

Learning to Predict Short-Term Volatility with Order Flow Image Representation

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Abstract—Introduction: The paper addresses the challenging problem of predicting the short-term realized volatility of the Bitcoin price using order flow information. The inherent stochastic nature and anti-persistence of price pose difficulties in accurate prediction.

Methods: To address this, we propose a method that transforms order flow data over a fixed time interval (snapshots) into images. The order flow includes trade sizes, trade directions, and limit order book (LOB), and is mapped into image colour channels. These images are then used to train both a simple 3-layer Convolutional Neural Network (CNN) and more advanced ResNet-18 as well as ConvMixer augmented with hand-crafted features. The models are evaluated against classical GARCH, Multilayer Perceptron trained on raw data, and a naive guess method that considers current volatility as a prediction.

Results: The experiments are conducted using price data from January 2021 and evaluate model performance in terms of root mean square error (RMSPE). The results show that our order flow representation with a CNN as a predictive model achieves the best performance, with an RMSPE of 0.85 ± 1.1 for the model with aggregated features and 1.0 ± 1.4 for the model without feature supplementation. ConvMixer with feature supplementation follows closely. In comparison, the RMSPE for the naive guess method was 1.4 ± 3.0 .

I. INTRODUCTION

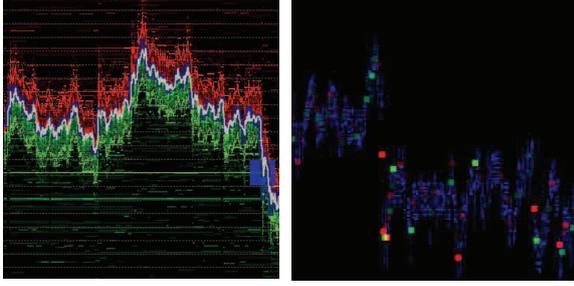
A large body of research has been mostly focusing on predicting long-term volatility, ranging from daily to annual prediction [1]–[3]. This makes sense in ensuring that underlying assets, e.g. commodities, will be delivered at the agreed price and the option price will not be too high. Along the classical approaches for volatility prediction e.g. the autoregressive conditional heteroskedasticity [4], the generalized auto-regressive conditional heteroskedasticity (GARCH) [5], the heterogeneous autoregressive model (HAR) [1], the heterogeneous autoregressive model of realized variant (HAR-RV) [6] [7], several approaches to predicting long-term volatility using neural networks (NN) have been proposed [8]. Ge et al. compared Temporal Convolutional Networks, and Temporal Fusion Transformer among others in predicting the volatility of S&P500, NASDAQ and several commodities with the help of exogenous inputs such as indices SZSE, BSE SENSEX, FTSE100 and DJIA, exchange rates US-YEN, US-EURO and other fundamentals. The authors demonstrated the superiority of the aforementioned models in predicting the next month's volatility [9]. Short-term volatility, on the other hand, is

also vitally important for maintaining a "healthy" market structure and in particular providing liquidity. High-frequency trading strategies that market-making funds and hedge funds commonly use [10], employ various extensions of classical autoregressive models. Applying NNs for short-term volatility prediction is challenging due to the stochastic nature of markets' behavior, implying a lack of repetitive patterns. Hence, information on order distribution and trade dynamics becomes more crucial than at the macroscale (days and years), hence the necessity to analyze different data modalities emerges.

The motivation for this paper comes from discretionary traders who employ intraday trading strategies (scalping strategies). This class of traders relies on market order flow in order to identify support and resistance levels, frequency of trades, and their size distribution to detect market reversals and breakouts. Fig. 1(a) illustrates an example of the order flow that visualizes the Bid and Ask sides of the LOB and large trades. The fig. illustrates an event when a large Bid limit order sitting in the LOB is filled by a large market sell order (a large blue square). This large selling indicates a sell pressure and hence a downturn might be anticipated by the trader. The paper tests the hypothesis of whether a relatively simplistic CNN can learn to capture such events and predict price volatility short-term as well as compare it to more sophisticated models such as ConvMixer and ResNet18. The paper also illustrates that the proposed approach allows for interpretability.

II. TERMINOLOGY

Realised Volatility: The paper aims at predicting the realized volatility (RV). As defined by [11] and [12], the RV measures the change in price by taking the square root of the sum of the squared returns. Defining the log return for time t and $t + \tau$ as $r_{t,\tau} = P(t + \tau) - P(t)$, where $P(t) = \log(p_t)$ and p_t is price at time t , the realized variance R is calculated as $R_{t+\tau} = \sum_{i=0}^n r_{\tau_i, \tau_{i+1}}^2$ where $t \leq \tau_0 < \tau_1 < \dots < \tau_n \leq t + \tau$ are timestamps of sample points from the target period. Finally, the RV is simply the square root of the realized variance $RV = \sqrt{R}$. An accurate prediction of future volatility will help traders anticipate potential risks and opportunities in the future. The objective is to predict RV on $(t, t + \tau)$, where τ is the forecast horizon.



(a) an order flow visualised by a real trading terminal (b) a constructed image representing real order flow

Fig. 1: (a) The Bid/Ask levels are shown in green/red respectively. The colour intensity is proportional to the size of a limit order. Blue blocks represent large trades, with the size being proportional to the size of a trade e.g. encodes T&S information. (b) Both sides of the limit orders are shown in blue. The colour intensity is proportional to limit order size. Red and green blocks represent sell and buy trades, with the intensity being proportional to the size of a trade.

Limit order book: The LOB provides vital information on short-term asset behavior [13], [14]. The difference in price and order sizes at the Bid and Ask sides (order book imbalance) carry information that trading agents might use to make trading decisions. Moreover, the short-term price dynamics might depend on the frequency of trades, trade sizes, and the correlation in trade sides, and hence can contribute to explaining short-term volatility. Therefore, a hypothesis is tested that the Time & Sales (T&S) and the LOB provide vital information for improving short-term volatility forecasting.

Order Flow: The evolution of the LOB over time is called order flow and is a tool used by traders and trading algorithms. Formally, an order O consists of three parts: the executed time t_O (or current time for listed but not yet executed orders, limit orders), the order price p_O , and order volume or size V_O , resulting in a tuple $O := (t_O, p_O, V_O)$.

The T&S records represent executed/market orders, while the LOB stores the top limit orders, i.e., the price levels at which a buyer or a seller is willing to buy or sell correspondingly. The levels are sorted by price for both the Bid and Ask sides. Then, for a given time t , the order flow F refers to all orders, listed in the LOB or executed (LOB and T&S) between $(t - \Delta T, t)$, that is $O \in F_{t-\Delta T, t} \iff t - \Delta T \leq t_j \leq t$, where ΔT is the input size of the time series. An example of order flow superimposed with large trades is shown in Fig 1.

III. METHODOLOGY

Data: The perpetual futures contract (PFC) of BTC / USDT provided by the Binance public historical market data set [15] was used for experimentation. BTC/USDT represents the value of Bitcoin in tether dollars (USDT). According to Binance, among all the PFCs, the BTC/USDT PFC makes the majority of the daily trading volume. The data contains tick-level trades

and 20 levels of LOB on the Bid and Ask sides. Generally, the price of the contract closely follows the price at the start of the Bitcoin market due to the “funding fee” mechanism. The funding fee is a varying payment between long/short position traders depending on the difference between future contract price (mark price) and spot price that ensures that the mark price follows closely with the spot price. For example, when the mark price is higher than the spot price, traders at long positions pay extra fees to traders at short positions. Therefore, the volatility of perpetual futures contracts also mostly replicates that of the Bitcoin spot price. It is important to note that BTC/USDT can be traded with a leverage of up to 125, which could and usually results in slightly higher volatility due to potentially trigger stop cascades [16]. It is also worth noting that besides speculative trading, PFC is widely used for hedging against volatility risk in the cryptocurrency market.

Image Encoding: In order to simulate the market information presented to the trader (fig. 1(a)), an encoding heuristic that stores LOB and T&S information as a single image is developed. This also provides the means for employing either pre-trained or designed-from-scratch CNNs. It is important to note, that the idea of encoding market data into images is not new, for example, Ge et al. trained LSTM-CNN to predict monthly volatility [9] using images constructed from price data by employing Gramian Angular Fields and Markov Transition Fields [17], [18], however, these encodings are not intuitive and rely on mathematical tricks in the hope of improving the predictability, while our encoding simulates the representation used by professional traders.

A resolution of $m \times n$ pixels with c channels is chosen, with channels encoding a specific information. A unit time interval t and a unit value interval v are further defined. Let each column of pixels represents information in (t_i, t_{i+1}) of input data, and the rows represent order information in (v_j, v_{j+1}) . The pixel value p_{t_i, v_j} , ranging from 0 to 255, represents the normalized volume of limit orders at the corresponding row (value interval) and column (time interval).

$$p_{t_i, v_j} = (V_o) \iff [t_O \in (t_i, t_{i+1})] \wedge [p_O \in (v_j, v_{j+1})] \quad (1)$$

Then for each channel c_i , the image encodes any order settled in the time interval $(t_0, t_0 + n \cdot t)$ with order value in the range of $(v_0, v_0 + m \cdot v)$, where t_0 is the starting time of the input data, and v_0 is the minimum price which is captured for image encoding. Formally, for an image \mathbb{I} , the c_i channel encodes all orders in the order flow F , if the order is within the range of the image:

$$O \in \mathbb{I}_{c_i} \iff [O_t \in (t_0, t_0 + n \cdot t)] \wedge [p_O \in (v_0, v_0 + m \cdot v)] \quad (2)$$

To avoid confusion among multiple data modalities, each channel should only encode one piece of information. Intuitively, such an image is a ‘snapshot’ of order flow similar to fig. 1(a), where pixels represent the order’s time and value, while colours represent different modalities of the order flow.

TABLE I: Information presented as part of the dataset

Order Book		T&S	
Ask price	Ask price from level 1 to level 20	price	weighted average executed trade price in last second
Bid price	Bid price from level 1 to level 20	order count	number of executed trade orders in last second
Ask size	volume per Ask price from level 1 to level 20	size	total volume of executed trades in the last second
Bid size	volume per Bid price from level 1 to level 20	is_buyer	whether the buyer is the market maker

The value of t and v determines the ‘resolution’ of the snapshot. The size of the image determines the range of encoded data. Further, ϵ is defined as the time interval between each consecutive encoded image. When $\epsilon < t$, the encoded images overlap with each other, and when $\epsilon > t$, the image set is a sub-sampling of the original order flow.

To align with the input size of common pre-trained CNN models such as ResNet [19] or ConvMixer [20], the image resolution is set to 240×240 , with t measured in seconds and v in USDT. Hence each image contains information on the order flow for 4 minutes and the range is 240 tether dollars. The Red and Green channels encode market orders (trades). To amplify the effect of a market order, each trading pixel is padded to form a square. This will result in overlapping squares when several trades occur at about the same time, and the value of overlapped pixels is the sum of all these trades. Such implementation allows us to highlight regions with more active trading activities, which may lead to changes in volatility. Buy and sell orders are encoded by green and red channels correspondingly.

The blue channel encodes the LOB. The limit orders are unfortunately limited to the top 20 levels. For instance, in the case when the price goes down, the top of the LOB becomes occupied by new orders with lower prices, and the original top orders disappear from the LOB. However, since the old orders are not filled, and as long as the trader still has the intent to trade, an assumption is made that the order will be kept in the LOB at the same price level and with the same size until new information indicates that the order has changed, or the order is filled. In practice, agents may change their position by actively tracking the price as demonstrated in fig. 1(a). fig. 1(b) illustrates an example of encoded market data following the aforementioned procedure.

The pipeline: Based on the above trading information representation, the encoded image is generally suitable for any conventional 2D-CNN model. Several models with different structures are investigated to validate the performance using the proposed encoding method and further search for the most appropriate model.

The main model under testing consists of two parts: (a) the CNN, either a pre-trained one or trained from scratch and (b) a tabular (manually crafted) feature extractor as shown in fig. 2. The last layer of the network is replaced with a flattening layer, to produce a 1D vector. The features extracted from encoded images by the CNN model are combined with externally extracted features. Based on [14] and [21], a set of features is selected consisting of 393 aggregated features. Finally, a regression layer maps the aggregated feature vector to a predicted volatility value.

Models: The full list of the tested models with insights into their structural parameters is outlined next.

Naive Guess simply takes RV of the last minute and uses it as a prediction.

GARCH is a classical univariate model that uses past squared returns to predict volatility. The model requires two parameters order of autoregression (p), and order of moving average (q). A search over these parameters is performed by training the model with a relatively small subset. The model with $p = 1, q = 1$ had the best performance.

Multilayer Perceptron (MLP), is a fully connected network trained on the aggregated feature set described in III.

CNNpred-2D is based on [22] and takes multivariate input of dimension 85×240 . Typically the model has a first-layer kernel size of 1 to aggregate all features at each timestamp into one latent feature. The last fully connected layer is modified for regression.

CNN-1D takes raw order flow as input i.e. each second is represented by an 85-dimensional vector. The model is typically with 6 convolution layers with filter size 5, followed by pooling layers and affine regression layers.

LSTM-1D takes raw order flow as input (similarly to the CNN-1D). The model uses three LSTM layers followed by an affine regression layer.

ResNet-18 is a pretrained benchmark CNN-type of model with 18 residual blocks where each residual block consists of 2 convolution layers with kernel size 3×3 and batch normalizations. The last layer is replaced by a regression layer.

Naive-CNN is used to evaluate solely the CNN part without the aggregated feature vectors. The model has 3 convolution layers. Each layer is followed by batch normalization, pooling and ReLU activation. The last layer is a regression layer mapping 128 latent features into one output. The model configurations are shown in fig. 3.

ConvMixer-Aggr is similar to CNN-Aggr but with CNN being replaced by the pretrained state-of-the-art ConvMixer [20]. The model starts with a ‘patch layer’ with patch size 2 followed by batch normalization and GeLU activation [23]. Following the patch layer are 2 residual blocks where each residual block consists of one convolution layer with kernel size 5 and the other convolution layer with kernel size 1.

IV. RESULTS

: Prior to image normalization, pixels representing the trade size were clipped to the 99 percentile, in order to remove outliers, that otherwise suppress the intensities of all other pixels. The prediction target was the RV in the next 60 seconds. Table I outlines the information presented at every second in an input window. The images are generated in a

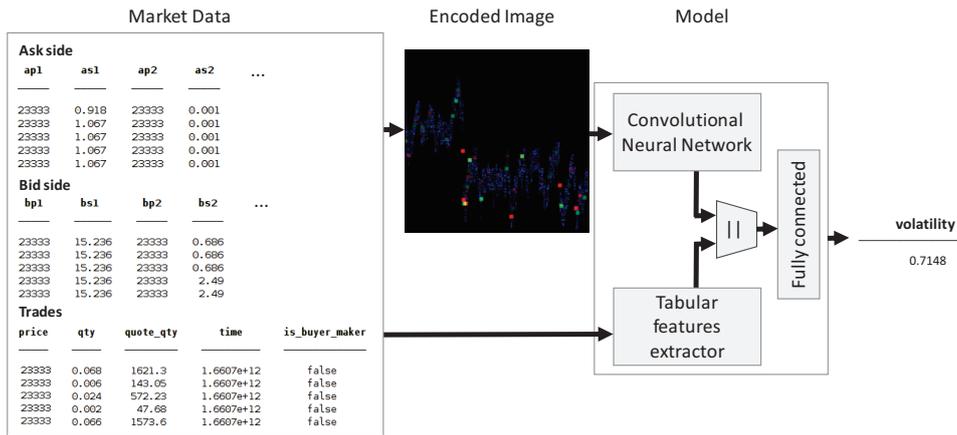


Fig. 2: Order flow is passed to the tabular feature extractor and to the image encoder. The encoded images are then passed to the CNN model. The outputs of both parts are concatenated and fed into the regression layer (fully connected layer).

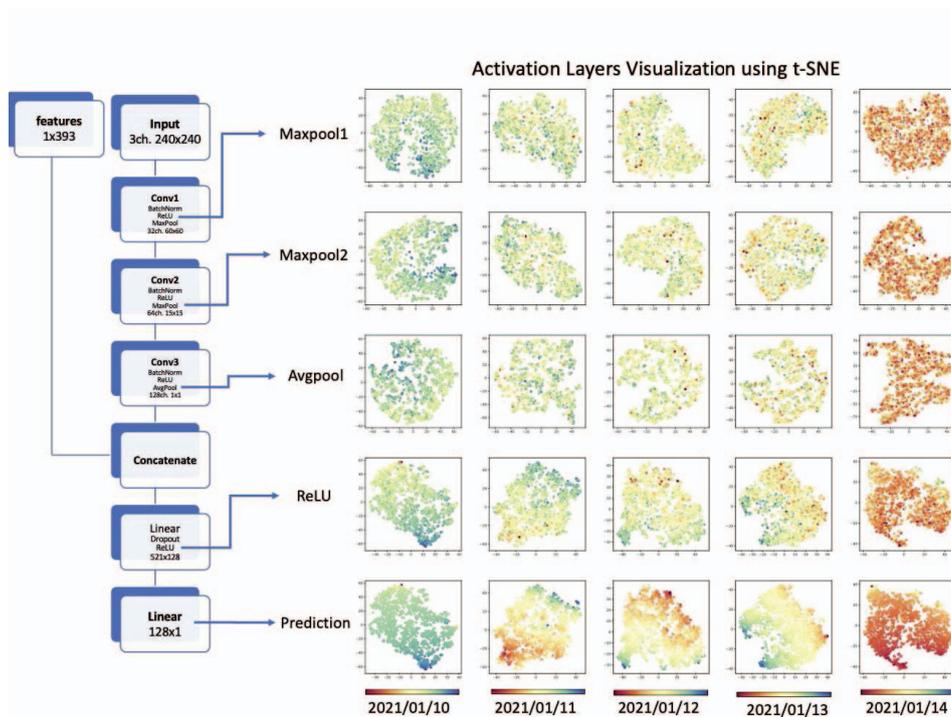


Fig. 3: (left) shows the structure of the base CNN model, (right) the weights of corresponding layers visualised with t-SNE at 0:05, 20th, June, 2022 to 23:50, 24th, June, 2022. Volatility range of the day is colored encoded. The volatility is normalized separately for each day, hence, there is no absolute correlation between samples with the same colour across days.

walk-forward approach. The ϵ is set to 10 seconds, so each pair of neighboring images have 230 seconds of overlaps. This results in 8616 images for each trading day. To avoid

information leaks when training models, the images are fed in time order. The dataset is split into the train, validation, and test sets with a size ratio of 3 : 1 : 1, where the timestamps

TABLE II: The mean and standard deviation of RMSPE computed for validation and test sets of the models trained on daily data from 1th Jan, 2021 to 30th Jan, 2021

Models	validation set	test set
Naive guess	0.414 ± 0.128	1.398 ± 2.992
GARCH	0.889 ± 0.603	-
MLP	0.582 ± 0.249	1.046 ± 1.099
CNNPred-2D	0.365 ± 0.084	1.079 ± 1.422
CNN-1D	0.579 ± 0.200	1.288 ± 1.435
LSTM-1D	0.346 ± 0.064	1.116 ± 1.709
ResNet-18	0.350 ± 0.056	1.225 ± 2.005
Naive-CNN	0.355 ± 0.060	1.005 ± 1.407
CNN-Aggr	0.309 ± 0.071	0.851 ± 1.110
ConvMixer-Aggr	0.519 ± 0.184	0.994 ± 1.057

of the test set are strictly after the training set to prevent information leaks. The performance of the aforementioned model was evaluated using the average Root Mean Square Percentage Error(RMSPE) $\rho = \sqrt{\frac{1}{N} \sum_{k=1}^N \left(\frac{\hat{y}_k - y_k}{y_k} \right)^2}$ and compared to the aforementioned models: RMSPE obtained for the range of 1th Jan, 2021 to 30th Jan, 2021 are presented in table II. On average the proposed CNN-Aggr model outperforms all other models, with the best average score. It also has the lowest standard deviation indicating a robust overall performance. ResNet-18 and ConvMixer-Aggr did not show better performance as one might have expected, this might be due to the fact that these models were pretrained on ImageNet consisting of real object images that are very different from the synthetic order flow images. Surprisingly, the naive guess can sometimes provide fairly accurate forecasting, especially when the price is stable across the day i.e. the corresponding minute volatility does not change too much. However, the standard deviation of naive guesses is much higher, implying less consistent prediction accuracy. Comparing the Naive-CNN and the CNN-Aggr models, the aggregation of additional features does improve the accuracy of prediction. To verify that the order book dynamics actually provides valuable market insights, the MLP model is trained solely on the hand-crafted features. This model performed better than Naive guess but worse than Naive-CNN, implying that the market dynamics represented in the form of images carry important information that is not captured by the additional features and vice versa, which explains why the CNN-Aggr model that can be seen as a combination of the MLP and naive CNN models outperformed each of these models alone.

Further, CNN-LSTM models are experimented with. The models use embeddings extracted from CNN as LSTM input. The embedding output of consecutive images from CNN is fed into the LSTM model as a time series. However, the models failed to further improve the prediction, regardless of whether the CNN-Aggr model or pretrained ResNet was used, this could be due to images being encoded and normalized individually, which results in breaking the correlation between consecutive images. The stochastic nature of the price behaviour makes the accumulated prediction residual error large.

V. INTERPRETABILITY

To interpret the behaviour of the models, the input data are passed through the trained model and output embedding vectors from each activation layer are recorded. Four activation layers are chosen for investigation as shown in fig. 3. Notice that the embedding vectors are of high dimension (e.g output of the Maxpool1 layer consists of 115200 values after being flattened), in order to visualize the distribution of these high-dimensional embeddings t-Stochastic Neighbor Embedding (t-SNE) [24] is employed. t-SNE struggles in mapping from very high dimensional space and hence the input space is first processed by Principle Component Analysis (PCA) reducing the dimensionality to 40. Fig. 3 shows the sample visualization results layer by layer for CNN-Aggr models trained on 5 different periods from the latest available daily order flows. Each point represents an input sample, with colours representing the normalized target volatility. At the first activation layer, the distribution of embedding vectors does not show any obvious patterns. As the input data propagate through layers, samples with high volatilities (green) and low volatilities (red) tend to separate. At the last activation layer, there is a clear gradual change in colour along the axes. High volatile samples (green) are split into two corners. Further analysis shows that the two corners correspond to an upward trend and a downward trend of input data. For the model trained on 21th, June, 2022, samples with clear downward trends and higher volatilities are more likely to be mapped to the top left of the plot, while samples with highly volatile upward trends are mapped to the bottom left corner (fig. 4). Samples representing trades within a trading channel i.e. sideways price movement and those associated with non-obvious trends are mapped to the right part of the plot. This corresponds to the prediction distribution shown in the last line in fig. 3. Generally, the model gives a higher volatility prediction for samples on the left side than on the right. Intuitively, this means a highly volatile market is likely to have high volatility in the future as well.

The choice of v_0 and v is quite important but challenging, which is due to the variability of the stock price range. Ideally, the range should capture as many orders as possible. When v is too large, the order flows are squeezed into a narrow band, and hence it becomes troublesome to extract useful information. In contrast, when v is too small, orders outside the value range are hidden from the model. By trial and error, v was set to 1, while $v_0 = O_{p_0} - m/2$. It would be interesting to further explore the effect of different value ranges.

VI. CONCLUSION AND FUTURE WORKS

An encoding method has been proposed that maps the order flow of the market and the limit orders into images. Several models have been trained on these data. A simple CNN model complemented by the aggregated features achieved the best prediction accuracy. The proposed pipeline can be easily generalized to predict the volatility of other asset classes as long as the top of the order book and the time and sales are provided.

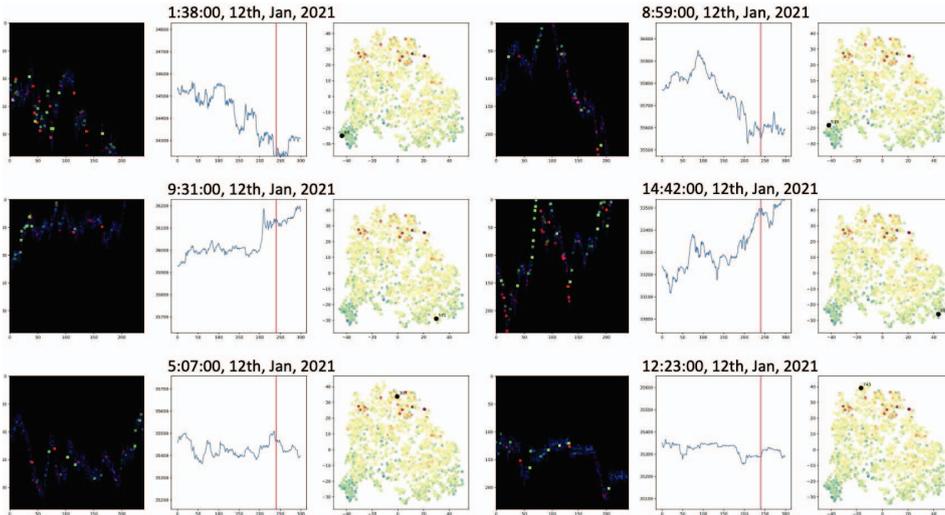


Fig. 4: t-SNE visualization of the last ReLU layer on 21th, June, 2022. 6 samples represent different market conditions. (left) input image; (mid) depicts the market price at the same time period including both the input and target periods on the left and right side of the red line; (right) shows the position of the sample (black dot) in the t-SNE plot of the last activation layer.

An important difference between the images representing order flows and images representing real-world objects is the temporal property of the former ones. To account for this, an attention-based temporal CNN [25] is probably a better choice. The configuration of the encoded images such as value range and unit value of pixels significantly affect the encoding quality. It is also worth further investigating network configurations to validate the robustness of the market data representation and the models.

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