**Bitcoin Price Prediction Using Time Series Forecasting**

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**ABSTRACT:**

This study explores the application of an ensemble of neural networks to predict the highly volatile Bitcoin prices and compares the results with a Naïve forecast model that acts as baseline model. Despite utilizing advanced deep learning techniques and diverse loss functions, the ensemble model’s performance closely mirrors that of the Naïve forecast. This outcome underscores the complexities of forecasting in open-ended systems like cryptocurrency markets.

**INTRODUCTION:**

Cryptocurrencies, particularly Bitcoin, have revolutionized the financial landscape, offering decentralized and borderless transactions. However, their inherent volatility poses significant challenges for investors, traders, and analysts. Accurate price predictions are essential for informed decision-making, risk management, and portfolio optimization. This paper aims to address this challenge by employing an ensemble of neural networks, leveraging historical data to forecast future Bitcoin prices, and establishing a Naïve forecast as a baseline for performance comparison. Bitcoin prices exhibit extreme fluctuations driven by factors such as market sentiment, regulatory changes and technological advancements. Traditional forecasting methods often struggle to capture these complex dynamics, necessitating innovative approaches. We leverage ensemble learning—an ensemble of neural networks—to address the Bitcoin price prediction challenge. Ensemble methods combine the predictions of multiple models. By training diverse models with different loss functions, we aim to improve prediction accuracy.

**LITERATURE REVIEW:**

Ensemble methods have been recognized for their superior performance over single-model approaches in various financial applications. This makes sense on a logical level as averaging predictions from multiple models should make predictions more accurate. Heaton et al. (2017) demonstrated the advantages of ensemble methods especially in the risk management and portfolio diversification, while Zhang et al. (2019) effectively reduced prediction error in stock market. The concept of neural network ensembles was introduced by Hansen and Salamon (1990).

**METHODOLOGY:**

The study utilized daily Bitcoin price data from 2010-07-17 to 2024-05-03, sourced from CoinCodex using the export feature they provide. Daily price data, including opening, closing, high, low, and volume, were features in the dataset. We mostly worked with the Date and Closing Price features of the dataset. The data was preprocessed by converting dates to datetime objects, reversing the DataFrame order since that’s how CoinCodex exports the data, and extracting the ‘Close’ price as ‘Price’. The ensemble model was constructed using three different loss functions (mae, mse, mape) to train sequential models with two dense layers of 128 neurons each. The median of these models’ predictions was used to enhance confidence levels.For Naïve forecast, we created a lagged series was by shifting the ‘Price’ column by one day, creating a simple yet effective baseline forecast. Then we split data into training and testing sets, with an 80/20 ratio, to evaluate the model’s predictive capabilities on unseen data.

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For Ensemble model we create window features that convert the data into labelled data by using 7 consecutive price datapoints as features for the 8th price datapoint being the label. The windowed features are used as input variables (X), and the current day’s price as the output variable (y), transforming the problem into a supervised learning task. Each neural network in the ensemble consisted of two dense(hidden) layers with 128 neurons each, employing the he\_normal initializer to optimize weight distribution for ReLU activations. Python functions that are written use 3 loss functions mae,mse and mape to create 3 Neural networks each time. We create 15 NN models this way where we have 5 NN for each loss function which have randomly assigned weights and bias. We convert the dataset into training and testing data and then to TensorFlow dataset to use batching and prefetching for efficient and fast processing. Callbacks such as EarlyStopping and ReduceLROnPlateau are implemented to prevent overfitting and to adjust the learning rate dynamically based on the model’s performance on validation data.

**RESULTS:**

The Naïve forecast forms our baseline model to compare performance of ensemble model to. As this model works by assigning predicted value to previously known value the forecast results are fairly accurate with a sort of lag in predicted curve. So, while mean Bitcoin value is 35526$, and average prediction is off by 763$(MAE) which is very close to the actual values.

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For predictions using Ensemble model, we go with 95% confidence prediction interval by plotting a range of bitcoin amount rather than 1 value. We do this by multiplying the value predicted by 1.96 as its seen 95% values fall under 1.96 standard deviations of the mean then adding and subtracting it from the predicted value to get a upper and lower boundary value.

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**CONCLUSION:**

Comparing the loss functions we see that the ensemble model is almost as good as naïve forecast.

This suggests that deep learning models might not be able to predict forecasts for any kind of open system with reasonable accuracy. On checking prediction curve for ensemble model, it looks like a lagged actual value curve which suggests the ensemble model has overfitted.

**A screenshot of a computer

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**A graph of blue rectangular objects

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**REFERENCES:**

1.He, K., Yang, Q., Ji, L., Pan, J., & Zou, Y. (2023). Financial Time Series Forecasting with the Deep Learning Ensemble Model. Mathematics, 11(4), 10541

2.Gastinger, J., Nicolas, S., Stepić, D., Schmidt, M., & Schülke, A. (2021). A study on Ensemble Learning for Time Series Forecasting and the need for Meta-Learning. arXiv preprint arXiv:2104.114752

3.IEEE. (2010). Forecasting financial time series with ensemble learning. IEEE Conference Publication3

4. Heaton, J., Polson, N. G., & Witte, J. H. (2017). Deep learning for finance: deep portfolios. Applied Stochastic Models in Business and Industry, 33(1), 3-12. doi:10.1002/asmb.22091.

5.Zhang, L., Aggarwal, C., & Qi, G. J. (2019). Stock price prediction via discovering multi-frequency trading patterns. Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2141-2149. doi:10.1145/3097983.30981162.

6.Hansen, L. K., & Salamon, P. (1990). Neural network ensembles. IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(10), 993-1001. doi:10.1109/34.588713.