Leveraging Image Processing for Time Series Classification

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Introduction & Problem Statement

- The main goal of this project is to explore if this combination of wavelet transformations (for data clarity) and CNNs (for pattern recognition) can effectively predict stock market movements, as seen in the day-to-day changes in financial data.
- Focus on two primary features of financial data: daily closing prices and trading volume.
- Apply continuous wavelet transformations to both the log returns and the volume data, converting them into denoised, visual representations that highlight underlying trends.
- Utilize both basic and advanced CNN models to analyze the transformed images, extracting hidden patterns within the financial data.
- The CNNs aim to identify subtle patterns in the transformed data, which are indicative of potential future movements in the stock market, specifically identifying if the market will move 'Up' or 'Down'.

Design & Method

- The design is initiated by utilizing Apple Inc.'s historical stock price data spanning from 1981 through 2023.
- The data undergoes processing through Discrete Wavelet Transform (DWT) for feature extraction, which segregates the data into components: the low-frequency trends are captured as approximation coefficients, and the high-frequency elements are isolated as detail coefficients.
- Noise in the data is minimized through a denoising step that thresholds detail coefficients, ensuring only significant trends are retained for the signal reconstruction. The cleaned signal is then ready for further analysis.
- The denoised signal is used to calculate the log returns, which are a measure of the percentage change in the stock prices, providing a normalized value that is typically easier to work with in financial analyses.
- A Continuous Wavelet Transform (CWT) is applied to the log returns to create a 2D power spectrum image. This spectrum represents the strength of different patterns or trends in the data over time.
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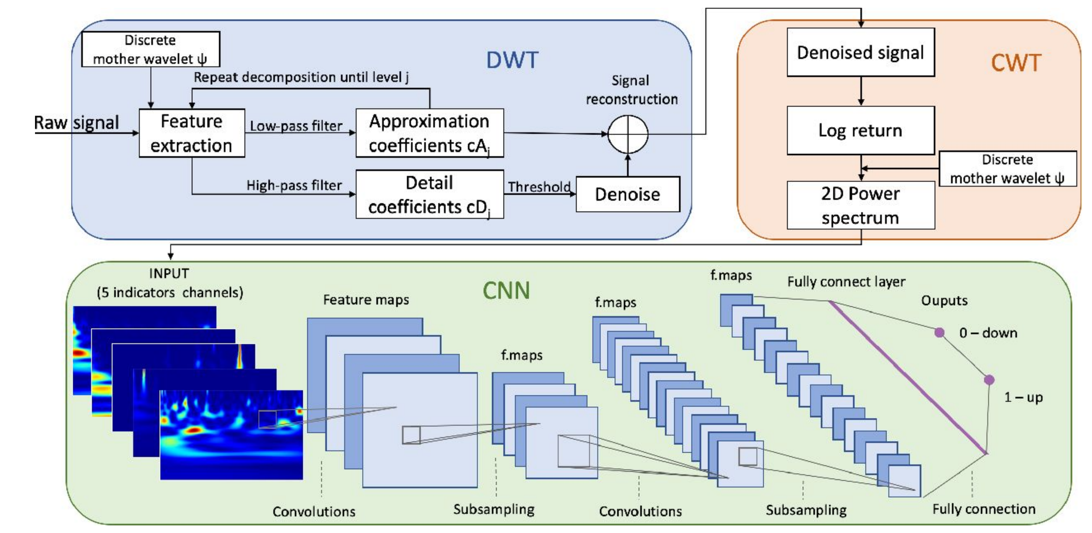
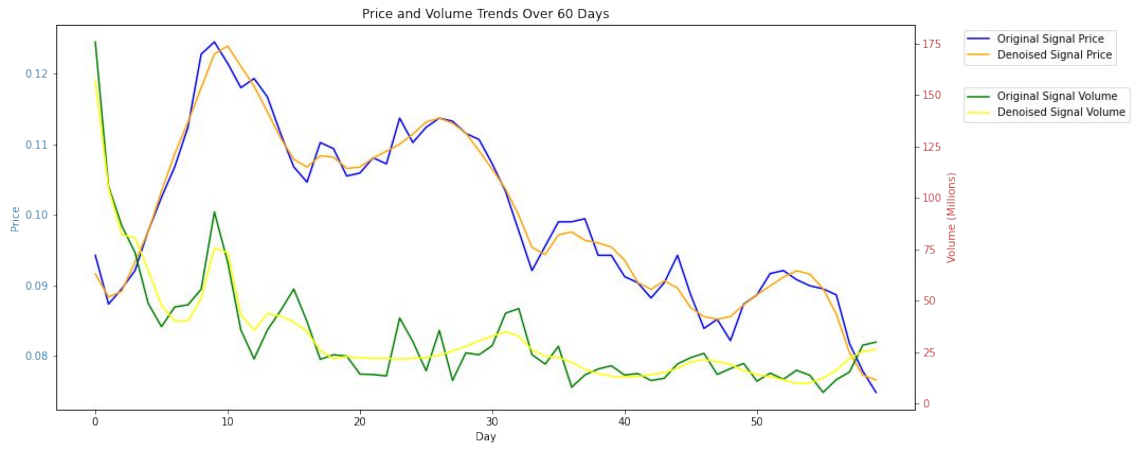
Design & Method Cont'd

Overall Design:

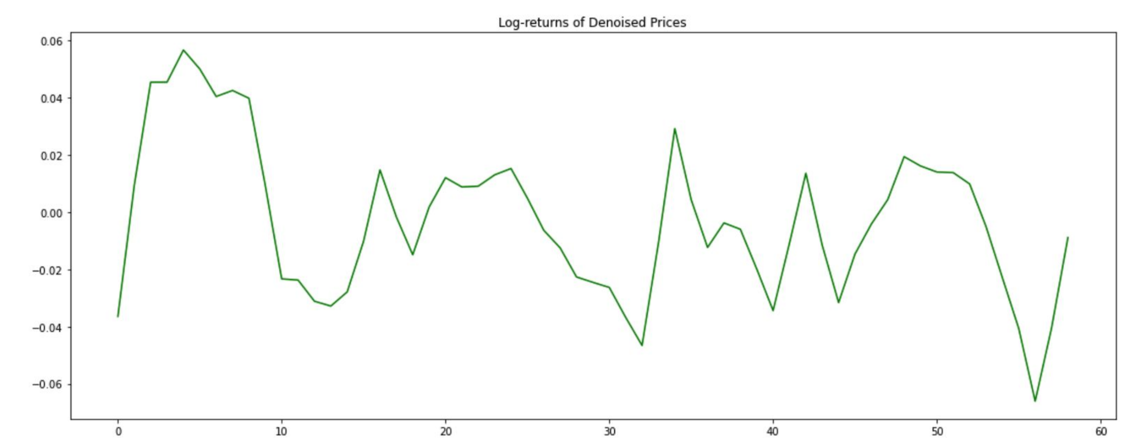


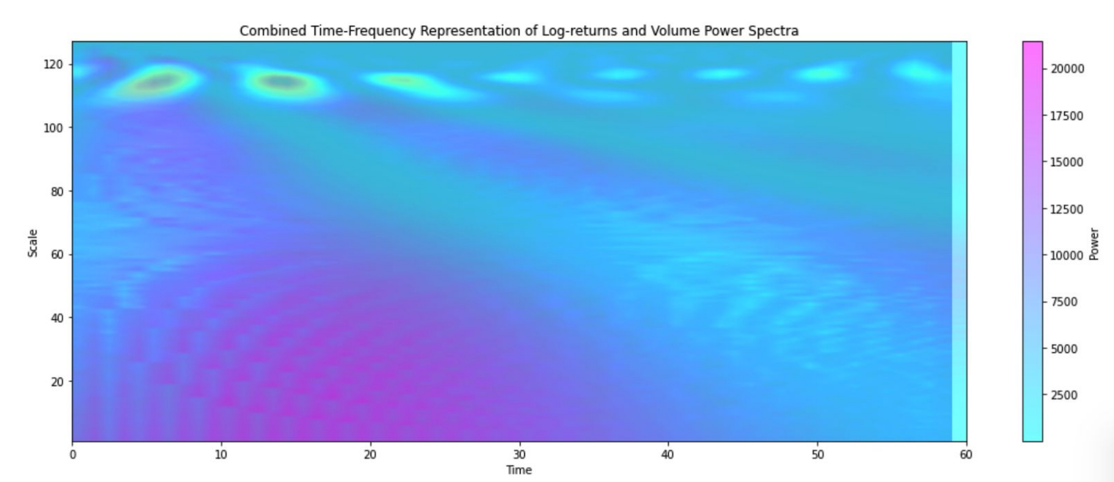
Result

closing Price and volume features after applying DWT



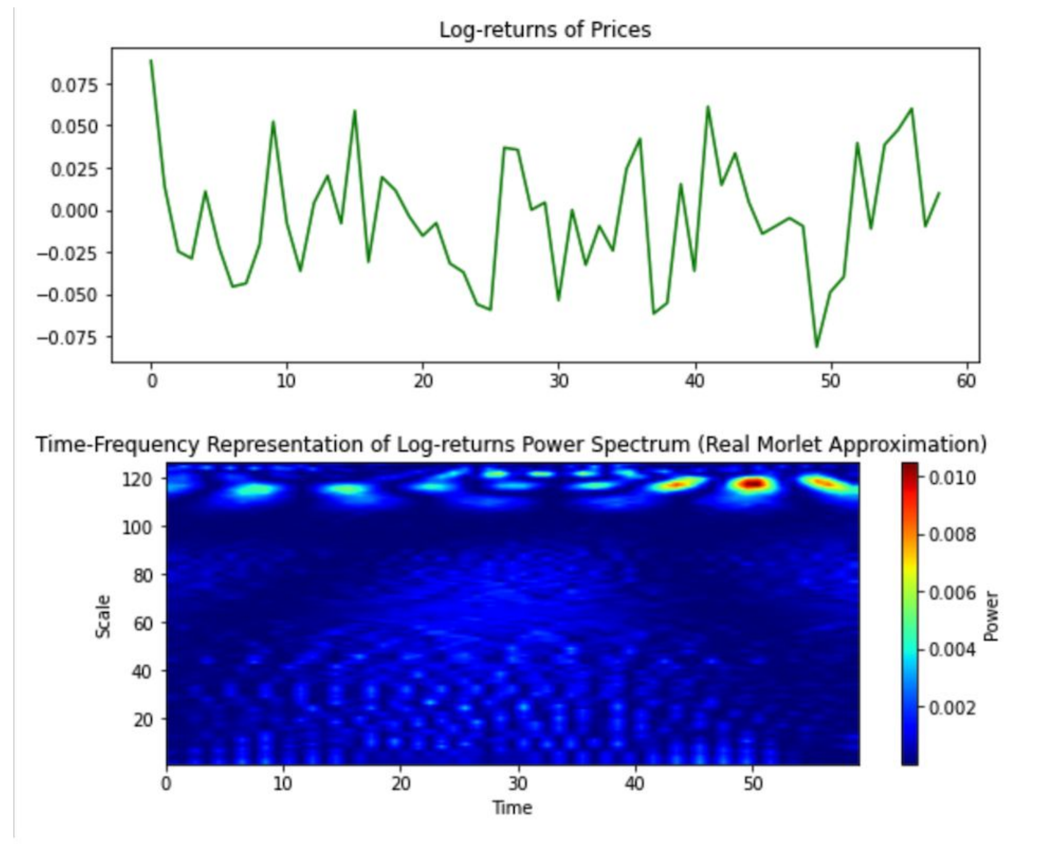
spectrogram with two features (closing price, volume) on denoised data



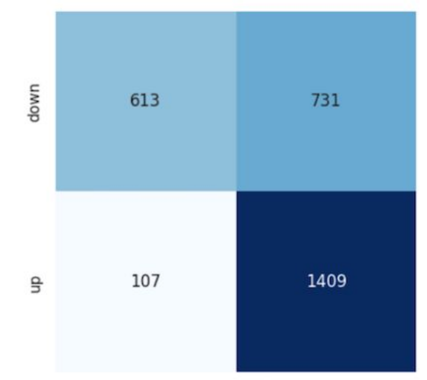


Result Cont'd

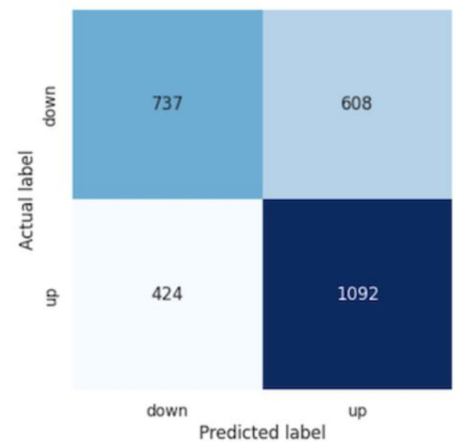
spectrogram with single features (closing price) on denoised data



- Confusion Matrix on **denoised data** with closing price as features



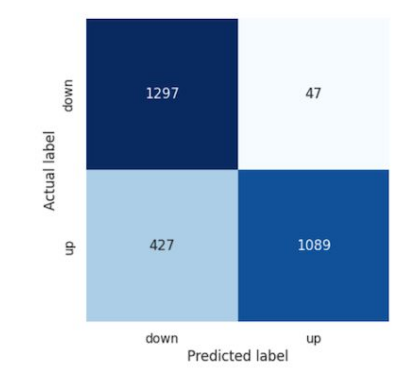
- Confusion Matrix on **denoised data** with closing price, volume as features



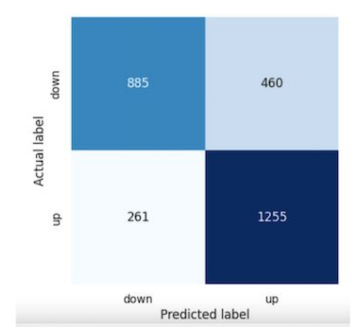
- MobileNet Pre-trained model trained on the **denoised data.**

No of features	Model	Accuracy	Precision	Recall	F1
closing price	MobileNetV2	70.7%	0.75%	0.69%	0.68%
closing price and volume	MobileNetV2	63.93%	0.64%	0.63%	0.63%

Confusion Matrix on **without denoised data** with closing price as features



Confusion Matrix on **without denoised data** with closing price, volume as features



Result Cont'd

- MobileNet Pre-trained model trained on the **without denoised data.**

No of features	Model	Accuracy	Precision	Recall	F1
closing price	MobileNetV2	83.43%	0.86%	0.84%	0.83%
closing price and volume	MobileNetV2	74.8%	0.75%	0.74%	0.74%

Discussion & Future Work

- The model using only closing price data outperformed the model using both closing price and volume in terms of accuracy, precision, recall, and F1 score when trained on non-denoised data. This suggests that the inclusion of volume as a feature in the non-denoised dataset may introduce noise or complexity that the model finds challenging to interpret effectively.
- When comparing models trained on denoised data, there's a noticeable decrease in performance across all metrics. This might indicate that the denoising process could be removing not just noise, but also potentially valuable information that the model could leverage for prediction.
- Propose the incorporation of more diverse datasets, including more granular intraday trading data or alternative financial indicators, to see if the model's predictive power can be enhanced.
- Suggest further refinement of the CNN architecture, such as experimenting with different layers, activation functions, or training techniques to improve accuracy.
- Plan for the deployment of the model in a real-world environment. This includes setting up a framework for live-testing the model's predictions against actual market changes and adjusting the model accordingly.

Reference

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- CNNs.https://arxiv.org/abs/2304.04912
- "Prediction of Financial Time Series Based on LSTM Using Wavelet", a study that proposes an ensemble method incorporating wavelet transform for addressing the nonstationary and nonlinear characteristics of financial data.https://www.hindawi.com/journals/mpe/2021/9942410/
- "Financial time series forecasting using optimized multistage wavelet", which focuses on the selection of the mother wavelet and level of decomposition in wavelet transforms for time series forecasting.
- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9030684/