Methodology for Predicting Future Votable Supply (FVS)

--By Chain_L and Team

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Executive Summary

The Future Votable Supply (FVS) prediction model for Optimism leverages a Long Short-Term Memory (LSTM) neural network to project future governance-ready supply based on historical data patterns and known future circulating supply. The model integrates historical OP token price, votable supply metrics, and projected circulating supply to deliver reliable, data-driven predictions.

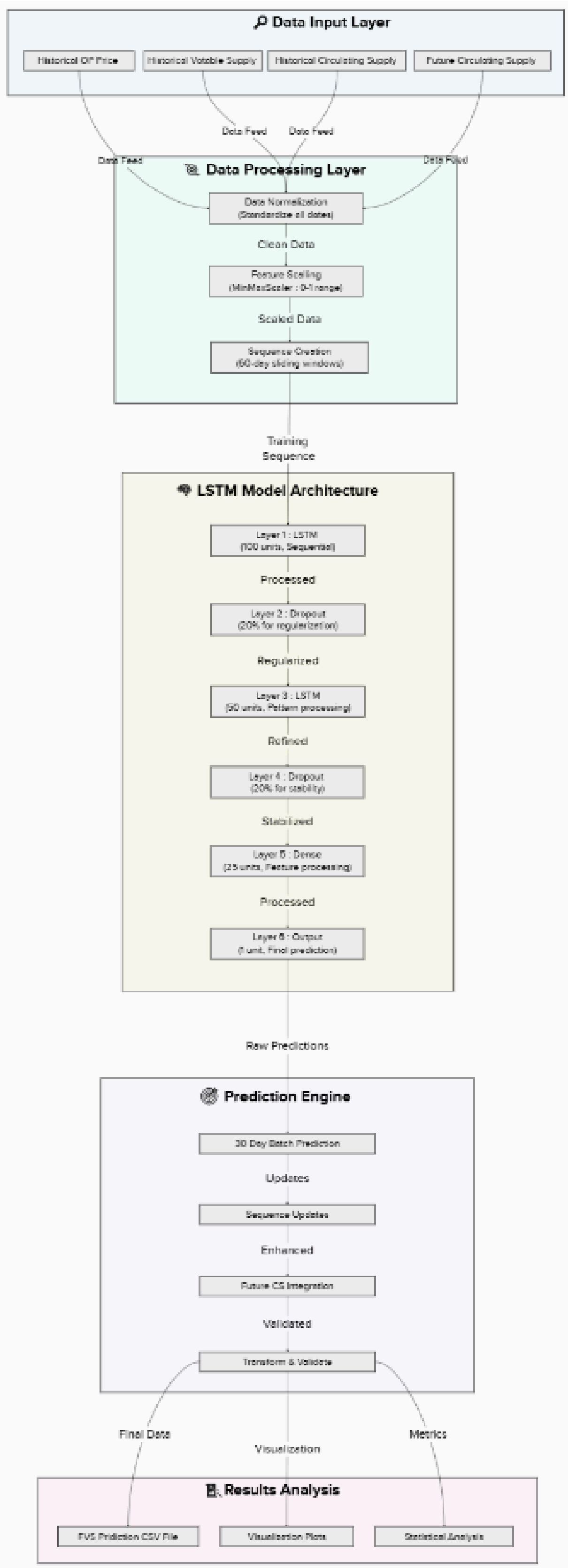
1. Approach Overview

The model follows a systematic, step-by-step methodology that includes:

- **Data Input:** Historical and future supply metrics, OP token price trends.
- **Learning Process:** Pattern identification through temporal analysis using historical data.
- **Prediction Method:** Batch-wise 30-day predictions utilizing a rolling window mechanism and dynamic circulating supply integration.
- **Model Update:** Continuous learning via adaptive updates during the prediction process.

2. Technical Implementation Details

Our implementation uses a sophisticated LSTM neural network architecture:



3. LSTM Neural Network Architecture

3.1 LSTM Neural Network Architecture

3.1.1 Architectural Components

- **Input Layer (LSTM - 100 Units):**
  - Processes sequential data patterns.
  - Retains long-term dependencies to track historical patterns.
  - Essential for identifying governance trends.
- **First Dropout Layer (20%):**
  - Reduces overfitting.
  - Ensures better generalization across unseen data.
- **Second LSTM Layer (50 Units):**
  - Refines pattern recognition from the initial layer.
  - Extracts high-level temporal features.
- **Second Dropout Layer (20%):**
  - Adds further regularization.
  - Mitigates noise in training data.
- **Dense Processing Layer (25 Units):**
  - Combines extracted features.
  - Prepares data for prediction.
- **Output Layer (Single Unit):**
  - Provides the final votable supply prediction.
  - Utilizes a linear activation function for precise output.

3.2 Key Technical Parameters

3.2.1 Computational Configuration

- **Sequence Length:** 60 days
  - Captures medium-term trends in the ecosystem.
- **Batch Size:** 30 days
  - Aligns with the governance cycle and ensures frequent updates.
- **Training Epochs:** 50 per batch
  - Facilitates robust learning without overfitting.

3.3 Data Processing Pipeline

3.3.1 Preparation Stage

- **Data Normalization:**
  - Standardizes timestamp formats and data scales.
- **Feature Scaling:**
  - Uses MinMaxScaler to convert data to a 0-1 range.
- **Sequence Generation:**
  - Generates overlapping windows for continuous learning.

3.3.2 Prediction Process

- **Rolling Window Update:**
  - Applies incremental learning from the most recent 60 days.
- **Dynamic Integration:**
  - Incorporates predicted future circulating supply into forecasts.

3.4 Training Strategy

- **Sequential Batch Training:**
  - Periodic retraining ensures adaptability to new trends.
- **Adaptive Learning Mechanisms:**
  - Adjusts to variations in governance metrics.

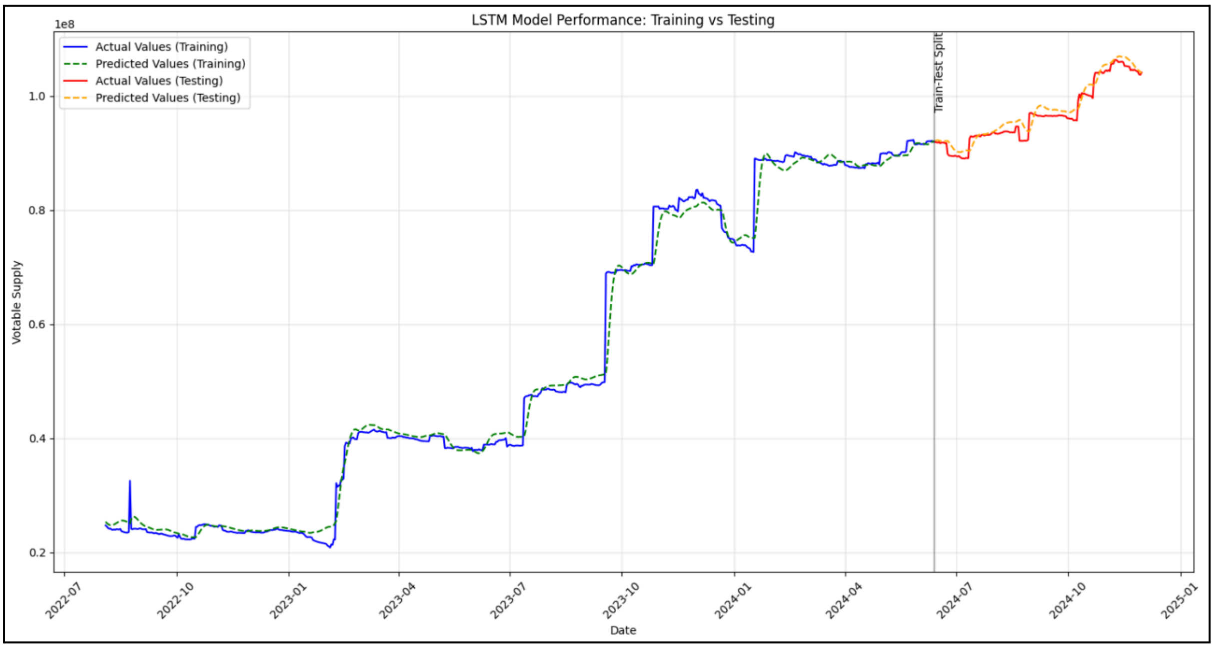
3.5 Validation and Output Mechanisms

- **Visual Trend Verification:**
  - Cross-checks predictions with historical patterns.
- **CSV Storage:**
  - Stores predictions for external analysis.
- **Statistical Analysis:**
  - Evaluates model performance using metrics like MAE and RMSE.

3.6 Model Performance and Visualization

To assess the accuracy and reliability of the LSTM model, two key performance graphs are included:

1. **LSTM Model Performance: Training vs Testing**



2. **Votable Supply: Historical and Predicted**