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Investigating the informativeness of technical indicators and news sentiment in financial market price prediction

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ABSTRACT

Real-time market prediction tool tracking public opinion in specialized newsgroups and informative market data persuades investors of financial markets. Previous works mainly used lexicon-based sentiment analysis for financial markets prediction, while recently proposed transformer-based sentiment analysis promise good results for cross-domain sentiment analysis. This work considers temporal relationships between consecutive snapshots of informative market data and mood time series for market price prediction. We calculate the sentiment mood time series via the probability distribution of news embedding generated through a BERT-based transformer language model fine-tuned for financial domain sentiment analysis. We then use a deep recurrent neural network for feature extraction followed by a dense layer for price regression. We implemented our approach as an open-source API for real-time price regression. We build a corpus of financial news related to currency pairs in foreign exchange and Cryptocurrency markets. We further augment our model with informative technical indicators and news sentiment scores aligned based on news release timestamp. Results of our experiments show significant error reduction compared to the baselines. Our *Financial News* and *Financial Sentiment Analysis* RESTFul APIs are available for public use.

1. Introduction

According to the Market Distribution Hypothesis (MDH) [1], the variance of market return at a given interval, is proportional to the amount of information received by the market participants [2–5]. News content and mood in specialized financial newsgroups alongside market information are helpful for market prediction [6–11]. Most of the previous works [4,12–14] only consider the effect of news and use Sentiment Analysis for mood calculation; however, they disregard the technical analysis of market data. Results of previous works [15–18] suggest that using both market data and news-based information is helpful for the market prediction problem; however, the study of the amount of information gain (IG) of mood and using most informative market data remains debatable.

The mood time series can be defined as the aggregated sentiment scores of news or postings during trading time intervals [19]. Domain-specific lexicons, such as Loughran–McDonald [20] and Framester [21], that are prepared by human experts do not consider the context of words. Machine learning-based methods [22–24] often suffer from the problem of market endogeneity [2] for automatic labeling of news in training sets based on the lag-based return. In [23,24] a piece of news is considered good/bad if the market volatility before and after news publishing is positive/negative, while [25] shows investors overreact to bad news in a short time even in a bullish market and under-react to good news in bad times; thus the classification is endogenous to the market volatility.

Recent methods in transformer-based natural language processing have shown promising results in financial market data analysis [17,26,27]. The result in [28] indicates that BERT-based sentiment analysis outperforms other embedding techniques such as FastText, Bidirectional Long Short Term Memory (LSTM), and multichannel Convolutional Neural Network (CNN). Unlike [27], which utilizes only news and market data embedding and disregard sentiment-based feature, authors in [17] leverage news content, sentiment, and market technical indicators, and use a BERT-based transformer model for general domain sentiment analysis. However, they do not consider fine-tuning the model for financial text sentiment analysis. Also, they concatenate the news representation vector and the sentiment score value in a compound vector that makes it difficult to distinguish the effects of currency pair mood in specialized newsgroups.

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In this work, we propose a FinBERT-based [29] news Sentiment aggregation model that incorporates Informative Market data for financial market Forecasting, called *FinBERT-SIMF*. FinBERT [29] is a BERT-based [30] transformer language model fine-tuned for financial domain sentiment analysis. Our model leverages sequential relationships between consecutive snapshots of informative market data and news sentiment scores for prediction of next time step via a two-layer Recurrent Neural Network. Following [23,31,32], we use news title for sentiment analysis. We calculate the sentiment mood time series via the probability distribution of news title embedding generated through FinBERT classifier layer. We then feed normalized form of sentiment and market-based features into a two-layer Recurrent Neural Network (RNN) followed by dropout and a dense layer for price regression. While most previous works [33–35] measure the informativeness of sentiment mood time series with linear Granger-Causality test [36], we propose the analysis of non-linear weights in the neural network model. The results show that considering both market data and mood in specialized newsgroups can significantly reduce the error for price regression. Our contributions include:

- We propose a predictive model called *FinBERT-SIMF* (FinBERT based Sentiment and Informative Market Feature) that leverages a pre-train model for financial sentiment analysis of news headlines and information in historical market data.
- We consider price regression problem solving leveraging both market and mood time series and analyze the Mean Absolute Percentage Error (MAPE) regarding each source of information.
- We evaluate our technique on currency pairs in the Forex and Cryptocurrency markets and implement *FinBERT-SIMF*[1] as an open-source API. Our *Financial News*[2] and *Financial Sentiment Analysis*[3] RESTFul APIs are available for public use.
- We analyze the information gain [37] and non-linear importance weights of neural networks to the technical indicators and mood time series for various financial market price regression.

2. Related work

Financial market predictions have been studied for more than half a century [38–43]. It is in the public mood that investors' emotions, thoughts, and plans for action arise [15,44–48]. There have been two lines of work predicting financial markets using sentiment analysis [8]. In the first one, researchers present Financial Sentiment Analysis (FSA) [31,49–51], and in the other line of work, public mood time series calculated based on aggregating sentiment score for each time interval [26,52,53]. From Natural Language Processing (NLP) viewpoint, market prediction via FSA investigation can be divided into three categories of lexicon-based, machine learning-based, and transformer-based approaches.

Lexicon-based methods, analysis the text sentiment based on the high quality of emotion dictionary and word polarity, while machine learning approaches rely on supervised learning and word features. In lexicon-based approaches, a domain-specific or domain adaptation lexicon such as Loughran–McDonald [16,54–57] and Sentiwordnet [16,23,24,58] respectively is constructed based on pre-defined manual rules. In the machine learning approach [59–61], based on the document, sentence [62], or aspect level sentiment [63], the in-domain classifiers are trained that are used in the sentiment analysis phase. However, with some pre-trained models, much more embedding methods, and significant improvement in transformer-based NLP [29,30,64] are growing in FSA.

Most domain-specific lexicons such as Loughran–McDonald and Framester [21] usually provided by human expert intervention, while the process of manually labeling of words' sense is a time-consuming process. Challenges such as defining the context-aware polarity of a particular word and Out of Vocabulary Words (OOV) still exist for accurate lexicon-based FSA [65]. Most machine learning-based methods use *Bag of Word* [66] for text representation and then a classifier such as naive Bayes, SVM, Random Forest train for FSA based on a lag correlation between headlines release time and the rate of market return [34,57] or human interventions labeling [67]. The sheer of textual features in BoW based methods causes the sparsity problem and the poor representation of contextualized semantic and syntactic roles of words, besides the challenge of the existence of OOV words in the test set still remaining.

The ability of embedding methods such as word2vec [68], Glove, FastText in the representation of semantic proximity in word vectors, promise better results in FSA. The result in [22,56] indicated that deep LSTM outperforms traditional machine learning-based methods (Support Vector Machine, Naive Bayes, Logistic Regression). However, the problem of polysemous words still exists in word2vec based text representation.

Recently transformer-based language model, fine-tuned for FSA [28], leverage contextualized word embedding to tackle the problem of words polysemy. The result indicated BERT-based sentiment analysis outperforms other embedding techniques such as FastText, Bidirectional LSTM, and multichannel CNN. Various BERT-based language models [29,30,64] generate contextualized word vectors that capture deep semantic and syntactic information. In [69], authors fine-tune uncased version of BERT model for FSA based on manually labeling the news data from financial newsgroups and predicting the trend (up/down binary classification) without using market data. Authors in [70–72] consider the trend prediction problem and show BERT based sentiment analysis outperforms to the other text representation. Also, Anbaee et al. [17] analyze the effect of incorporating news content and sentiment as well as technical indicators for major currency pairs price prediction in the FOREX market. They use DistilBERT [64] model for news sentiment analysis, while DistiBert model is fine-tuned from a general domain corpus. Cross-domain sentiment analysis refers to investigating a general domain pre-trained model for finance sentiment analysis problems [65]. FinBERT [29] utilizes a transformer with a self-attention mechanism [73] that learns long-term dependencies in sentence structure and it covers a broader spectrum of OOV words with WordPiece tokenization scheme, besides fine-tune from finance domain corpus for FSA.

In this work, we study the integration effect of the lagged-based sentiment mood time series, which we calculate via a BERT-based model fine-tuned for financial news *title* sentiment analysis. We study the integration effect of mood time series calculates based on each of these three categories of FSA, especially various pre-trained BERT-based language models. We consider price regression leveraging both market and mood time series and analysis the error rate for considering each source information. Most of the previous methods [33–35] measure the informativeness of sentiment mood time series with linear Granger-Causality test [36], while we analyze the information gain [37] of technical indicators and mood time series for various financial market price regression.

[1] https://github.com/FinBERT-SIMF/FinBERT-SIMF.

[2] https://robonews.robofa.cscloud.ir/Robonews/v1/.

[3] https://finbert-fsa.robonews.robofa.cscloud.ir/api/v1/.

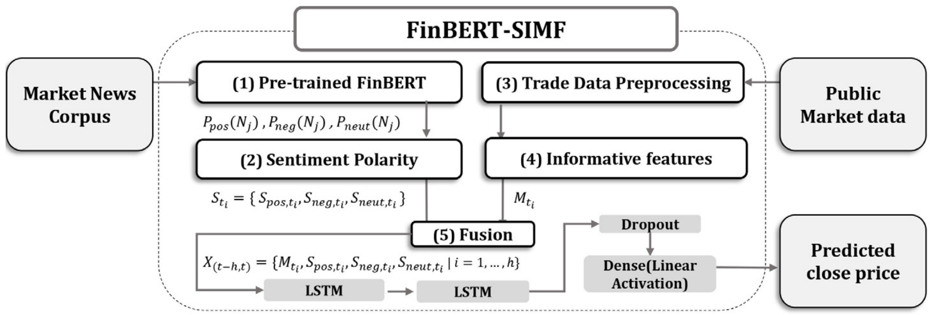


Fig. 1. Overview of our FinBERT-SIMF technique.

Table 1
Notations and symbols.

Notation	Description
$\mathcal{M}$	Set of Market data space including raw market data and technical indicators.
$M_t = (m_{1,t}, \ldots, m_{Q,t})'$	Market data time series of $Q = 14$ candidate features from $\mathcal{M}$ shown in Table 2
$N_{(t-h,t)}$	A sequence of news titles published during delay window h.
$S_t = (s_{pos,t}, s_{neg,t}, s_{neut,t})'$	The 3-dimensional vector for positive, negative, and neutral sentiments during consecutive trading time intervals.
$X_{(t-h,t)}$	Concatenated matrix of market data and mood time series during delay window h.
p	Target close price at timestamp $t + \Delta t$, where $\Delta t = 60$ min

Algorithm 1 Feature Preparation in *FinBERT-SIMF*

Input: $N_{(t-h,t)} = \{N_1, \ldots, N_u\}$ News sequence released during delay window h, where N_j = {news title, timestamp}, and $M_{(t-h,t)} \in \mathcal{M}^{q*h}$ is market data item during delay window h from q market data items of space $\mathcal{M}$.
Output: Matrix $X_{(t-h,t)}$ from concatenation of market data and mood time series
1: **for** i = 1 to h **do**
2: $\quad j, S_{pos,t_i}, S_{neg,t_i}, S_{neut,t_i} \leftarrow 0$
3: $\quad$ **while** $t_i < t_{(N_j)} < t_{i+1}$ **do**
4: $\quad\quad P(N_j) \leftarrow softmax(W * N_j^{[CLS]} + b)$
5: $\quad\quad S_{pos,t_i} \leftarrow S_{pos,t_i} + P_{pos}(N_j)$
6: $\quad\quad S_{neg,t_i} \leftarrow S_{neg,t_i} + P_{neg}(N_j)$
7: $\quad\quad S_{neut,t_i} \leftarrow S_{neut,t_i} + P_{neut}(N_j)$
8: $\quad\quad j \leftarrow j + 1$
9: $\quad$ **end while**
10: $\quad x_{t_i} \leftarrow [M_{(t_i)}, S_{pos,t_i}, S_{neg,t_i}, S_{neut,t_i}]$
11: $\quad i \leftarrow i + 1$
12: **end for**
13: **return** $X_{(t-h,t)} = \{x_{t_i} | i = 1, \ldots h\}$

3. Proposed approach

Our work is focused on leveraging mood time series and informative market data for financial market price prediction. As such, we first formally define the concept of mood time series and market data, as follows:

Definition 1 (*Mood Time Series*)**.** We define the mood time series $\{S_t\}$ as a 3-dimensional vector of observations $S_t = (s_{pos,t}, s_{neg,t}, s_{neut,t})'$ for positive, negative, and neutral sentiments during consecutive trading time intervals.

Definition 2 (*Market Data*)**.** We define the market data time series $\{M_t\}$ as a q-dimensional vector of observations $M_t = (m_{1,t}, \ldots, m_{Q,t})'$ during consecutive trading time intervals, where $m_q \in \mathcal{M}$ is a market data including raw values (close price and volume) and technical indicators. We use the most important q number of features from totally $Q = 14$ items shown in Table 2.

We propose *FinBERT-SIMF* for financial time series forecasting. Our approach consists of three phases: mood preparation, market-based feature preparation, and fusion and prediction as shown in Fig. 1. For mood preparation, we align news and market data based on timestamps in chronological order. Next, we calculate the predicted probability of the FinBERT model [29] for each news title and then calculate sentiment polarity time series based on Algorithm 1. In market-based feature preparation, we select more informative features amongst public market information and technical indicators. In the fusion phase, we pass the concatenated matrix of prepared features based on a delay window into RNN layers followed by a dense layer for currency pairs price regression. Table 1 presents notations that we use throughout the paper.

3.1. Mood preparation

Let $N_{(t-h,t)}$ be a sequence of news titles published during delay window h. We explain in Section 5.1 how we determine h. Algorithm 1 describes sentiment polarity calculation between two consecutive time steps (lines 4–8). Following [27], we investigate [*CLS*] token embedding for news representation in FinBERT sentiment classification model (Block 1). Therefore $P(N_j)$ = softmax $(W * N_j^{[CLS]} + b)$ be the predicted probabilities of news title embedding $N_j^{[CLS]}$ through FinBERT model in three categories of *positive*, *negative* and *neutral* where W is the weight vector and b is bias value of classifier layer in FinBERT, which learned through end to end fine-tuning FinBERT model [29] by minimization of cross entropy loss function. For all news published between the two timesteps, we sum up the predicted probability of each category (Block 2). We then use z-score normalized form of $\{S_t\}$ as our mood-based features.

3.2. Market-based feature preparation

Most of the FOREX market predictive models use short-term prediction. Authors in [23,24,27] have studied the investors' reactions to the Forex market within an hour from the news release. We also use short-term market price prediction and focus on a regular hourly time frame; as such we define $\Delta t = 60$ minutes. Following [17,74], our set of market-based features $\mathcal{M}$ includes Close Price, Volume, Exponential Moving Average (EMA), Moving Average Convergence–Divergence (MACD), On Balance Volume (OBV), Bollinger Bands (BBs), Stochastic, Awesome Oscillator (AO), Williams, Relative Strength Index (RSI), Accumulation/Distribution Index (ADI) and Average True Range (ATR).

Let $\{M_t | t = 1, \ldots, T\}$ be z-score normalized form of market data, where T is the total number of training samples (Block 3).

Table 2
Technical indicators definition [74].

Indicator	Definition
Close price	The last price at which an asset traded during the regular trading time interval (day, hour, week)
Volume	The amount of an asset that changes hands between open and close in the regular time interval.
EMA	Weighted moving average which places a greater weight and significance on the most recent data point.
MACD	Trend-following momentum indicator, which shows the relationship between two moving averages of an asset.
OBV	Relates the price and the positive/negative changes of volume of an asset.
BBx	That are volatility bands (Low, Mean, High) placed below, middle and above a moving average using two standard deviations along latest time steps.
Stochastic	Shows the location of the close price relative to the high–low range over a set number of periods.
AO	Shows the trend direction and measures the pace of the price fluctuation by comparing current and past values.
Williams	Shows the current closing price in relation to the high and low of the past N days.
RSI	Measure the velocity and magnitude of price movements based on the closing prices of a recent trading period.
ADI	Measure the divergences between the stock price and the volume flow.
ATR	Shows how much an asset moves, on average, during a given time frame.

At the first stage, we sort market features in Table 2 from high to low degree of information gain from target close price. For all market features $m_q \in \mathcal{M}$, we calculate $I(m_q, p)$ as the amount of information gain of feature from the target close price p in the next timestamp from Eq. (1), where the probability density function $P(m_q, p)$ is estimated from the entropy of k nearest neighbor distances [37].

$$I(m_q, p) = D_{KL}(P(m_q, p) \parallel P(m_q)P(p)) \tag{1}$$

Then we monitor $\hat{g}$ as the optimized Mean Absolute Percentage Error (MAPE) loss function $\hat{g}_{MAPE}([M_{1:q}, S]) = \underset{g \in \hat{g}}{argmin} \frac{1}{T} \sum_{l=1}^{T} \left| \frac{g([M_{1:q}, S]_{l-h:l} - p_{l+\Delta t})}{p_{l+\Delta t}} \right|$ by recursive elimination of features from low to high degree of informativeness, where parameters of regression function g is learned during an end-to-end training of our model.

For the RNNs layer, we use LSTM to store and access a longer range of contextual information in the sequential input, and also to handle the vanishing gradient problem. The formulations of the LSTM are:

$$i_t = \sigma_g(W_i x_t + U_i a_{t-1} + b_i)$$

$$f_t = \sigma_g(W_f x_t + U_f a_{t-1} + b_f)$$

$$o_t = \sigma_g(W_o x_t + U_o a_{t-1} + b_o)$$

$$\hat{c}_t = \sigma_c(W_c x_t + U_c a_{t-1} + b_c)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \hat{c}_t$$

$$a_t = o_t \odot \tanh(c_t)$$

where $X = x_1, x_2, \ldots, x_h$ is the input vector, W_i, W_f, W_c, W_o are the weight matrices of the input vector, and U_i, U_f, U_c, U_o are the weights matrices of recurrent connections and b_i, b_f, b_c, b_o are biases. Also, $\odot$ is element-wise production, σ_g is sigmoid function and σ_c is hyperbolic tangent function and $a_1, a_2, \ldots, a_h$ represent a sequence of semantic features.

Each common unit in LSTM has a cell and three gates as follows: an input gate i, an output gate o and a forget gate f. All of these three gates in a memory block contribute with each other to save and flow important information based on new information in recent time stamp and previous hidden and cell states. The input gate decides which recent information should flow to the current memory block. As such, gave the heaviest weights to important market data. Therefore at the final stage, we select features that achieved the largest L^2 norm of W_i weights of the second LSTM layer as our market-based feature (Block 4).

3.3. Fusion and prediction

After sentiment polarity calculation and market data preprocessing, we align news with market data based on timestamps in chronological order. Then, we propose a simple fusion strategy by concatenation of mood time series $S_{t-h,t}$ and market data $M_{t-h,t}$ as a compound matrix $X_{(t-h,t)}$ (line 10 in Algorithm 1). We feed $X_{(t-h,t)}$ into LSTM layers followed by dropout to avoid overfitting. Regarding extracted feature from $X_{(t-h,t)}$ via RNNs layers, we use the hidden state of the second LSTM layer as the final feature. Note that extracted features are based on the mood in specialized newsgroups and market data during the delay window of h arranged in the temporal order. As such, at the last layer of our model, we put a dense layer with a linear activation function to predict the close price value for the next hour.

4. Experiments

4.1. Dataset

News dataset. Previous works mostly focus on news-based *stock* market prediction, while the influence of news in *Forex* and *cryptocurrency* market predictions is less studied [9–11,67]. Chen et al. [27] propose an approach for selecting the most relevant news for Forex market prediction as the associated texts are too redundant and full of noise. In order to address the challenges of using relevant news for currency pairs prediction in Forex and cryptocurrency markets, we scrape specialized economic news related to target currency pairs. Our news scraping service is available for public use [75]. The research community can benefit from recent financial news which scraped from various financial newsgroups.[4] Following our recent work [17], Table 4 shows statistics of *MarketNews* dataset and its subsets. In our*MarketNews* dataset, the target currency-pair for each news is manually determined by about 150 human experts/news authors as the list of news keywords and for prediction of each currency pair, we select only a subset of news with such currency pair keywords. Our news dataset contains 33-month of financial news items from September 2018 to May 2021. For training our predictive model, we explore news subsets according to news keywords EUR/USD, GBP/USD, USD/JPY, and BTC/USD (indicated by human experts in newsgroups) as shown in Table 5. Fig. 2 shows examples of relevant news on the EUR/USD daily chart. News sentiment from the FinBERT model is shown in color boxes, red for negative news and green box for positive news. Table 3 show examples of news related to currency pairs with sentiment polarities from FinBERT model.

Market dataset. We collected the market dataset from September 2018 to December 2020 from Finnub. Following our

[4] www.fxstreet.com and www.newsbtc.com and www.cointelegraph.com and www.investing.com.

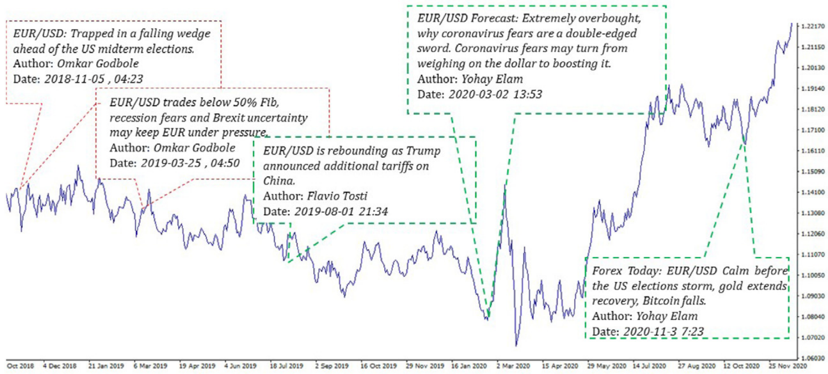


Fig. 2. EUR/USD daily chart and examples of related news headlines.

Table 3
News examples.

Title	Pair	P_{pos}	P_{neg}	P_{neut}
Germany's Merkel on coronavirus: We are in a very serious situation now	EURUSD	0.03	0.85	0.11
USD/JPY drops below 113 as dollar weakens on early midterm election results	USDJPY	0.02	0.95	0.03
GBP/USD: Drops back below 1.3900 on US dollar bounce, Brexit woes ahead of UK PMI	GBPUSD	0.02	0.96	0.02
Bloomberg Analyst Sees Bitcoin at $13K Despite Hints of Deep Breakdown	BTCUSDT	0.89	0.05	0.06

Table 4
News dataset statistics.

Corpus	Total news document	Keywords count	Sentences length	Size
EUR/USD news	7411	16,987	16.87	5 MB
GBP/USD news	4469	16,237	17.78	3 MB
USD/JPY news	5829	14,345	17.45	3 MB
BTC/USDT news	4159	4746	9.7	1 MB

recent work [17], we use Finnhb REST API for market data scraping.[5] Finnub scrapes Forex data from FXCM broker and Cryptocurrencies data from Binance crypto Exchange. Each record is timestamped in the GMT time zone every 60 min and contains Low, High, Open, Close price as well as the trading Volume information corresponding to four currency pairs. We use Binance:BTC/USDT for bitcoin price prediction.

4.2. Experiment setting

We use MAPE loss function and adaptive moment (ADAM) estimation for loss value minimization over all instances in the training set with an initial learning rate of 0.001 except for *BTC/USDT* which we set it to 0.1 to avoid the model falling into a local minimum. The batch size is set to 32. The minimum number of training epochs is 30 with early stopping by monitoring validation set loss. We use Keras in Tensorflow 2 for the implementation. We build a corpus consisting of all news related to the target currency pair in Forex or cryptocurrency markets and then apply BERT tokenizer for news title tokenization. For contextualized word embedding, we choose the FinBERT

5 https://finnhub.io scrape from www.fxcm.com and https://www.binance.com.

Table 5
Dataset statistics.

Dataset		Time Interval	#Instance	#News
EUR/USD	Training	2018-09-24 to 2020-05-26	10,380	3731
	Validation	2020-05-27 to 2020-10-23	2594	1322
	Test	2020-10-24 to 2021-05-04	3243	2359
USD/JPY	Training	2018-09-23 to 2020-05-26	10,357	2621
	Validation	2020-05-27 to 2020-10-23	2595	692
	Test	2020-10-24 to 2021-05-04	3245	1156
GBP/USD	Training	2018-09-23 to 2020-05-26	10,381	4912
	Validation	2020-05-27 to 2021-10-23	2594	410
	Test	2020-10-24 to 2021-05-04	3243	507
BTC/USDT	Training	2020-06-24 to 2021-01-11	4576	2329
	Validation	2021-01-12 to 2021-03-03	1143	542
	Test	2021-03-04 to 2021-05-05	1429	1288

implementation [76] trained on TRC2 data set and fine-tuned on Financial PhraseBank [77] dataset for financial sentiment analysis [61]. We use Technical Analysis (TA) python package [78] to calculate technical indicators. The newsgroup publishes an average of 12.03 news with standard deviation 7.06 per day for EUR/USD currency pair and we have a max number of 5 news per hour in *EUR/USD news*. We align news and market data based on *hourly* timestamps in chronological order and consider 60% for training samples, 20% for validation, and 20% for the test set as shown in Table 5.

4.3. Implementation

We implement *FinBERT-SIMF* on top of *MarketPredict* [17] microservices architecture and only implement our predictive model for both *Model training services* and *Prediction services*.

5. Results and analysis

We evaluate our method against the baselines and discuss the features informativeness and error analysis of the proposed *FinBERT-SIMF* method.

5.1. Feature selection analysis

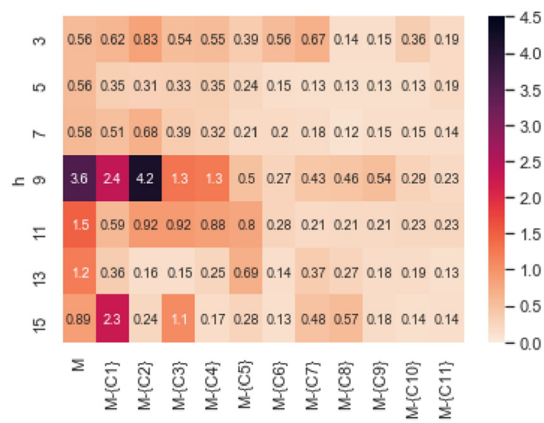
We evaluate the sensitivity of hyper-parameters of our *FinBERT-SIMF* model in the selection of important q number of technical indicators from space $\mathcal{M}$ shown in Table 2 as well as delay window length h. To evaluate the effectiveness of various technical indicators, we propose using an information gain-based strategy for feature selection from space $\mathcal{M}$. Column **IG** in Table 6 shows $I(m_q, p)$ as the mutual information of each feature in $\mathcal{M}$ based on Eq. (1). For all currency pairs, we sort market data items

Table 6
Analysis of information gain and L^2 norm of W_i non-linear weights in the second RNN layer corresponding to market data and mood time series.

Feature	EUR/USD		USD/JPY		GBP/USD		BTC/USDT	
	IG	Weight	IG	Weight	IG	Weight	IG	Weight
Close	3.4450	2.2429	3.4076	1.7116	3.5012	1.3854	3.9462	22.4904
EMA	2.8139	2.0410	2.72111	1.6445	2.8025	1.2032	3.3755	22.6036
BB-Mean	2.6151	1.8932	2.48347	1.6465	2.5440	1.2964	3.1825	22.5484
BB-High	2.7000	1.7738	2.5231	1.6203	2.5033	1.1927	3.1388	22.3512
BB-Low	2.6720	1.8059	2.5337	1.7078	2.4878	1.2640	3.1282	22.9452
OBV	1.3258[a]	1.4514	1.6064[a]	1.1636	1.4298	1.15256	2.6562	31.3090
ADI	1.5577	1.1158	1.733[a]	1.1869	1.8213	1.2260	3.2460	28.4342
ATR	0.2937	1.3086	0.2775	0.9576	0.2003[a]	0.9317	1.5258	18.5931
Volume	0.1017	0.9549	0.0620	1.2606	0.0629[a]	0.6888	0.2102	17.5009
MACD	0.1954	1.2217	0.1844	1.0629	0.2359	0.7283	0.7403	17.4853
AO	0.1312	0.8831	0.1003	0.9712	0.1806	0.6986	0.5865	15.8211
RSI	0.0711	1.1345	0.0384	1.2432	0.1190	0.8094	0.1020	16.5193
Stochastic	0.0491	0.8630	0.0166	1.2946	0.0418	0.7257	0.0446	17.6166
Williams	0.04917	0.8893	0.0166	1.2968	0.0418	0.7239	0.0447	17.5844
S_{pos}	0.0061	1.6941	0.0251	1.6041	0.0026	1.07401	0.0084	23.0713
S_{neg}	0.0112[a]	1.0194	0.0046	1.5608	0.0034[a]	1.0122	0.0131	20.1156
S_{neut}	0.0237	1.1603	0.0023	1.6292	0.0138	1.0213	0.0431[a]	24.2752

[a]Indicates data items negatively correlated with the target close price of the corresponding market.

based on information gained from target close price p as shown in **IG** column in Table 6. We Also report the importance weights of all features based on the model weights analysis during the first round of this experiment in the **weight** column of this table, where the FinBERT-SIMF uses all market and mood based data. Then, we recursively eliminate market-based features from low to high degrees of informativeness and perceive the validation accuracy versus different values of delay window length h. Fig. 3 depicts the heat map plot of sensitivity analysis of EUR/USD validation MAPE loss versus both h and q settings. We test h values from 3 to 13 and the X axis in this figure shows various set of market data that use for model training. For example, term $\mathcal{M} - \{C_1\}$ means we use all indicators in space $\mathcal{M}$ except $C_1 = Williams$, therefor we use the top $q = 11$ market data versus different delay window lengths for model training. The best result for this experiment was achieved for $h = 7$ h and $q = 4$ most informative features including *close price*, *EMA*, *OBV* and *BB-Mean*. For other currency pairs, we do these experiments in the same way and for all, we found the best results for $h = 7$ h and the top $q = 4$ most informative features. Among highly correlated Bollinger bands with each-others, we used ones that give the heaviest weight from the model. At the rest of this section, we discuss the insights of information gain analysis.



$\mathcal{M}$	Close, EMA, BB-Mean, OBV, ADI, Volume, ATR, MACD, AO, RSI, Stochastic, Williams
C_2	Stochastic, Williams
C_4	AO, RSI, Stochastic, Williams
C_6	ATR, MACD, AO, RSI, Stochastic, Williams
C_8	ADI, Volume, ATR, MACD, AO, RSI, Stochastic, Williams
C_{10}	BB-Mean, OBV, ADI, Volume, ATR, MACD, AO, RSI, Stochastic, Williams

Fig. 3. Sensitivity analysis for different values of q and h for EUR/USD with respect to MAPE Loss on the validation set for hourly market prediction. Lighter areas represents more accurate predictions.

5.1.1. Informativeness of market-based features

The weight column in Table 6 depicts the L^2 norm of W_i weights of the second LSTM layer of our FinBERT-SIMF corresponding to each market-based feature in $\mathcal{M}$ when we set $h = 7$ h ago. The W_i weight in the input gate of LSTM's memory block is used to assess the importance of the new information carried by the input vector. According to experiments we do for all currency pairs and also results of our experiments for EURUSD settings shown in Fig. 3, models with different delay window lengths, attend to the top three informative features in the same order. Top informative features based on both **IG** and **weight** columns in Table 6 for currency pairs in the FOREX and cryptocurrency market belong to the Close price, EMA and Bollinger bands. These indicators are the most traditional indicators that investors used for technical analysis in the financial markets. All of these indicators are trend-following and carried a lot of information about the target close based on our analysis. Bollinger bands measure the upper and lower bands of price volatility and EMA calculates the average price while giving the largest weights to recent price. These indicators have a close multi-modal probability distribution with the target close price probability distribution, therefor input gate of the LSTM layer gives the heaviest weight to them. Another important factor for price fluctuation, especially in the cryptocurrency market is the volume of assets that changes hands. We notice in the turbulent bitcoin market OBV gives the largest weight from our model. Also, the fourth most important indicator in the FOREX currency pairs is ADI and OBV, whether both relate to volume and price fluctuations. Other indicators have low information gain and based on results shown in Fig. 3, by removing these indicators the accuracy increased.

5.1.2. Informativeness of mood-based features

Some technical indicators calculated based on historical information, besides researchers such as [79], suggest the time-varying effect of mood time series in the financial market. Regarding the inter-dependency of using market and mood data versus different delay window lengths, we analyze the validation accuracy of EURUSD versus different delay window lengths in Fig. 3. We notice when we train other models, with different delay window lengths and use all indicators in $\mathcal{M}$, these models gave W_i weights to the market features in a similar order as the **weights** column in Table 6 corresponding to the model with delay window $h = 7$. This indicates there is interdependency between sentiment-based features and delay window length because in this experiment we preserve all sentiment-based features. The best results were achieved when we set delay window length $h = 7$ h ago. The last three rows in Table 6 depict the input gate of LSTM's weights corresponding to positive, negative, and neutral score time series for prediction of close price. For all currency pairs, the model attended the news-based features as well as the selected indicators. It seems a longer sequence contains more historical information in theory, while the results of this experiment suggest the sequence does not be too long since the importance of recently published news sentiment.

5.2. Model architecture validity

In order to assess the validity of using RNNs in network architecture for price regression, we compare our model with respect to the following architectures:

- Dense: We do not consider delay window length, and for each timestamp prediction, we concatenate only the previous timestamp mood and market data ($h = 1$). Then, we replace LSTMs in Fig. 1 with two dense layers followed by a dropout and dense layer with a linear activation function. The first one has 64 nodes and the other one has 32 nodes. We use ReLU as an activation function for both.
- Conv1D: We replace LSTMs in Fig. 1 with two Conv1D layers followed by maxpoolings and dropouts and a dense layer with a linear activation function. We find the best delay window length for this model and the other settings are the same as our model.

The results of this experiment in Table 8 show our model architecture with two LSTMs units outperforming other models. LSTMs units in our model can capture contextual information and temporal dependencies between sentiment and market information while replacing LSTMs with dense layers does not perfectly capture temporal contextual information. Our model with LSTMs outperforms Conv1Ds, because of the ability of LSTM to capture complex temporal relationships based on different lags, while Conv1D can capture temporal information between neighborhood data items.

We further evaluate the sensitivity analysis of our model for fusion strategy by concatenation of mood and market-based selected features. We found when we extract features from $X_{(t-h,t)}$ via two stacked LSTM layers, the model outperforms the model that relies on the concatenation of extracted features from two separate LSTM layers for $S_{t-h,t}$ and market data $M_{t-h,t}$.

5.3. Comparison with the baselines

We compare our methods against some modification of our *FinBERT-SIMF* in mood data preparation and then performed ablation studies in second categories of baselines for evaluating the role of information sources for price regression in various markets. Aim at studying the effectiveness of lexicon-based, machine learning-based and transformer-based sentiment analysis in price regression problem, we adopted our sentiment mood time series calculation explained in algorithm 1 based on each of the following setting as shown in Table 7 and compare the results against our *FinBERT-SIMF* proposed method in Table 8. We performed the non-parametric Wilcoxon signed-rank test for *FinBERT-SIMF* and p-values for all cases are below 0.05 and hence differences are statistically significant.

Table 7
Variations of our *FinBERT-SIMF* proposed model.

Model name	Training data	Text representation	Sentiment analysis
FinBERT-IMF	Only trade data	–	–
FinBERT-SF	Only mood data	[*CLS*] token embedding	transformer-based (FinBERT)
Loughran_Donald-SIMF	News and trade data	–	lexicon-based (Loughran MacDonald)
Glove-SIMF	News and trade data	Glove embedding	Machine learning-based (MLP)
DistilBERT-SIMF	News and trade data	[*CLS*] token embedding	transformer-based (DistilBERT)
FinBERT-SIMF	News and trade data	[*CLS*] token embedding	transformer-based (FinBERT)

- *Loughran_Donald-SIMF*: Following [16], we use the domain-specific Loughran–Donald lexicon to calculate the mood time series. We use the same settings for delay window and market-based features for *Loughran _Donald-SIMF* as *FinBERT-SIMF*.
- *Glove-SIMF*: Following [57], we train a Multi-Layer Perceptron (MLP) sentiment classifier and for labeling, same as [23, 57], we consider market volatility an hour after news publishing timestamp and apply average Glove embedding [80] for news title text representation. We use probability distribution of positive, negative and neutral mood for sentiment score calculation. We setup experiments for tuning delay window and market-based features same as *FinBERT-SIMF*.
- *DistilBERT-SIMF*: DistilBERT [64] leverages knowledge distillation during the pre-training phase and decreases the inference time in real-time usage. We use a fine-tuned version for sentiment analysis [64]. [64] trained for two classes (positive/negative) sentiment analysis and we calculate only negative/positive scores. We conduct experiments for tuning delay window and market-based features same as *FinBERT-SIMF*. Other settings was the same as our model.

The results in Table 8 show the superiority of our *FinBERT-SIMF* against other variations of our method. We notice that transformer-based FinBERT fine-tuned for financial sentiment analysis outperforms Loughran_Donald-SIMF lexicon-based and Glove-SIMF machine learning-based sentiment analysis. This indicates the superiority of transformer-based sentiment analysis against lexicon-based methods used in [16]. Besides, the negative effect of automatic labeling of news in training set for Glove-SIMF based on lag-based currency pair return severely affects the performance of the method used by [57]. *FinBERT-SIMF* outperforms DistilBERT-SIMF for all currency pairs. This shows the importance of fine-tuning BERT-based language models for FSA corpus, while DistilBERT fine-tuned for general domain sentiment analysis and did not handle neutral sentiment analysis.

5.3.1. Ablation study

To evaluate the impact of various information sources for price regression, we carry out ablation studies. We compare our *FinBERT-SIMF* method against two modifications FinBERT-IMF and FinBERT-SF. In FinBERT-IMF we switch off any mood based inputs and in FinBERT-SF we switch off any market-based input in our model architecture (Fig. 1). For both FinBERT-IMF and FinBERT-SF we do delay window tuning and for FinBERT-IMF, we used the top 4 most informative features same as our model. The results in Table 8 show *FinBERT-SIMF* has a smaller prediction

Table 8
Comparison of the mean absolute percentage error (MAPE) loss. Differences between *FinBERT-SIMF* and others are determined to be statistically significant based on Wilcoxon signed-rank test.

Method	EUR/USD		USD/JPY		GBP/USD		BTC/USDT	
	Validation loss	Test loss	Validation loss	Test loss	Validation loss	Test loss	Validation loss	Test loss
Dense	3.64	6.88	55.24	55.035	1.88	5.77	76.52	80.73
Conv1D	14.06	27.91	1.52	2.68	1.90	10.84	73.28	78.96
FinBERT-IMF	3.623	6.965	2.695	3.085	0.691	6.434	68.09	74.696
FinBERT-SF	3.14	6.99	0.7587	0.8964	0.186	0.8995	62.56	79.62
Loughran _Donald-SIMF	3.032	4.568	2.020	3.132	0.643	6.231	67.092	73.581
Glove-SIMF	1.923	2.436	1.087	1.768	0.546	2.321	60.027	84.069
DistilBERT-SIMF	0.10	1.090	0.722	0.564	0.137	0.417	59.349	71.149
BERT-BoEC	2.694	5.147	2.224	2.942	0.611	6.383	65.185	73.214
BHAM	3.243	6.166	2.689	3.082	0.691	6.422	67.536	75.087
FinBERT-SIMF	**0.121**	**0.291**	**0.200**	**0.307**	**0.084**	**0.122**	**55.334**	**67.949**

error than FinBERT-IMF that only use market-based input. This indicates the informativeness of news sentiment for financial decision support. Also, we notice the superiority of *FinBERT-SIMF* against *FinBERT-SF*, which indicates using only news information cannot benefit for price regression. The superiority of *FinBERT-SIMF* against these two modifications for all currency pairs prediction indicates investors should pay attention to both technical analysis and mood in specialized newsgroups.

We further study the effect of incorporating news content and mood as well as technical indicators by comparing *FinBERT-SIMF* against two time series forecasting methods that directly use news content embedding and technical indicators:

- *BERT-BoEC*: Anbaee et al. [17] presented a concept-based news representation method that leverages information in the news title and body and sentiment. After performing BERT-BoEC text representation from news content and sentiment values via DistilBERT, a hybrid model is composed of a Recurrent CNN for feature extraction from the financial news and an LSTM layer for feature extraction from technical indicators.
- *BHAM*: The BERT-based Hierarchical Aggregation Model (BHAM) [27], first performs [*CLS*] token through BERT for news title and then groups news based on timestamp and then applies a SOTA based summarization. This model uses a multi-layer perceptron for feature extraction from trading data and then predicts the market trend based on jointly using text information and trading data. We adopted this model to hourly market price prediction.

The superiority of *FinBERT-SIMF* and BERT-BoEC against the BHAM indicate the importance of feature extraction from time series via RNNs. When we compare our method against BERT-BoEC, our method outperforms BERT-BoEC for all currency pairs. Fig. 4 depicts the prediction plot for the test set of three currency pairs EUR/USD, USD/JPY, and GBP/USD. This figure clearly shows the strong ability of our model for generalization of price regression during six months of the test set, while the non-stationary and multimodal nature of financial time series severely affect the performance of BERT-BoEC in validation and test sets. The complex structure of BERT-BOEC could not generalize the moving average of price, while the simple network structure and our simple fusion strategy before feature extraction via RNNs for the composition of mood and market data in *FinBERT-SIMF* reduce the error in validation and test set.

5.4. Error analysis and limitation

We plot the hourly predicted price of our *FinBERT-SIMF* for EURUSD, GBPUSD, and USDJPY. These figures show the strong ability of our *FinBERT-SIMF* for trend behavior modeling during the six-month data samples in the test set, which helps investors for accurate decisions making. The GBPUSD plot (graph c) depicts the efficacy of *FinBERT-SIMF* for trend behavior prediction as well as price regression with a 0.12% error in the test set. Correlation analysis in Table 6 shows the target price negatively correlated with negative score time series, which indicates the efficacy of FinBERT in sentiment analysis. The news titles *"GBP/USD retreats below 1.3900 as relation fears stay strong ahead of NFP"* and *"UK Manufacturing Production drops 2.3% MoM in January vs. −0.8% expected"* are two examples that FinBERT gave 99% for negative scores for both. *FinBERT-SIMF* has a good ability for USDJPY price prediction with 0.3% error, while these errors mostly belong to the last two months in which the prediction values are drifted below the average price, but in the same behavior. In the case where the test interval has an upward trend, we normalized the test data using the average of the test data, while the model trained based on normalized values with the average of the training set and this caused the gap between actual close price and predicted values. We plan to resolve the concept drift problem by the adaptive normalization strategy proposed in [81]. For EURUSD also the model predicts trend behavior effectively, while during the Jan 2021 predicted prices have a wrong spike. It seems at the end of the year and the beginning of the new year EURUSD exchange rate is influenced by the injection of money via stakeholders in governments and institutions rather than the news.

For BTCUSDT, we notice the large loss values in the validation and test set for all methods we compared with each other in Table 8. In the bitcoin market, the moving average price changes intermittently, and investors are heavily influenced by the news. In *FinBERT-SIMF* we investigate a z-score normalization strategy, which cannot generalize price fluctuation over intermittent moving averages. We plan to use adaptive normalization strategy [81] as a future work. In *FinBERT-SIMF*, we use only news title for sentiment analysis, while Daudert in [44] shows the superiority of the fine-grained financial sentiment analysis method against FinBERT that uses all information in news title and body. We notice the BTCUSDT target close price time series has a negative correlation with neutral sentiment score time series. When we look at the sentiment score of some news titles given through FinBERT, we see there is some news that FinBERT predicts a neutral tone, while actually having a mixture of neutral and negative tone. We plan to use information in the news body for ambivalence sentiment handling proposed in [82] as well as finer-grained sentiment analysis proposed in [44,83–86] as to future work.

6. Conclusion and future work

In this work, we proposed a market prediction open-source tool leveraging the informative market data including price, volume, and a set of technical indicators as well as tracking mood

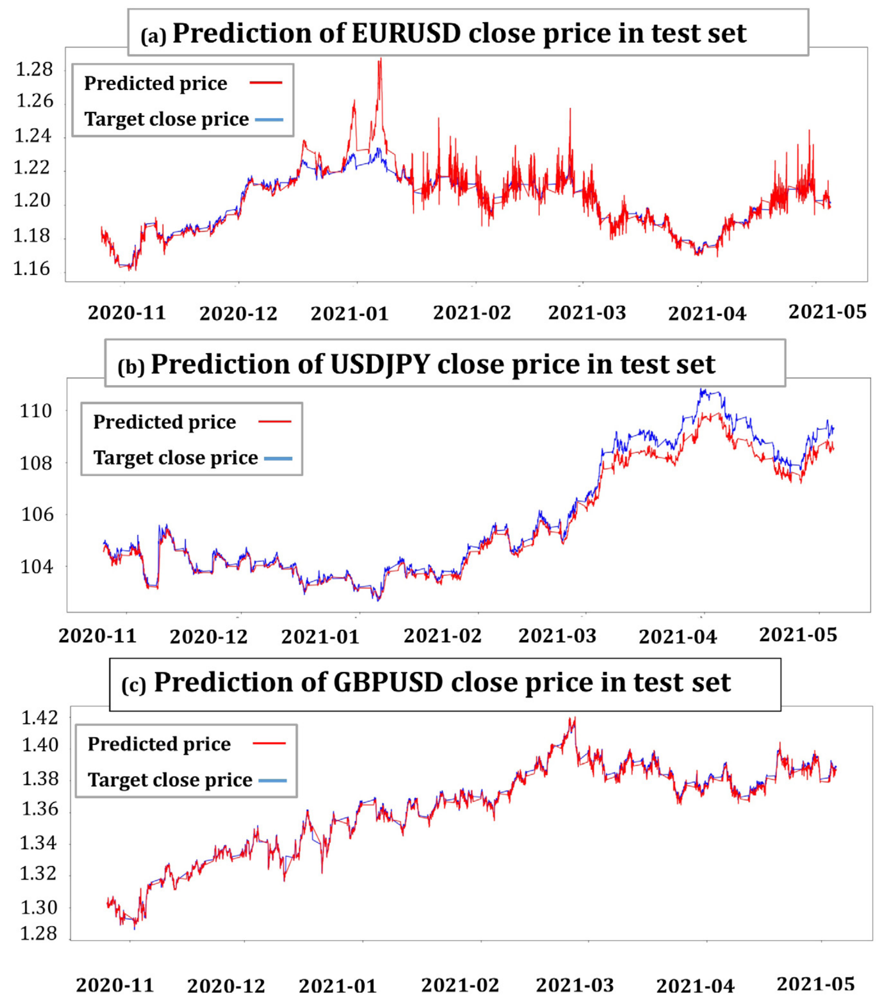


Fig. 4. Proposed method predicted close prices for the six months of hourly time-frame in tests set.

in specialized newsgroups. For market feature selection, we consider the amount of information gain of market data from target close price of various currency pairs in FOREX and Cryptocurrency markets as well as the importance weight of recurrent neural network to the technical indicators. Our predictive model leverages the emotional distribution of news in BERT-based fine-tuned for financial sentiment analysis, where FinBERT captures deep information about semantic and syntactic role of words in news title. After news and market data temporal alignment, news sentiment scores time series is calculated. This results in a snapshot of mood time series and informative market data. We then utilize a recurrent neural network to jointly extract features from emotional and technical market information. We evaluated the effectiveness of using both news sentiment and informative indicators for price regression on Forex and Cryptocurrency markets. Experimental results show the effectiveness of incorporating the mood of financial news in market prediction. We plan to incorporate fine-grained sentiment analysis based on news content and generalization of our method for other markets like gold and oil as our future work.

CRediT authorship contribution statement

Saeede Anbaee Farimani: Conception and design of study, Acquisition of data, Software, Analysis and/or interpretation of data, Writing – original draft. **Majid Vafaei Jahan:** Conception and design of study, Supervision, Funding acquisition, Writing – review & editing. **Amin Milani Fard:** Conception and design of study, Supervision, Writing – review & editing. **Seyed Reza Kamel Tabbakh:** Conception and design of study, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors would like to acknowledge the financial support of Iran's Ministry of Science, Research and Technology for this project under the grant number 12-99-02-000049. The funding source had no impact on the study design, collection, analysis, and interpretation of data; in the writing of the report; and in the decision to submit the article for publication.

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