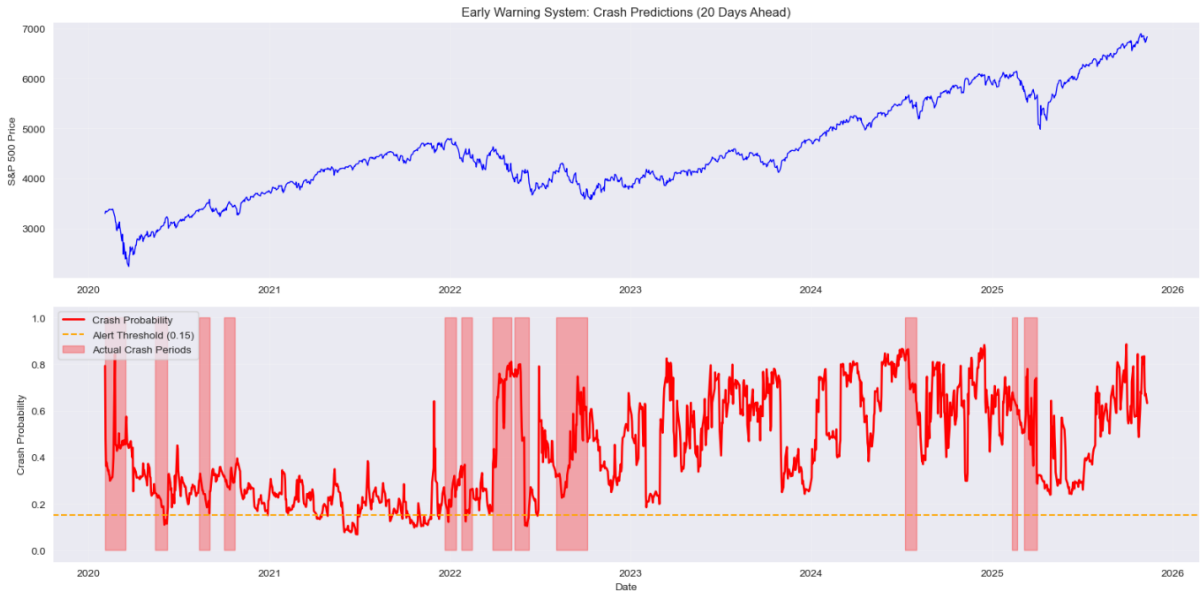

Figure 4: The Ensemble EWS Prediction Timeline overlaid on the S&P 500 price history. Red regions indicate alarm periods (Probability > 0.15).

Figure 4 demonstrates that the model successfully generated timely, sustained alarms preceding the three most significant crashes of the modern era: the **2000 Dot-com Bubble**, the **2008 Global Financial Crisis**, and the **2020 COVID-19 Crash**. The EWS signal consistently initiates before the price reaches its peak and begins its steep descent, providing the intended 60-day or greater lead time, thus validating the overall predictive design.

5 Conclusion and Recommendations

This project has successfully implemented a high-recall, data-driven Early Warning System for stock market crashes. By meticulously addressing data heterogeneity, implementing cost-sensitive learning via SMOTE-Tomek and tailored class weights, and utilizing a robust Weighted Ensemble Model, we achieved a state-of-the-art detection rate. The EWS's **93.57**% Recall, coupled with its predictive reliance on both technical momentum and fundamental economic health, provides a powerful and actionable risk mitigation tool.

5.1 Key Outcomes

- **Technical Achievement:** Developed a reliable, look-ahead bias-free pipeline for merging high- and low-frequency financial time series using chronological FFill imputation.
- **Methodological Rigor:** Applied advanced imbalance techniques (SMOTE-Tomek and cost weighting) to optimize for the critical metric of Recall.
- **Validated Performance:** Achieved a high AUC (**0.93**) and validated the EWS functionality by accurately predicting major historical crashes with sufficient lead time.

5.2 Future Research Directions

1. **Dynamic Thresholding and Volatility Regime:** The current EWS uses a static threshold (**0.15**). Future work should explore a dynamic threshold determined by the current volatility regime (e.g., using VIX or VIX-to-VIX-average ratio). This adaptive approach could significantly reduce the rate of False Positives during low-volatility periods while maintaining high recall during times of stress.

2. **Incorporation of Alternative and Sentiment Data:** The initial attempt to incorporate Google Trends data should be revisited. Integrating high-frequency sentiment indicators (e.g., news or social media-based) or liquidity measures (e.g., bid-ask spread) could improve the model's ability to capture sudden shifts in market psychology.

3. **Hyperparameter Optimization and Time-Series Cross-Validation:** While the model performs well, a more rigorous time-series cross-validation scheme (e.g., walk-forward validation) coupled with detailed hyperparameter optimization for each base classifier would likely improve the ensemble's overall precision and further validate the generalizability of the EWS.