ethereum

ETH Price Prediction Using Temporal Fusion Transformer (TFT) Model

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Algorithmic Trading

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Problem Statement

Cryptocurrency markets exhibit high volatility, making reliable price prediction a challenging but highly rewarding task

The goal is to build a predictive model that can generate actionable signals for trading (Buy, Sell, Hold)

Key challenges include data noise, overfitting, and market unpredictability.

Data Overview

- Hourly Data was collected from Alpaca's Crypto Historical Data API, specifically for BTC/USD and ETH/USD from January 2021 to December 2024
- Data was resampled into 4-hour intervals to fit the trading strategy
- **Data Features**:
  - Prices (close values) of ETH and BTC
  - Trading volume for BTC and ETH
  - Generated features: Moving averages (daily, weekly, monthly), volatility, and Relative Strength Index (RSI) for ETH.

Temporal Fusion Transformer (TFT)

- A deep learning model for time series forecasting that combines **attention mechanisms** to focus on important time steps and **recurrent layers** (GRU/LSTM) to capture temporal dependencies.
- **Attention & Recurrent Layers**:
- **Attention**: Dynamic weights allocated with important time steps to capture relevant past observations.
- **Recurrent Layers:** Use GRU layers to model temporal dependencies and trends in sequential data.

- The Temporal Fusion Transformer (TFT) approach was selected for its strength in handling sequential data and forecasting multi-step horizons.
- The TFT is ideal for time series forecasting with multiple input features and non-linear relationships.

TFT Features in My Model:

- Uses **Bitcoin price** (categorical) and (numerical) technical indicators as input features.
- A range of technical features were engineered to capture market trends and volatility:
    - Moving averages (daily, weekly, monthly) for both BTC and ETH.
    - Volatility based on 24-hour rolling standard deviation
    - 7-day rolling correlation between BTC and ETH prices.
    - ETH-specific Relative Strength Index (RSI) to capture momentum
- These features were then normalized using MinMaxScaler to prepare for model training.

Parameters

- **Hidden Size**: The hidden size of 128 allows the model to capture complex relationships in the data without overfitting.
- **Attention Heads**: 4, capture multiple patterns from the input sequence, allowing it to focus on different aspects of the time series data.
- **Dropout Rate**: prevent overfitting by randomly dropping units during training, ensuring the model generalizes better on unseen data
- **Hyperparameters**:
  - Learning Rate: **0.001-** The learning rate controls the size of weight updates during training, and tuning this parameter ensures the model converges efficiently.
  - Batch Size: **32** - balance between training speed and model convergence.
  - Epochs: **100** - simulations

<u>**ETH closing price** is the target variable</u>

Model Training and Optimization

- The TFT model was trained on the feature-engineered dataset using Mean Squared Error (MSE) loss.
- **Training Details**:
  - 100 epochs with early stopping to avoid overfitting.
  - Adam optimizer with learning rate decay
  - Batch size of 32, with a training-validation-test split (70%-15%-15%)
- Model performance was monitored using training and validation loss, with significant improvements seen in the initial epochs.

Model Performance

- Epoch loss represents the model's error after processing one full pass (epoch) of the entire training dataset.
- During training, the model tries to minimize loss to improve prediction accuracy.
- Validation loss is computed on a separate dataset that the model hasn't seen during training. It helps assess the model's ability to generalize to unseen data.
- The model seems to improve performance as it learns but still there might be overfitting/noise in data

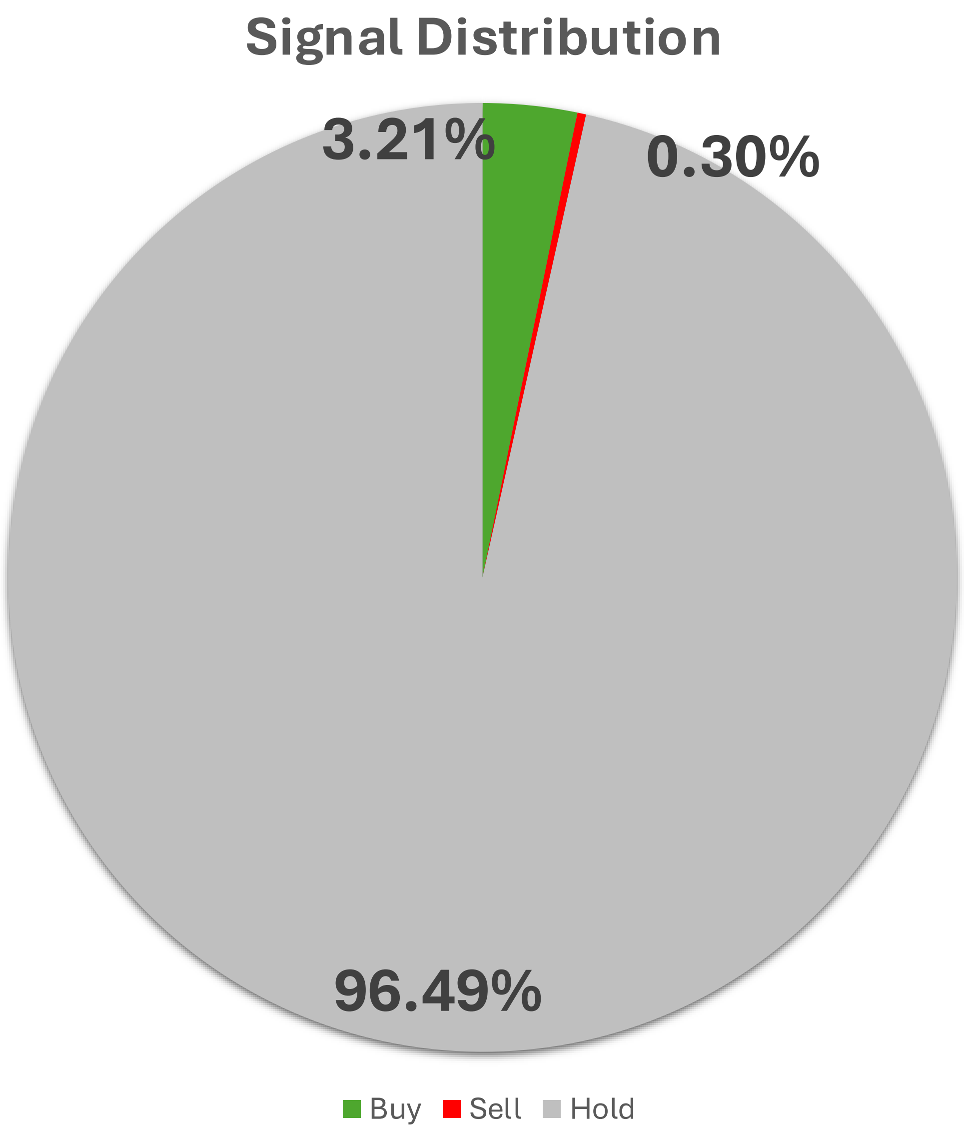
Epoch	Training Loss	Validation Loss
1/100	1892.0983	1982.1041
11/100	1633.0344	1876.0083
21/100	1521.6844	1822.0009
31/100	1422.1814	1765.0003
41/100	1301.0366	1425.0002
51/100	1299.0081	1232.0231
61/100	1197.0033	1195.0201
71/100	1185.002	1091.0011
81/100	1002.0018	1051.0123
91/100	985.0014	1010.1231
100/100	896.0014	987.1231

Back testing Strategy

- **Signal Generation**:
  - Buy signal is generated when the predicted ETH price increases by more than **1%** from the previous 4-hour period
  - Sell signal is triggered when the predicted ETH price decreases by more than **2**% from the previous 4-hour period
  - In other conditions, the model triggers a Hold signal.
- **Portfolio Management**:
  - The initial portfolio value was set at $10,000.
  - The strategy allows for the purchase of up to 75% of the portfolio's value in ETH when a Buy signal is triggered.
  - The model sells up to 20% of the portfolio value when a Sell signal is triggered.
- **Back test Timeline**:
- Model trained and validated on data from 2021-2023.
- Tested for 2024 (until Dec 2,2024)

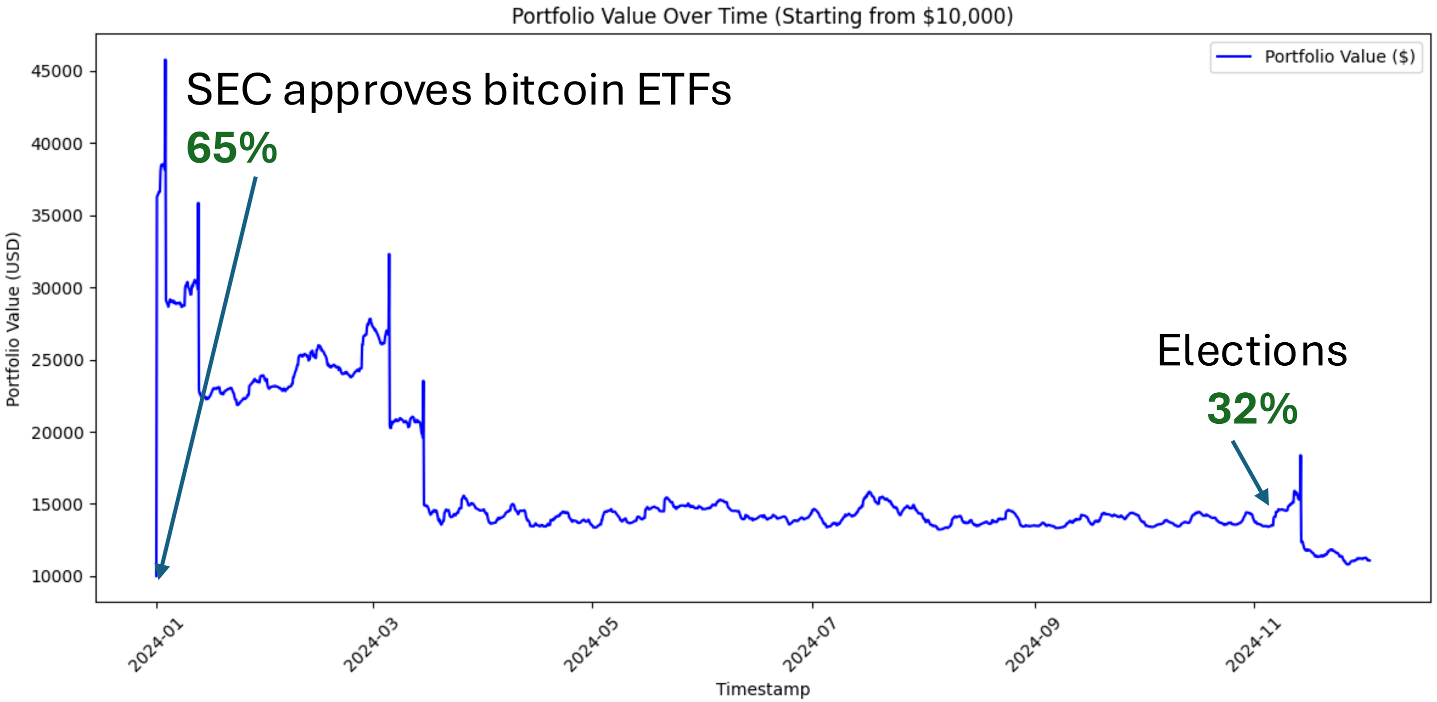
Execution of Trades

- Over the course of 2024, the model generated a total of 2023 signals, with the following distribution:
- **Buy Signals**: 65 (1% delta)
- **Sell Signals**: 5 (2% delta)
- **Hold Signals**: 1953
- The vast majority of the signals were **Hold** (96.5%), reflecting a conservative approach by the model."



Final Portfolio Evaluation

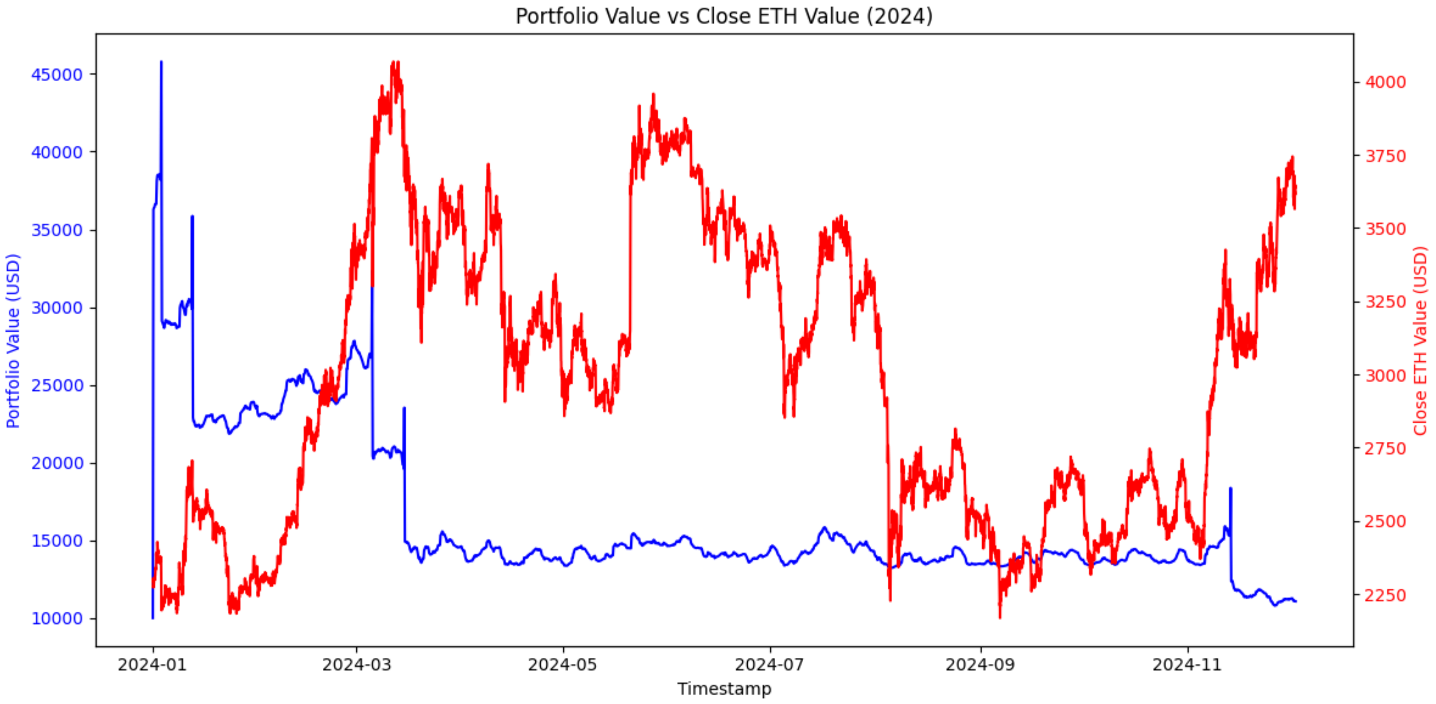
- Final Portfolio Value (as of Dec 2, 2024): $11,071.54
- Total Profit from Buy Signals: $136.80
- Total Loss from Sell Signals: -$11.06
- Overall Cumulative PnL: Positive, but with **high volatility**



Risk Metrics

- **Sharpe Ratio**: 0.0158
- **Maximum Drawdown**: -76.43%

- A relatively low Sharpe ratio indicates that the strategy generated only a modest return for risk taken
- High drawdown indicates a risk of significant losses, especially in market downturns.



Key Takeaways

- The Temporal Fusion Transformer model demonstrated promising results in ETH price prediction and trading signal generation.
- The back test yielded a positive portfolio return, though risk management (e.g., drawdowns) needs improvement.
- Signal distribution heavily favored Hold signals, with Buy and Sell signals accounting for a small portion of decisions.
- The model’s performance in volatile conditions indicates potential for future refinement.

Ideas to Improve Model

- **Larger Dataset:** TFT models require a large dataset to process accurate models with apt results. Alpaca API is limited to crypto data since 2021.
- **Use a powerful computer**: Running TFT models require great computing power generated by GPU’s (Nvidia)
- **Additional Features**: Integrate macroeconomic indicators, sentiment analysis, and cross-cryptocurrency data to improve predictive power.
- **Risk Management**: Implement stop-loss orders, dynamic position sizing, and portfolio diversification to minimize drawdowns.
- **Model Enhancement**: Tune hyperparameters, apply regularization techniques, and test the model in different market conditions (bull, bear, and high-volatility scenarios).

Thank you

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