DIGITAL CURRENCY FORECASTING

1. Factors Influencing Model Choice:

Nature of Data: The dataset comprises time-series data of digital currency prices, which exhibit temporal dependencies and nonlinear patterns. Hence, a model capable of capturing sequential information and complex relationships over time is required.

Complexity of Patterns: The presence of multiple features such as opening price, high price, low price, closing price, and trading volume suggests that the underlying patterns may be multifaceted. Therefore, a model with sufficient complexity to capture these nuances is necessary.

Performance Metrics: The choice of model is influenced by the evaluation metrics used to assess its performance. In this case, mean squared error (MSE) and mean absolute error (MAE) are commonly used to gauge prediction accuracy, guiding the selection of a suitable model architecture.

2. Model Selection Rationale:

LSTM (Long Short-Term Memory): LSTMs are well-suited for sequential data modeling, making them an ideal choice for time-series forecasting tasks. Their ability to retain information over long periods and selectively update memory cells enables them to capture temporal dependencies effectively.

Sequential Model Architecture: The sequential nature of the data and the requirement to capture temporal relationships justify the use of a Sequential model architecture in Keras, which allows for easy stacking of layers.

Dense Layers: Dense layers are employed to introduce nonlinearity into the model and facilitate learning of complex patterns present in the data.

3. Main Challenges Encountered:

Data Preprocessing: Cleaning and preprocessing the dataset to ensure consistency and compatibility with the chosen model architecture posed initial challenges, especially with handling missing values and standardizing features.

Hyperparameter Tuning: Optimizing hyperparameters such as the number of LSTM units, batch size, and number of epochs required iterative experimentation to achieve optimal model performance.

4. Key Takeaways from Results and Analysis:

Single Feature LSTM

Model Training: The LSTM model is trained over 100 epochs, with progress reported in terms of loss (mean squared error) and mean absolute error for both training and validation sets.

Key Takeaways:

The model demonstrates decreasing loss and mean absolute error over epochs, indicating improvement in performance.

Mean squared error and mean absolute error values are relatively low, suggesting that the model is learning the underlying patterns in the data effectively.

RMSE Calculation:

After training, the model's predictions are evaluated using the Root Mean Square Error (RMSE) metric to assess the accuracy of the predictions.

The **RMSE value is calculated to be 18.12**, indicating the average magnitude of the errors between the predicted digital currency prices and the actual prices.

Analysis of Predictions:

The comparison reveals that some predictions closely match the actual values, while others may exhibit deviations.

5. Insights and Recommendations:

Decision Support: The trained models can serve as decision support tools for investors and traders, aiding in the formulation of trading strategies and risk management.

Market Analysis: Analysis of model predictions and examination of feature importance can provide valuable insights into market dynamics and factors influencing digital currency prices.

6. Alternative Models and Improvements:

Ensemble Methods: Ensemble methods such as Random Forests or Gradient Boosting Machines could be explored as alternative models to LSTM, offering robustness and improved performance.

Feature Engineering: Further exploration of feature engineering techniques, including the creation of lagged variables or additional technical indicators, may enhance the predictive power of the models.

7. Future Research Directions:

Model Refinement: Continual refinement and fine-tuning of model architectures and hyperparameters to improve prediction accuracy and generalization capabilities.

Integration of External Factors: Investigating the impact of external factors such as news sentiment, macroeconomic indicators, or regulatory developments on digital currency prices and incorporating them into predictive models.