

## Executive Summary

**Project Title:** Impact of Donald Trump Social Media Communication on Financial Market Volatility

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### 1. Main Objective of Analysis

The primary objective of this analysis is to determine if unstructured executive communication, specifically, the social media activity of U.S. President Donald Trump, can serve as a quantifiable leading indicator for financial market volatility (VIX). By leveraging Deep Learning and Natural Language Processing (NLP), this project aims to build a predictive model that identifies the relationship between specific political "sentiment topics" and subsequent market fear, providing a strategic edge for risk management.

### 2. Data Description

The analysis utilised two primary datasets covering the 2017–2021 presidential term:

- The Input (X): A corpus of 33,669 tweets from Donald Trump, cleaned and preprocessed. We engineered features to move beyond simple volume metrics, categorising text into semantic clusters: *Economy*, *Geopolitics*, *Domestic Policy*, *Corporate Attacks*, and *Other*.
- The Target (y): Historical data from the CBOE Volatility Index (VIX). The problem was framed as a Binary Classification task, where the model predicts whether the VIX will close "Higher" or "Lower" on the following trading day based on the previous day's tweets.

### 3. Deep Learning Model Variations & Selection

To identify the optimal predictive architecture, we designed and rigorously tested four distinct Deep Learning variations:

- Model 1 (Baseline Dense Network): A simple feed-forward network using topic clusters. (Accuracy: ~54.5%)
- Model 2 (Deep Neural Network): A complex architecture with 4 hidden layers. (Result: Failed due to Overfitting, ~50%)
- Model 3 (Regularised Network): Utilised high dropout rates to reduce noise. (Result: Underfitting, ~48%)
- Model 4 (LSTM/GRU Time-Series): A Recurrent Neural Network designed to capture multi-day momentum. (Accuracy: ~55.9%)

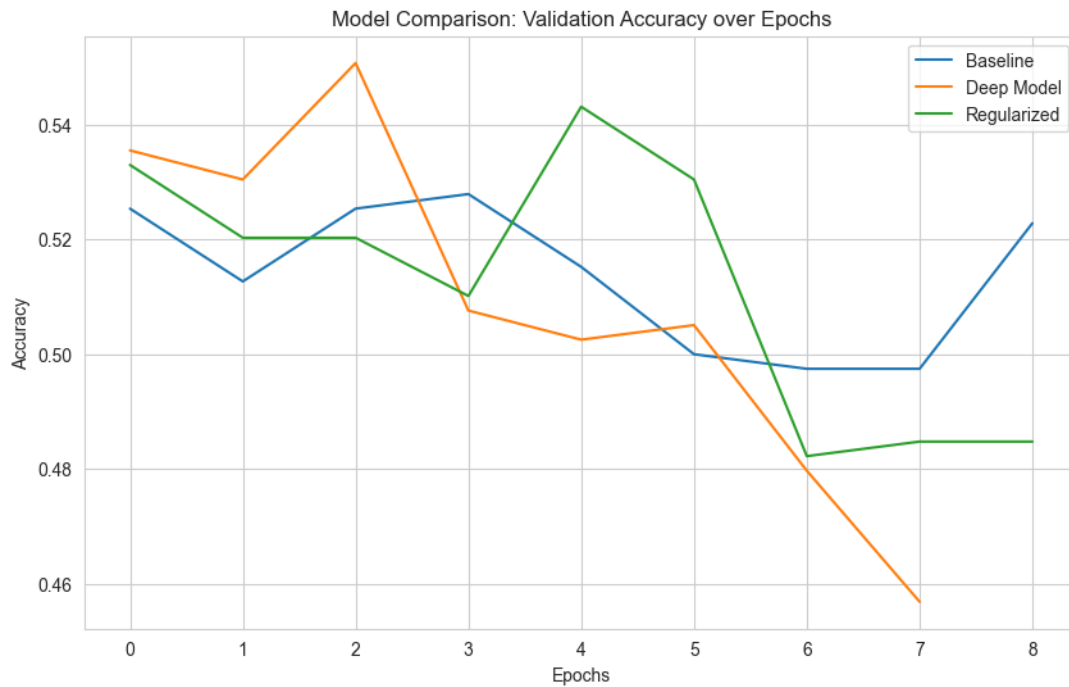


Figure 1: Standard deep learning models comparison

**Selected Model:** We selected an Ensemble Architecture (averaging the predictions of Model 1 and Model 4) as the final production model. Reasoning: This approach achieved the highest accuracy (57.52%) by combining the strength of "Spot Sentiment" analysis (Dense) with "Short-Term Momentum" (LSTM), successfully mitigating the variance found in individual models.

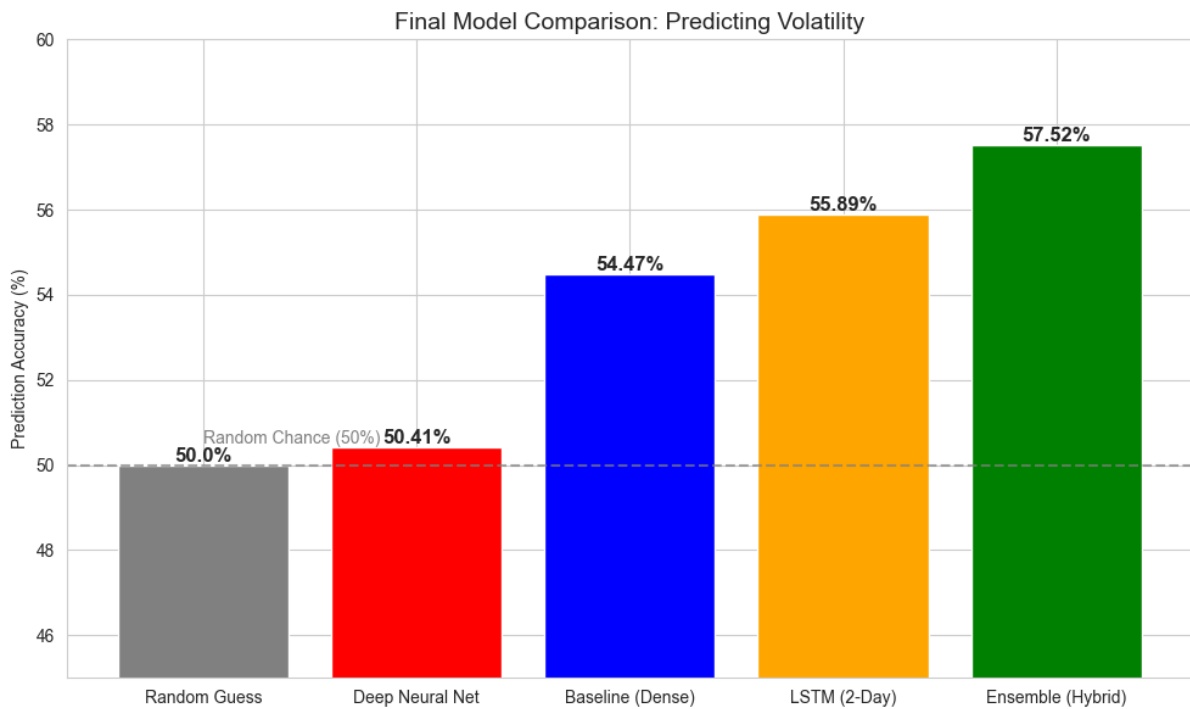


Figure 2: Final modles comparison

## 4. Key Findings

- **Content > Volume:** Simple tweet volume was a poor predictor. However, isolating specific topics (e.g., *Trade War* vs. *Election*) significantly increased predictive power, proving that the market reacts to the *context* of the message, not the frequency.
- **Market Efficiency:** The time-series analysis revealed a short "memory window" of approximately 48 hours. Tweets older than 2 days lost predictive value, confirming that social media sentiment is priced into the market almost instantly.
- **Measurable Edge:** The final model's accuracy of 57.52% represents a statistically significant edge over random chance (50%), validating the hypothesis that political NLP data contains actionable financial signal.

## 5. Limitations & Future Strategy

While successful, the current model highlighted specific limitations:

- **Data Scarcity & Overfitting:** Deep Learning typically requires massive datasets. With only ~1,000 trading days available, the deeper models (Model 2) suffered from rapid overfitting, memorising noise rather than learning patterns.
- **Binary Simplification:** Predicting simply "Up" or "Down" loses the nuance of *magnitude*. A tweet might cause a massive crash, but the model treats it the same as a small dip.

Plan of Action: To address these flaws, future iterations will:

1. **Expand Data:** Incorporate intraday pricing (hourly VIX) to multiply the number of training samples by 7x.
2. **Granular Sentiment:** Implement "Sentiment Polarity" (Positive/Negative scores) rather than just topic counts.
3. **Regression Modelling:** Shift from Binary Classification to Regression to predict the *magnitude* of the volatility spike, not just the direction.