International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Link : https://ijiemr.org/downloads/Volume-12/Issue-05

10.48047/IJIEMR/V12/ISSUE05/18

Title **DL-Guess Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction**

Volume 12, Issue 05, Pages: 168-178

Paper Authors

Dr. N Swapna, Masam bhanu goud, P.Sampath, Rishikesh subedhar, Tirunagari subodhkrishna

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

DL-Guess Deep Learning and Sentiment Analysis-Based Cryptocurrency Price Prediction

1. **Dr. N Swapna,** Associate professor & Head of the Department, MTech (Phd),Department of CSE, (Vijay Rural Engineering College(VREC)), swapnanaralas@gmail.com

2. **Masam bhanu goud**, BTech, Department of CSE, (Vijay Rural Engineering College(VREC)) Masambhanugoud@gmail.com

3. **P.Sampath**, BTech, Department of CSE, (Vijay Rural Engineering College(VREC)) sampathpabha818@gmail.com

4. **Rishikesh subedhar**, BTech, Department of CSE, (Vijay Rural Engineering College(VREC)) Subedharrishikesh@gmail.com

5. **Tirunagari subodhkrishna**, BTech, Department of CSE, (Vijay Rural Engineering College(VREC)) Subodhkrishna3021@gmail.com

ABSTRACT: Cryptocurrencies are peer-to-peer transaction systems that use the secure hash algorithm (SHA)-256 and message digest (MD)-5 methods to protect data transactions. Cryptocurrency values are exceedingly volatile, follow stochastic moments, and have achieved unpredictability. They are frequently used for investment and have replaced traditional forms of investment like as metals, estates, and the stock market. Their commercial prominence necessitates the creation of a strong forecasting model. However, given to its reliance on other cryptocurrencies, bitcoin price forecast is difficult. Many academics have employed machine learning and deep learning models, as well as other market sentiment-based algorithms, to forecast cryptocurrency prices. Because all cryptocurrencies belong to the same class, a rise in the price of one cryptocurrency might cause a price change for other cryptocurrencies. The emotions from tweets and other social media platforms were also used by the researchers to improve the performance of their suggested system. Motivated by this, we offer in this study a hybrid and resilient framework, DL-Gues, for cryptocurrency price prediction that takes into account its interdependence on other cryptocurrencies as well as market attitudes. For validation, we investigated Dash price prediction utilising price history and tweets of Dash, Litecoin, and Bitcoin for different loss functions. To test the applicability of DL-GuesS on additional cryptocurrencies, we inferred findings for Bitcoin-Cash price prediction using the price history and tweets of Bitcoin-Cash, Litecoin, and Bitcoin.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Keywords *– Cryptocurrency, complex systems, fusion of cryptocurrency, price prediction, VADER, sentiment analysis, deep learning, systems of systems.*

1. INTRODUCTION

A cryptocurrency is a digital type of money that was designed to be used as a regular method of transaction. To protect the confidentiality of financial transactions, it employs cryptographic methods like as SHA-256 and MD-5. In the current environment, financial transactions cannot be carried out without the participation of third-party entities such as banks, but cryptocurrency removes this need. Cryptocurrencies are now an accepted part of society. It was initially presented as Bitcoin in 2008, with the goal of replacing the whole cash exchange system with a universal digital money system [1]. To make the system transparent, safe, and dispersed, this newly developed financial system is independent of centralised financial institutions like as banks, governments, and other organisations. To maintain system integrity and consistency, methods such as proof-of-work (PoW), proof-of-stack (PoS), and other consensus algorithms were devised. When it was created, cryptocurrency exchange rates were quite low. However, due to its volatility character, its market begins to grow over time. To far, almost 4200 crypto currencies are circulating in the market, with a market valuation of $2.23 billion (till April 2021). Popular cryptocurrencies like as Bitcoin and Ethereum are the largest donors, accounting for 78% and 12% of the total [2]. This bitcoin market surge has enticed many people, investors, and businesses to invest directly or indirectly [3]. The bitcoin market surge is awkward owing to its volatility nature. Cryptocurrency values swing dramatically over time. Within a decade, the price of Bitcoin increased from $0.08 in 2010 to $64000 in April 2021 [2]. Ethereum prices grew from $0.67 in January 2018 to $2346 in April 2021, following the same pattern [2]. These patterns justify the bitcoin market's volatility. Furthermore, additional variables like as volume, mining difficulty, popularity, and the price of competing crypto coins all contribute to the volatility of cryptocurrency values.

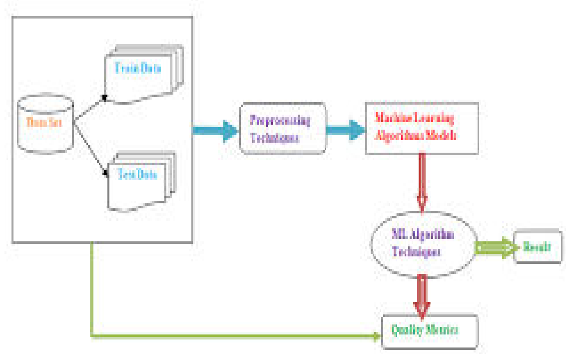

Fig.1: Example figure

Researchers from all around the world have utilised theories such as the efficient market

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

hypothesis (EMH) and the alternative market hypothesis (AMH) to study bitcoin market patterns and volatility. According to the EMH theory, the prices at which cryptocurrencies are exchanged are always fair and represent all available information. Furthermore, as the difficulty of the mining challenge grows, so will the price of the related coin [4]. However, in practise, this theory does not function, and in order to solve the shortcomings of EMH, a new theory, AMH, was established with the addition of behavioural finance. Still, we may achieve nice results by using EMH like the authors of [5] do, but they are not exact.

2. LITERATURE REVIEW

Stochastic neural networks for cryptocurrency price prediction:

With the development of blockchain technology in recent years, there has been a significant surge in the use of Cryptocurrencies. Cryptocurrencies, on the other hand, are not seen as an investment prospect owing to the market's unstable nature and excessive price volatility. Because of their deterministic character, most of the techniques presented in the literature for cryptocurrency price forecasting may not be appropriate for real-time price prediction. Motivated by the aforementioned concerns, we present a stochastic neural network model for predicting cryptocurrency prices. The suggested method is based on random walk theory, which is often used in financial markets to simulate stock values. To replicate market volatility, the proposed approach introduces layer-wise randomization into the observed feature activations of neural networks. In addition, a strategy for learning the pattern of market response is incorporated in the prediction model. For Bitcoin, Ethereum, and Litecoin, we trained the Multi-Layer Perceptron (MLP) and Long Short-Term Memory (LSTM) models. The findings suggest that the proposed model outperforms the deterministic models.

Efficiency in the markets of crypto-currencies

We demonstrate that the amount of market efficiency in the five main cryptocurrencies varies greatly over time. Prior to 2017, bitcoin marketplaces were primarily inefficient. This supports current findings in the field. However, between 2017 and 2019, the bitcoin markets became more efficient. This contradicts other, more recent findings on the subject. One explanation for this is because we use a larger sample size than earlier research. Another crucial reason is because we use a rigorous measure of efficiency, allowing us to decide whether or not the efficiency is substantial. On average, Litecoin is the most efficient cryptocurrency, while Ripple is the least efficient.

Cryptocurrency price prediction using news and social media sentiment

Bitcoin was presented to the world in a document that was anonymously published and signed by the pseudonym Satoshi Nakamoto. A large number of cryptocurrencies were produced in the ensuing years as a result of its immense success. This exponential rise is mostly due to the market's extraordinary volatility, which has piqued the curiosity and involvement of many individuals, primarily for profit. Cryptocurrency aficionados often share and learn about news and ideas on social media sites, the most prominent of which being Twitter. In this work, we investigate the degree to which Twitter sentiment analysis may be utilised to forecast cryptocurrency price variations. We first collected tweets and price data for seven of the most prominent cryptocurrencies, which we then processed to do sentiment analysis using Valence Aware Dictionary for Sentiment Reasoning (VADER). Augmented Dicky Fuller (ADF) and Kwiatkowski Phillips Schmidt Shin (KPSS) tests were used to assess time-series stationarity, followed by Granger Causality testing. While price swings seem to impact emotion for Bitcoin, Cardano, XRP, and Doge, Ethereum and Polkadot were determined to be predictable based on a bullishness ratio. Finally, the predictability of price returns is investigated using Vector Autoregression (VAR), with remarkably accurate projections made for two of the seven cryptocurrencies. Price projections for Ethereum and Polkadot, in particular, were 99.67% and 99.17% accurate, respectively.

Prediction of Bitcoin exchange rate to American dollar using artificial neural network methods

The trading of cryptocurrencies is increasingly a popular sort of investing. The cryptocurrency market has been regarded similarly to the forex and stock markets. However, because to its volatility, there is a need for a prediction tool to assist investors in making investment choices for cryptocurrency trading. Artificial Neural Network (ANN) computing-based methods are now widely employed in stock and currency market forecasting. There has been a lot of study on ANN predictors using equities and forex as case studies, but none on cryptocurrencies. As a result, this study investigated a number of ANN methods for predicting the market value of one of the most popular cryptocurrencies, Bitcoin. The ANN approaches will be used to create a model that predicts the following day's closing value of Bitcoin (next day prediction). Backpropagation neural network (BPNN), genetic algorithm neural network (GANN),

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

genetic algorithm backpropagation neural network (GABPNN), and neuro-evolution of augmenting topologies are the four ANN approaches evaluated in this research (NEAT). The approaches are assessed based on their accuracy and complexity. The experiment revealed that BPNN is the best technique, with a MAPE of 1.998 0.038% and a training time of 347 63 seconds.

Machine learning models comparison for bitcoin price prediction

Bitcoin has become the most valued cryptocurrency in recent years. However, Bitcoin values have been exceedingly volatile, making it impossible to forecast. As a result, the goal of this study is to find the most efficient and accurate model for predicting Bitcoin values using multiple machine learning methods. Several regression models using scikit-Iearn and Keras libraries were tested using 1-minute interval trade data from the Bitcoin exchange website bitstamp from January 1, 2012 to January 8, 2018. The Mean Squared Error (MSE) was as low as 0.00002 and the R-Square (R 2) was as high as 99.2% in the top findings.

3. METHODOLOGY

Researchers from all around the world have utilised theories such as the efficient market hypothesis (EMH) and the alternative market hypothesis (AMH) to study bitcoin market patterns and volatility. According to the EMH theory, the prices at which cryptocurrencies are exchanged are always fair and represent all available information. Furthermore, as the difficulty of the mining challenge rises, so will the price of the related coin. However, in practise, this theory does not function, and in order to solve the shortcomings of EMH, a new theory, AMH, was established with the addition of behavioural finance. Still, we can achieve decent results by using EMH like the authors do, but it is not accurate/

Disadvantages:

1. As the difficulty of the mining challenge rises, so will the price of the related cryptocurrency.
2. We can still achieve decent results by using EMH as the authors do, but it is not correct.

Many academics have employed machine learning and deep learning models, as well as other market sentiment-based algorithms, to forecast cryptocurrency prices. Because all cryptocurrencies belong to the same class, a rise in the price of one cryptocurrency might cause a price change for other cryptocurrencies. The emotions from tweets and other social media platforms were also used by the researchers to

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

improve the performance of their suggested system. Motivated by this, we offer in this study a hybrid and resilient framework, DL-Gues, for cryptocurrency price prediction that takes into account its interdependence on other cryptocurrencies as well as market attitudes.

Advantages:

1. The robustness of DLGuesS, we evaluated the performance of DL-GuesS for two distinct cryptocurrencies and compared the results.
2. In terms of forecasting bitcoin values, the suggested DL-GuesS beats existing systems. DL-GuesS.

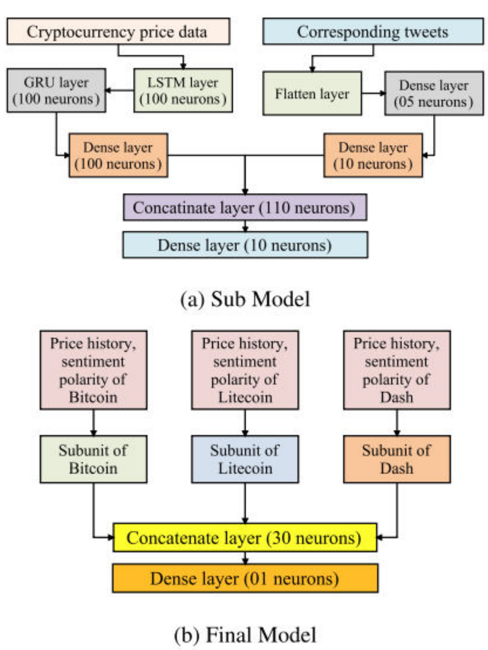

Fig.2: System architecture

MODULES:

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will put data into the system using this module.
- Processing: we will read data for processing using this module.
- Splitting data into train and test: Using this module, data will be separated into train and test models.
- Making the model LSTM - GRU - Logistic Regression - Random Forest - Decision Tree - Support Vector Machine - MLP - Voting Classifier - (LR + RF + MLP) - ARIMA for Forecasting. Calculated algorithm accuracy.
- User signup and login: Using this module will result in registration and login.
- User input: Using this module will result in predicted input.
- Prediction: final predicted shown

4. IMPLEMENTATION

ALGORITHMS:

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

CNN + LSTM: A CNN-LSTM model is made up of CNN layers that extract features from input data and LSTM layers that forecast sequences. A time series is a temporal sequence of data that is primarily used for sequential data. Because it handles sequences better, LSTM is the chosen DNN algorithm. CNN is often beneficial for capturing neighbourhood information, such as in a picture.

LSTM: A deep learning architecture based on an artificial recurrent neural network, long short-term memory (LSTM) (RNN). For situations requiring sequences and time series, LSTMs offer a promising solution.

GRU: Gated recurrent units (GRUs) are a recurrent neural network gating technique established in 2014 by Kyunghyun Cho et al. The GRU functions similarly to a long short-term memory (LSTM) with a forget gate, but with fewer parameters since it lacks an output gate.

Logistic Regression: Logistic regression is a Machine Learning classification technique that predicts the likelihood of certain classes based on specified dependent variables. In summary, the logistic regression model computes the logistic of the outcome by adding the input characteristics (in most situations, there is a bias component).

Random Forest: A Random Forest Method is a supervised machine learning algorithm that is widely used in Machine Learning for Classification and Regression issues. We know that a forest is made up of many trees, and the more trees there are, the more vigorous the forest is.

Decision tree: A decision tree is a non-parametric supervised learning technique that may be used for classification and regression applications. It has a tree structure that is hierarchical and consists of a root node, branches, internal nodes, and leaf nodes.

SVM: Support Vector Machine (SVM) is a supervised machine learning technique that may be used for both classification and regression. Though we call them regression issues, they are best suited for categorization. The SVM algorithm's goal is to identify a hyperplane in an N-dimensional space that clearly classifies the input points.

MLP: Another artificial neural network technique with several layers is the multi-layer perceptron (MLP). Although obviously linear issues may be addressed with a single perceptron, it is not well suited to non-linear applications. MLP may be used to address these difficult challenges.

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

Voting classifier: A voting classifier is a machine learning estimator that trains numerous base models or estimators and predicts based on the results of each base estimator. Aggregating criteria may be coupled voting decisions for each estimator output.

ARIMA: ARIMA models are commonly designated as ARIMA (p,d,q), where p represents the order of the autoregressive model, d represents the degree of differencing, and q represents the order of the moving-average model. ARIMA models employ differencing to turn a non-stationary time series into a stationary one, and then use previous data to forecast future values.

5. EXPERIMENTAL RESULTS

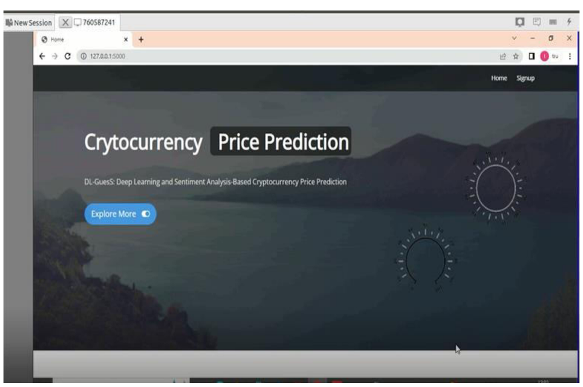

Fig.3: Home screen

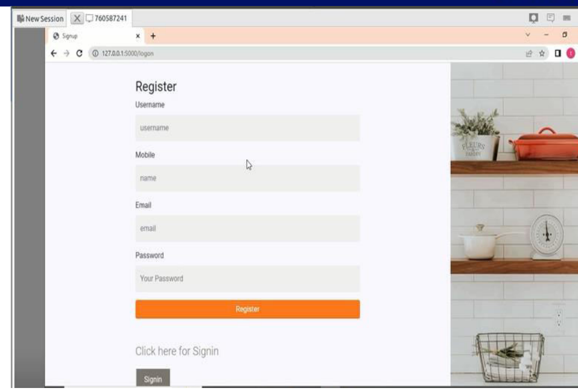

Fig.4: User registration

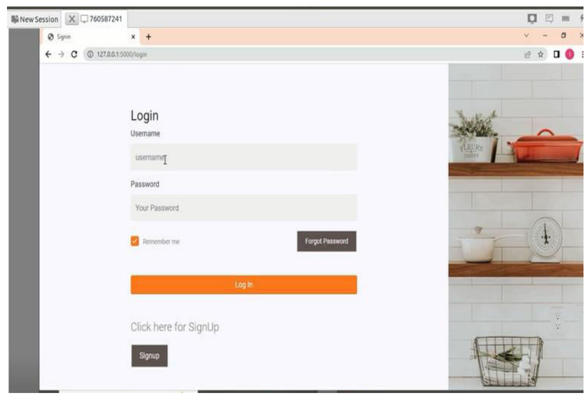

Fig.5: user login

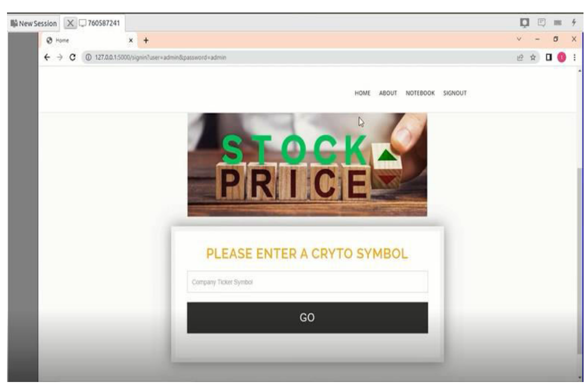

Fig.6: Main screen

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

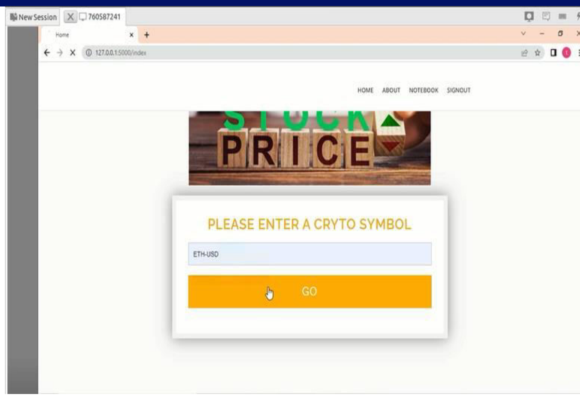

Fig.7: User input

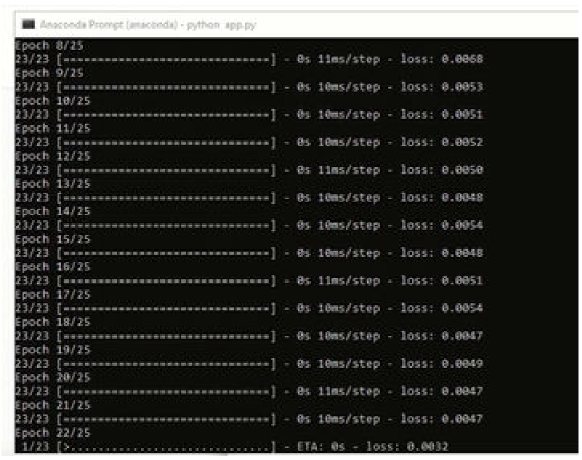

Fig.8: Prediction result

6. CONCLUSION

We examined current techniques for bitcoin price prediction in this article. Many of them are being used by fin-tech enterprises to capitalise on the benefits of bitcoin price prediction models. However, the unpredictable nature of the market and the many dependent elements make forecasting difficult. In this research, we develop a hybrid model, DL-GuesS, for bitcoin price prediction that takes into account price history and current Twitter emotions. To explain the robustness of DLGuesS, we evaluated its performance for two distinct cryptocurrencies and compared the findings, i.e., loss functions, with prior studies. In terms of forecasting bitcoin values, the suggested DL-GuesS surpasses existing algorithms. DL-GuesS.

REFERENCES

[1] S. Nakamoto. (2009). Bitcoin: A Peer-to-Peer Electronic Cash System. Cryptography Mailing List. [Online]. Available: https://metzdowd.com

[2] CoinMarketCap. (2021). Today's Cryptocurrency Prices by Market Cap. Accessed: 2021. [Online]. Available: https://coinmarketcap.com/

[3] P. Jay, V. Kalariya, P. Parmar, S. Tanwar, N. Kumar, and M. Alazab, ''Stochastic neural networks for cryptocurrency price prediction,'' IEEE Access, vol. 8, pp. 82804–82818, 2020.

[4] R. Sharma. (2019). Do Bitcoin Mining Energy Costs Influence its Price? Accessed: 2019. [Online]. Available: https://www.investopedia. com/news/do-bitcoin-mining-energy-costs-influence-its-price/

International Journal for Innovative Engineering and Management Research

PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL

www.ijiemr.org

[5] V. L. Tran and T. Leirvik, ‘‘Efficiency in the markets of crypto-currencies,’’ Finance Res. Lett., vol. 35, Jul. 2020, Art. no. 101382.

[6] C. Lamon, E. Nielsen, and E. Redondo, ‘‘Cryptocurrency price prediction using news and social media sentiment,’’ SMU Data Sci. Rev., vol. 1, no. 3, pp. 1–22, 2017.

[7] A. Radityo, Q. Munajat, and I. Budi, ‘‘Prediction of Bitcoin exchange rate to American dollar using artificial neural network methods,’’ in Proc. Int. Conf. Adv. Comput. Sci. Inf. Syst. (ICACSIS), 2017, pp. 433–438, doi: 10.1109/ICACSIS.2017.8355070.

[8] T. Phaladisailoed and T. Numnonda, ‘‘Machine learning models comparison for bitcoin price prediction,’’ in Proc. 10th Int. Conf. Inf. Technol. Electr. Eng. (ICITEE), Jul. 2018, pp. 506–511.

[9] M. Wimalagunaratne and G. Poravi, ‘‘A predictive model for the global cryptocurrency market: A holistic approach to predicting cryptocurrency prices,’’ in Proc. 8th Int. Conf. Intell. Syst., Modelling Simulation (ISMS), May 2018, pp. 78–83.

[10] I. A. Hashish, F. Forni, G. Andreotti, T. Facchinetti, and S. Darjani, ‘‘A hybrid model for bitcoin prices prediction using hidden Markov models and optimized LSTM networks,’’ in Proc. 24th IEEE Int. Conf. Emerg. Technol. Factory Autom. (ETFA), Sep. 2019, pp. 721–728.