Comparative Analysis of Image-Based and Time-Series Deep Learning Models

for Cryptocurrency Market Prediction

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Introduction

Cryptocurrency Market Challenges

High volatility and complexity

- The cryptocurrency market experiences extreme price fluctuations, driven by factors like market sentiment, regulatory news, and technology shifts. This makes it difficult to predict price movements accurately.

Need for Accurate Prediction

- Precise market predictions are critical for traders seeking to maximize profits and minimize risks. Developing effective prediction models can lead to significant competitive advantages in trading strategies.

Unstable Data

- The cryptocurrency market operates globally 24/7, with high fluctuations in trading volume and data. This makes it difficult to maintain consistency in data collection and analysis, which can impact the performance of prediction models.

Introduction

Literature on Cryptocurrency market prediction using machine learning

Statistical methods & Machine Learning

Fischer et al. (2018)

- Random forest, logistic regression
- Predicting the relative performance of 40 major cryptocurrencies

Chen et al. (2019)

- Linear statistical methods, machine learning approaches
- Comparison of prediction performance for cryptocurrency prices

Dutta et al. (2019)

- Various neural network approaches
- Bitcoin price prediction

Time-Series based Deep Learning

McNally et al. (2016)

- Elman recurrent neural network, LSTM, ARIMA
- Performance comparison for cryptocurrency market prediction

Alessandretti et al. (2018)

- Gradient boosting classifier, LSTM
- Predicting daily returns

Lahmir and Bekiros (2018)

- LSTM, generalized regression neural network
- Comparing prediction performance for cryptocurrency prices

Others

Betancourt and Chen (2020)

- Deep ***reinforcement learning***
- Daily cryptocurrency trading predictions based on 20-day price, volume, and market cap data

Jiang et al. (2023)

- CNN (**image-based, charts**)
- Image-based stock prediction

No studies on cryptocurrency market prediction using image-based deep learning methods!

Introduction

Image-Based Deep Learning Modeling

Visual Pattern Recognition

- Detects trends, support/resistance levels, and other technical patterns that are crucial for financial analysis.

Utilizes Spatial Information

- Convolutional or transformer-based models can exploit the spatial relationships in chart data for more accurate predictions.

Time-Series Based Deep Learning Modeling

Temporal Pattern Analysis

- Time-series models process data in chronological order, analyzing patterns of change in historical data to forecast future trends.

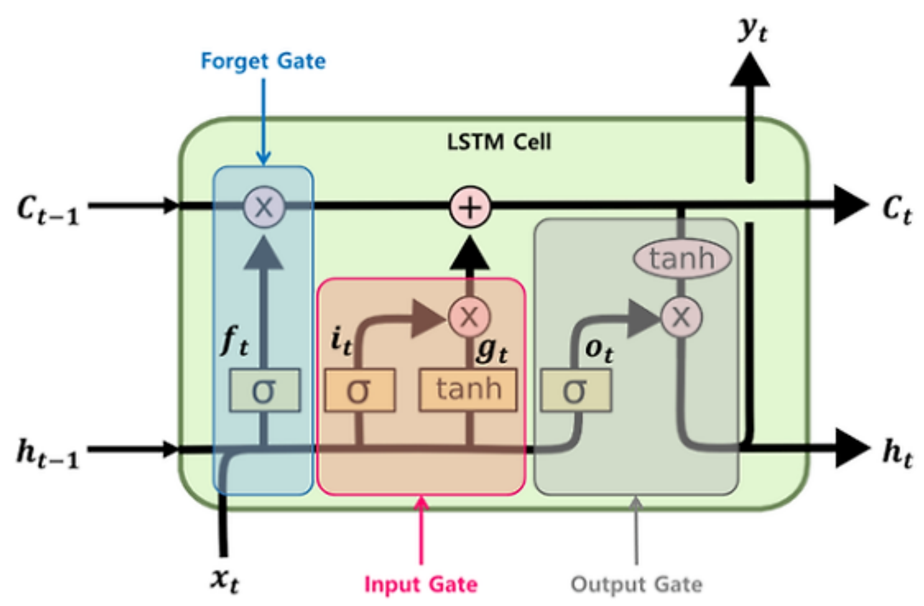
Capturing Long-Term Dependencies

- These models can reflect important long-term trends and correlations in time-series data, allowing for more precise predictions in complex markets like cryptocurrency.

We want to investigate how prediction results differ across deep learning methods when the input data and features are the same

Overview of Models

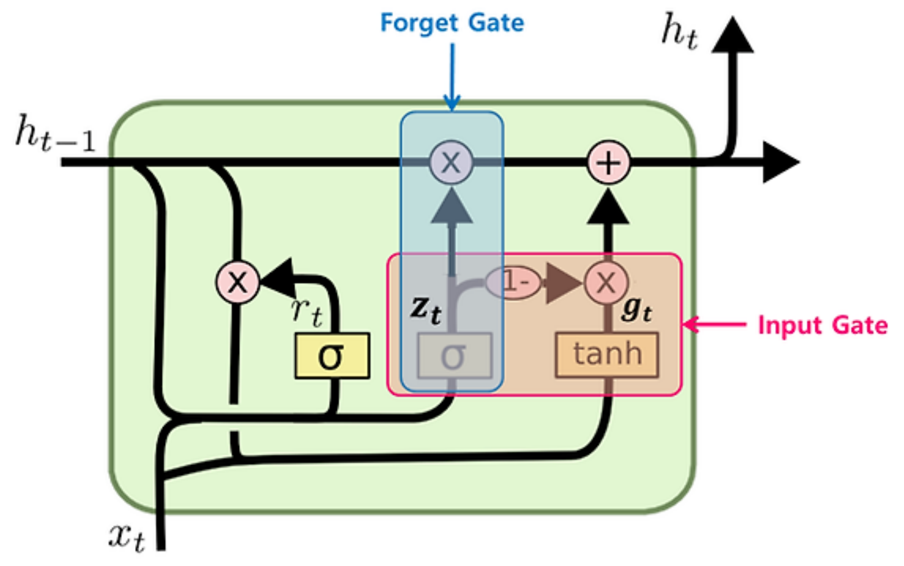
Time-Series Models



LSTM

Hochreiter and Schmidhuber. (1997)

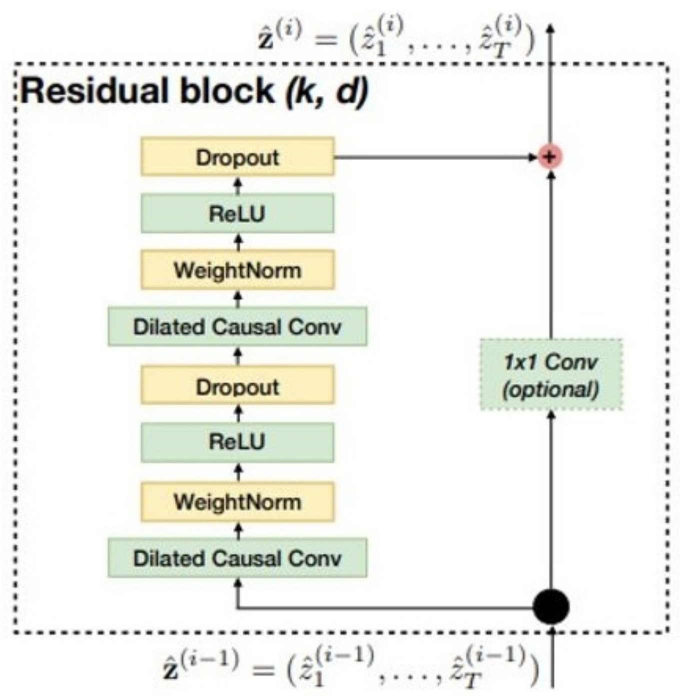
- To address the vanishing gradient problem in traditional RNNs, which struggled with long-term dependencies.



GRU

Cho et al. (2014)

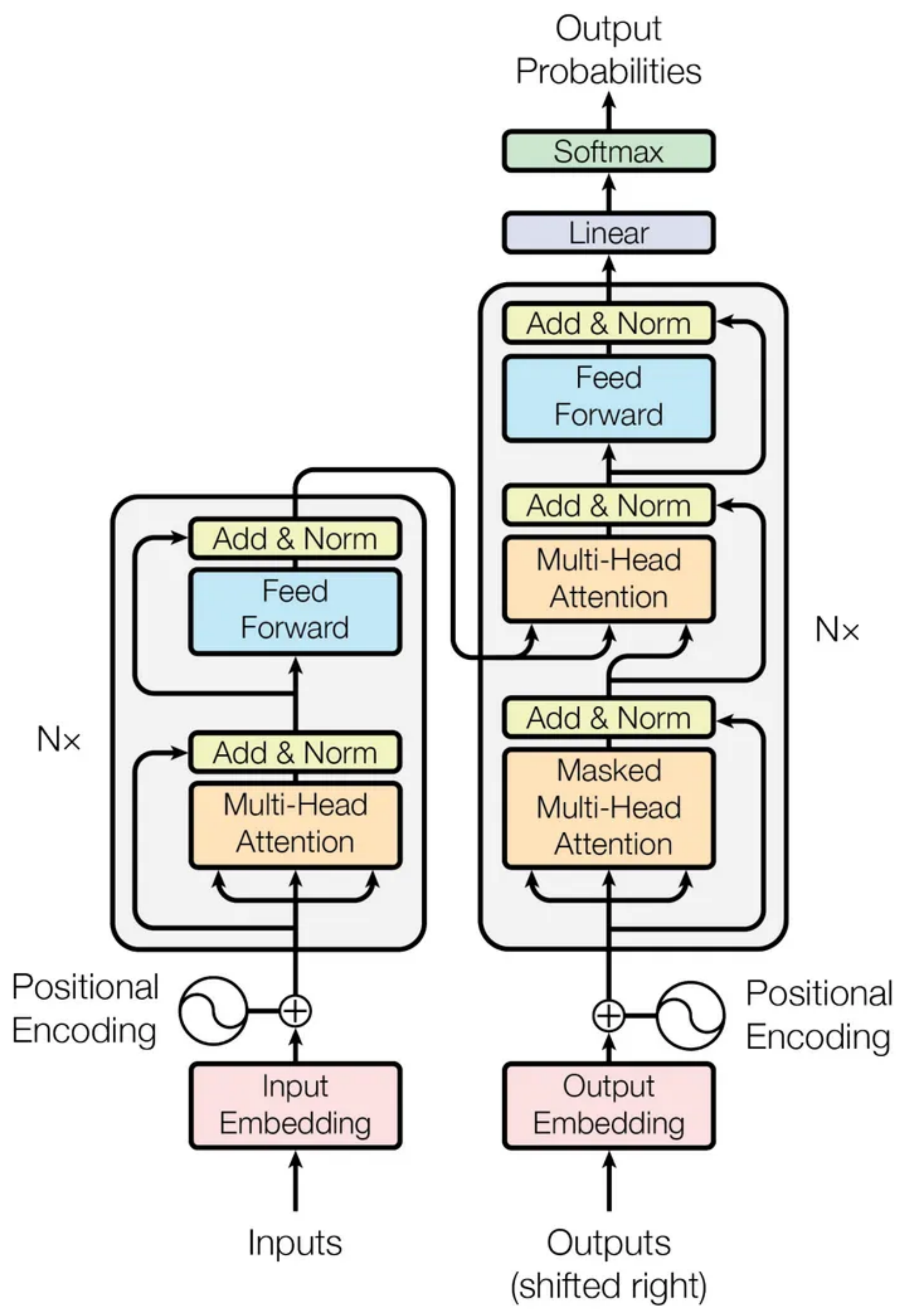
- To simplify LSTM while maintaining similar performance, reducing complexity for easier training.



TCN

Lea, Colin, et al. (2017)

- To provide a convolutional approach for handling sequential data, enabling better parallelization and efficiency.



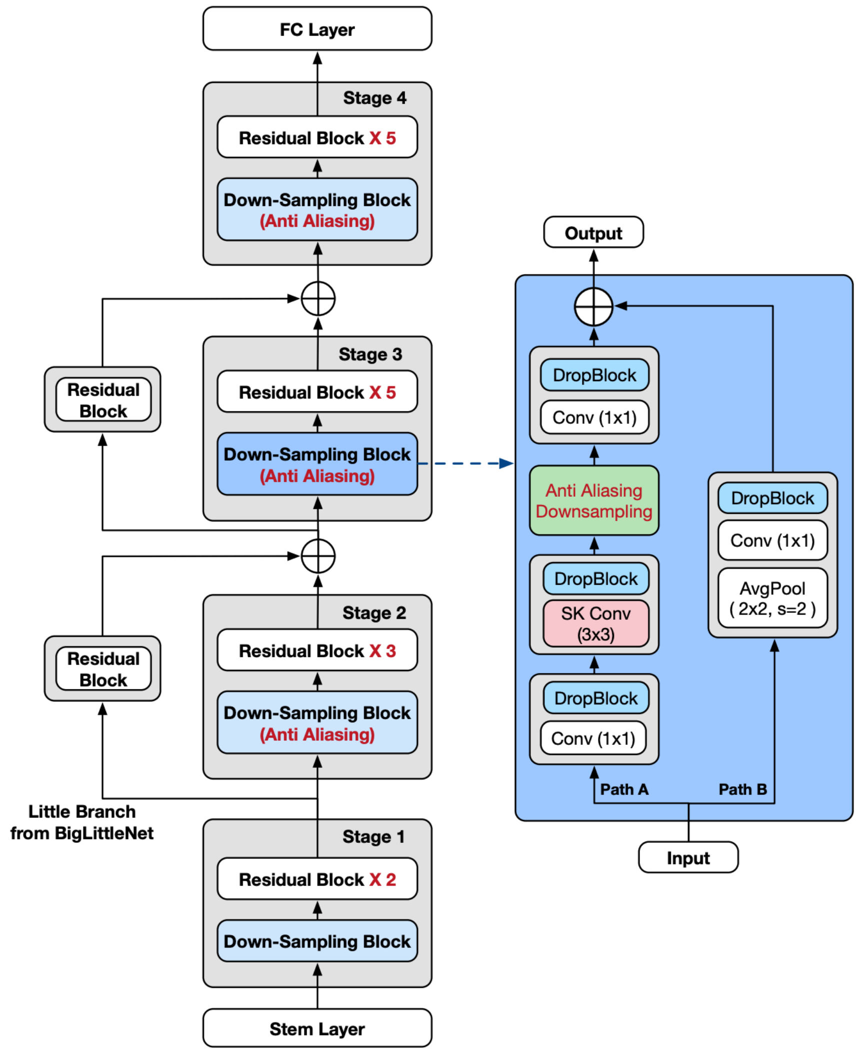
Transformer

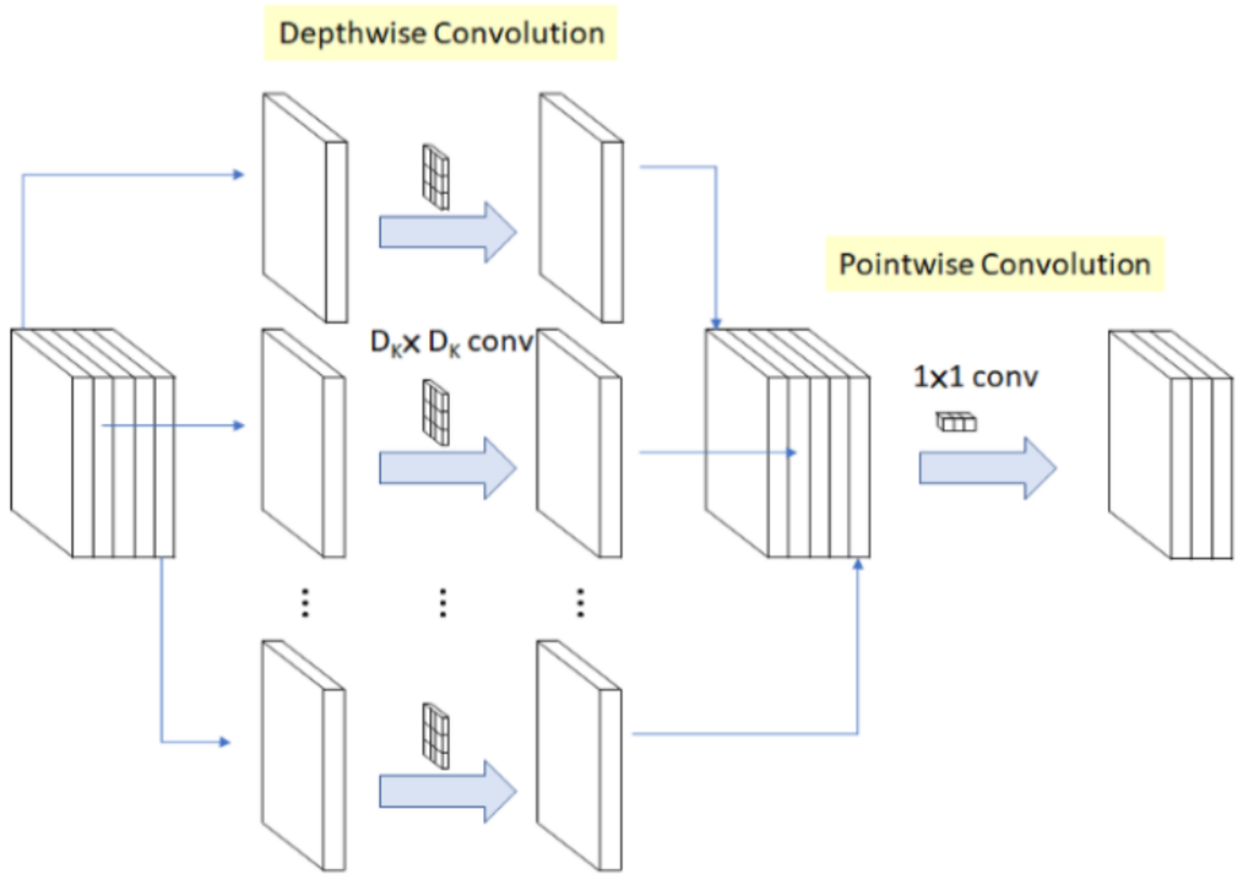
Vaswani et al. (2017)

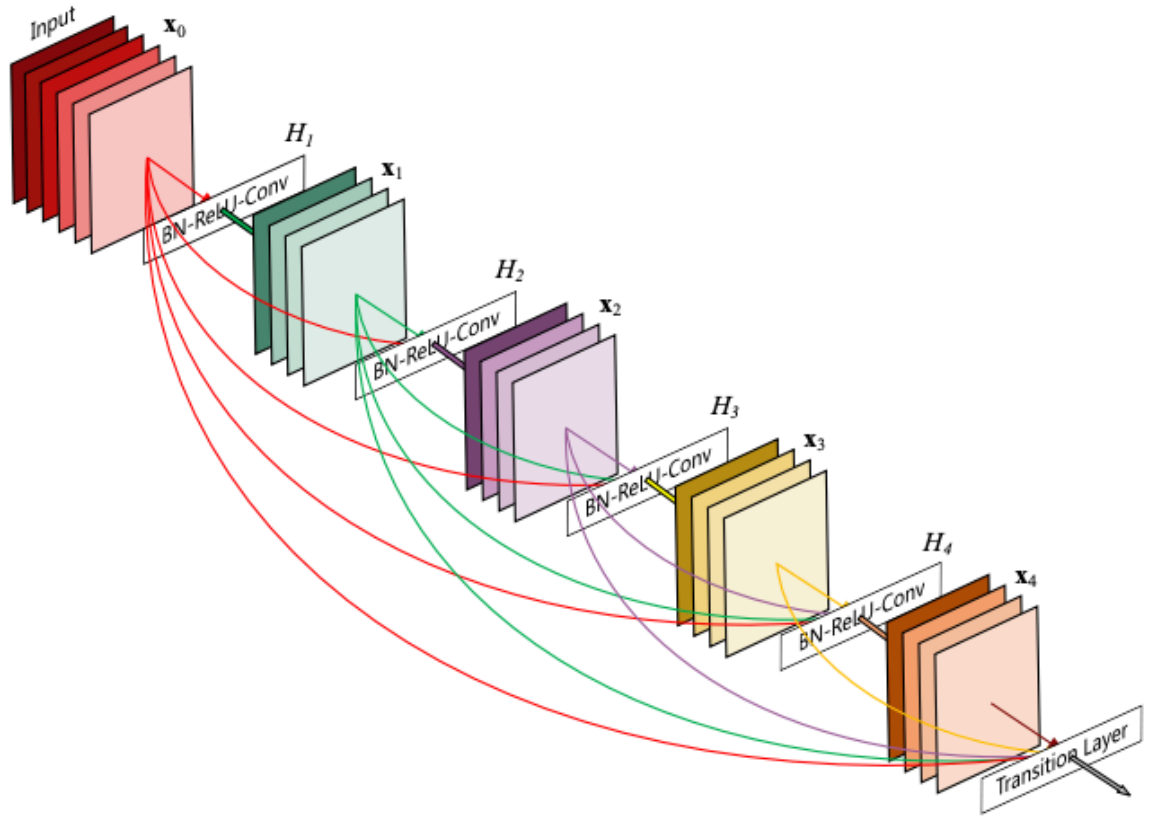
- To overcome limitations of RNNs and CNNs, enabling efficient processing of sequences with long-range dependencies through self-attention.

Overview of Models

Image-Based Models







ResNet

He, Kaiming, et al. (2016)

- To solve the vanishing gradient problem in deep networks.

MobileNet

Howard et al. (2017)

- To enable efficient CNNs for mobile and embedded devices.

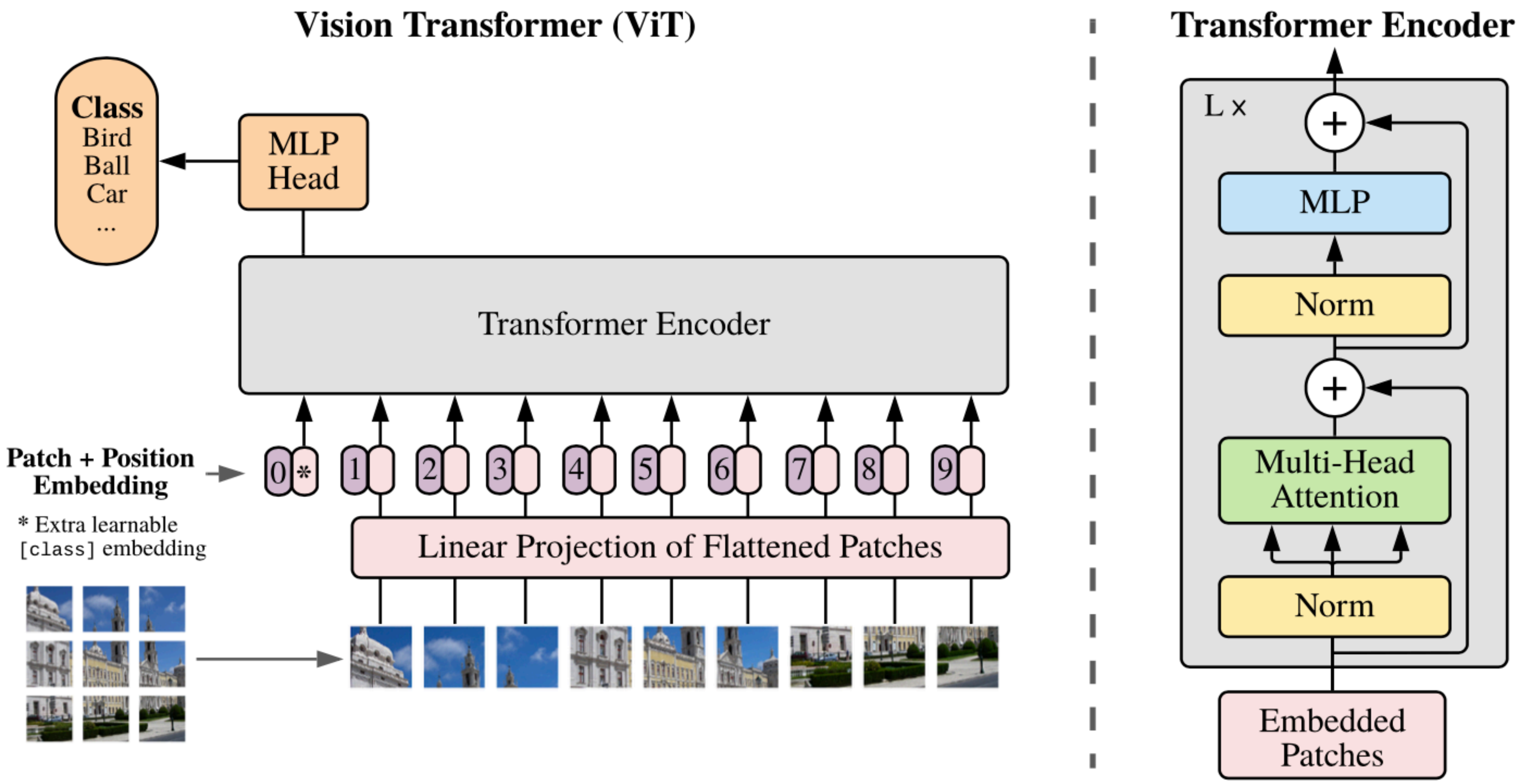
DenseNet

Huang, Gao, et al. (2017)

- To enhance feature reuse and reduce the number of parameters.

Overview of Models

Image-Based Models



Vision Transformer (ViT)

Dosovitskiy, A. (2020)

- Building on the success of Transformers in the field of Natural Language Processing (NLP), the idea emerged that they could also perform well in image processing.
- The image is split into patches that are tokenized and, using self-attention, each patch learns its relation to others.
- Transformers surpass CNNs by capturing global patterns and learning relationships between patches simultaneously.

Data and Methodology

Data Sources & Selection Criteria

CRYPTO COMPARE

OHLC (Open, High, Low, Close) and Volume data

- Period: February 2018 to December 2023
- Daily Data

CoinMarketCap

Top 100 cryptocurrencies by market capitalization(excluding stablecoins)

Data and Methodology

Top 100 Cryptocurrencies on February 02, 2018

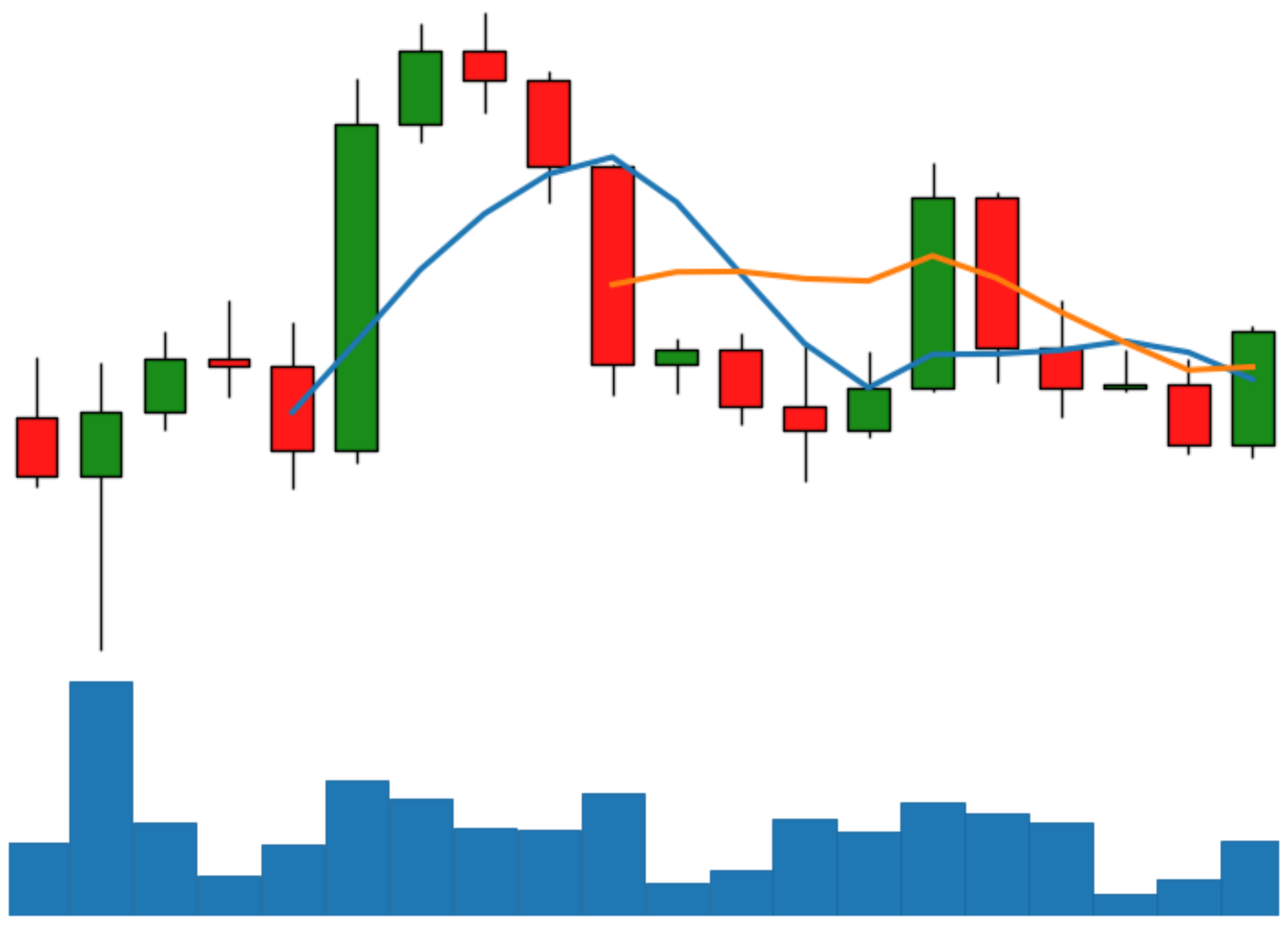
Rank	Name	Symbol	Market Cap	Price	Circulating Supply	volume (24h)	% 1h	% 24h	% 7d
1	Bitcoin	BTC	$10,190,038,593.97	$825.37	12,346,025 BTC	$11,300,875.00	-0.03%	-1.25%	-6.75%
2	Litecoin	LTC	$568,440,705.88	$22.40	25,376,204 LTC	$3,546,106.00	0.37%	-0.94%	-7.62%
3	XRP	XRP	$168,555,395.10	$0.02156	7,817,889,792 XRP	$112,300.54	-0.03%	3.65%	6.99%
4	Peercoin	PPC	$121,775,514.33	$5.7693	21,107,370 PPC	$855,817.50	-0.64%	-3.12%	-4.30%
5	Nxt	NXT	$66,887,849.48	$0.06689	999,998,016 NXT	$150,626.78	3.25%	0.47%	-14.05%
6	Omni	OMNI	$53,732,367.19	$86.74	619,478 OMNI	$17,114.18	4.24%	10.99%	-22.34%
7	Dogecoin	DOGE	$53,548,741.65	$0.001279	41,857,077,248 DOGE	$2,000,717.63	6.66%	-13.01%	-20.87%
8	Namecoin	NMC	$43,247,803.90	$5.4557	7,927,093 NMC	$732,770.50	0.02%	-3.45%	-11.11%
9	Quark	QRK	$24,838,589.61	$0.1004	247,482,608 QRK	$206,069.33	-0.93%	-2.28%	12.70%
10	BitShares PTS	PTS	$20,423,494.21	$14.44	1,413,980 PTS	$47,811.55	3.86%	12.70%	16.71%
11	Megacoin	MEC	$14,452,781.99	$0.6569	22,002,200 MEC	$37,601.32	5.23%	3.58%	1.82%
12	WorldCoin	WDC	$14,181,219.26	$0.3301	42,955,200 WDC	$67,850.11	3.07%	1.77%	-2.59%
13	Primecoin	XPM	$12,906,285.55	$3.0209	4,272,396 XPM	$63,828.77	0.40%	-2.93%	-11.25%
14	Infinitecoin	IFC	$9,670,060.72	$0.0001074	90,004,496,384 IFC	$19,282.50	-0.32%	-3.32%	-21.93%
15	Feathercoin	FTC	$9,240,475.67	$0.2889	31,987,300 FTC	$59,291.48	-0.03%	-4.35%	-11.24%

2018.02.02 Market Cap(Snapshot)

Data and Methodology

Input Representations

Image-Based Model (Charts)



2022.02.23 BTC

- Financial chart images (candlestick, MAV, Volume-bar)

Time-Series Model

	Price	Open	High	Low	Vol.	Symbol
Date						
2019-09-20	0.05257	0.05003	0.10000	0.04570	2026065.70	HBAR
2019-09-21	0.04787	0.05257	0.05835	0.04543	3900910.54	HBAR
2019-09-22	0.03940	0.04787	0.04838	0.03640	15361687.28	HBAR
2019-09-23	0.03783	0.03940	0.04235	0.03429	13057416.48	HBAR
2019-09-24	0.02961	0.03783	0.04887	0.02938	7744853.68	HBAR

- Sequential numeric data.
- (OHLC - Open, High, Low, Close and Volume)

Data composition

- Train Set (2018.02.01-2022.02.21): 57,183 Set
- Validation Set (2022.02.22-2023.04.29): 31,924 Set
- Test Set (2023.04.30-2023-12-31): 19,842 Set

Output: Returns for the following day

Comparative Results

Model Performance Comparison

Image-Based Model

Model	Accuracy	Precision	Recall	F1-Score
ResNet	**0.9895**	0.9921	0.9868	**0.9926**
MobileNet	0.9777	0.9628	**0.9937**	0.9780
DenseNet	0.9852	**0.9997**	0.9706	0.9849
ViT	0.9850	0.9933	0.9767	0.9849

- Models like ResNet, MobileNet, DenseNet, and Vision Transformer (ViT) consistently achieve higher accuracy and F1-scores compared to time-series models.
- The ability to process spatial data via convolutional or transformer-based architectures gives these models an edge in representing complex market behavior.

Time-Series Model

Model	Accuracy	Precision	Recall	F1-Score
LSTM	**0.5031**	0.5037	**0.9396**	**0.6558**
GRU	0.4976	0.5141	0.0537	0.0973
TCN	0.4968	**0.5176**	0.0188	0.0362
Trasnformer	0.5014	0.5064	0.4156	0.4565

- LSTM, GRU, and TCN all show poor recall and F1-scores, reflecting difficulty in capturing complex patterns over time.
- Sequential models are limited by the chaotic and nonlinear nature of the cryptocurrency market.

Discussion

Why Image-Based Models Excel

Capture complex patterns and spatial relationships

- Image-based models can detect intricate market patterns (e.g., trends, support/resistance levels) and leverage spatial relationships, providing deeper insights into price movements that may be missed by raw numerical data.

Rich integration of multiple indicators

- Financial charts combine various technical indicators (e.g., moving averages, RSI, volume) into a single visual representation, allowing models to process and analyze different layers of market information more effectively.

Intuitive and scalable interpretability

- Charts are not only easier for human traders to interpret but also offer models the ability to learn from global patterns without being affected by data scaling, making them robust and intuitive for decision-making.

Even with the same information of input data and features, by converting their representations we can obtain more relevant information.

Discussion

Limitations of Time-Series Models

Difficulty in handling nonlinear and chaotic market behavior

- Time-series models often struggle to accurately capture the highly volatile and chaotic nature of cryptocurrency markets, where price movements can be unpredictable.

Sequential data dependency

- Time-series models rely on strict sequential data processing, which can limit their ability to capture long-range dependencies or relationships between distant time points effectively.

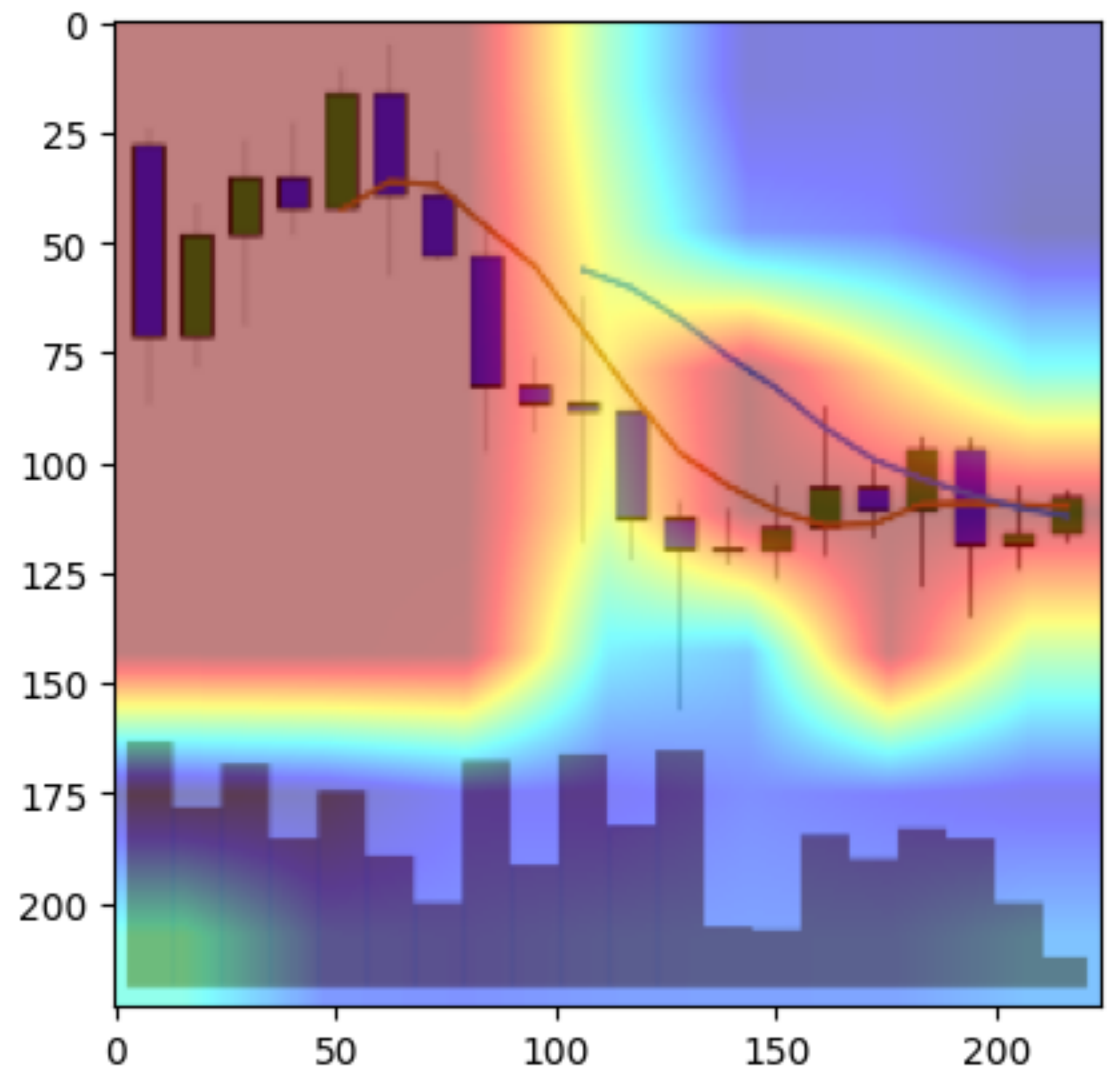
Sensitivity to noise and overfitting

- Due to the highly volatile and noisy data in cryptocurrency markets, time-series models are prone to overfitting and may struggle to generalize well across different market conditions.

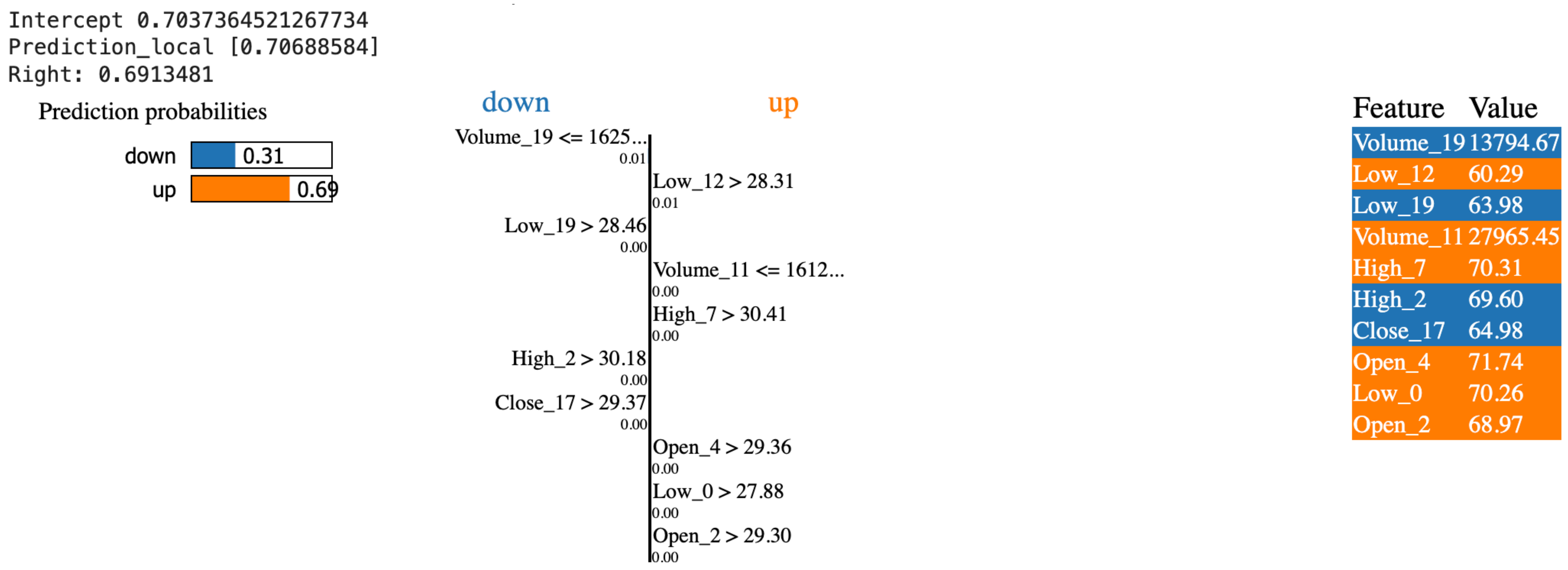
Comparative Results

More advantage - explainable AI (XAI)

Image-Based Model



Time-Series Model



- Class Activation Map (CAM)
- The areas highlighted in color represent the regions that the model recognized as contributing to the prediction of a specific pattern.
- The closer the color is to red, the higher the importance of that area.

- Local Interpretable Model-agnostic Explanations(LIME)
- LIME highlights important features that contribute to predictions and simplifies the decision-making process of complex models.
- Visualization of the degree to which features contribute to predictions: orange supports an increase, while blue supports a decrease.

Conclusion

Key Takeaways

- Image-based models are more effective for cryptocurrency market prediction
- Even with the same information, the representation of input values still matters
- This approach offers significant potential for building more accurate and profitable trading strategies in robot-advisor industry
- Image-based models have more advantages in interpreting which factors explain the prediction results

Future Research

- Comparison of portfolio analysis
  - Conduct an empirical analysis by constructing a long-short portfolio based on the predictions from image-based and time-series based models
  - Investigate the profitability and risk-adjusted returns of these portfolios

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