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Cryptocurrency Payment Platform with an Artificial Intelligence Supported Recommendation System

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Abstract

Nowadays, cryptocurrencies distributed over the internet are frequently used in commercial activities. However, the rapidly growing trading volume and high volatility of digital currencies make the decision-making process of investors increasingly complex. The sudden price changes of the cryptocurrency markets pose great risks to investors. Furthermore, the time and additional cost losses incurred when transferring assets between different exchanges make this complex process even more difficult. In the cryptocurrency industry, which is growing with increasing initiatives, the importance of providing solutions where investors can manage their entire portfolios on a single platform and trade quickly and easily is paramount. In response to this need, a platform has been developed that provides instant access to price fluctuations in the cryptocurrency market, where users can evaluate arbitrage opportunities between different exchanges and select the most optimal trading options. Technologies such as Java 17, Spring Boot 3.1 and WebFlux (Reactive Programming) and Microservice Architecture have been used for the backend part of the platform. The frontend of the platform is developed using React.js 18.2, Flutter 3.10, TypeScript and Redux. Various machine learning models have been tested for the asset transfer suggestions that the platform will offer to the user, and as a result, a Long-Short Term Memory (LSTM) based model has been developed that makes the most accurate predictions. According to the results of the performance tests applied on the developed platform, the transaction time has been accelerated by an average of 7.7 times compared to the manual scenario. User evaluations further confirmed that users not only find the platform powerful but also use it with an extremely easy and satisfying experience.

Keywords: Cryptocurrency Trading Platform, Cryptocurrency Portfolio Optimization, Machine Learning, Bitcoin, Cryptocurrency Payment Platform

1. Introduction

In recent years, the global economy has been rapidly transforming due to technological advancements. Digitalization has radically changed the structure of financial transactions, enabling the transfer of money and payment systems to digital platforms. In this context, e-currencies and digital payments have started to play an increasingly central role in the financial system, in addition to traditional currencies.

One of the most important innovations of this digitalization process has been the development of cryptocurrency (David Yermack, 2013). Cryptocurrency offers a self-sufficient peer-to-peer transaction network that works with cryptographic proof without the need for a central authority, allowing users to make transactions directly. Meanwhile, users are facing the large trading volume and sudden price fluctuations of digital currencies, which makes it difficult for users to execute the right trade at the right time. In other words, the cryptocurrency markets' rapidly changing dynamics and high volatilities make the decision-making processes very complex. For this reason, the importance of instant data access and price comparison between exchanges becomes evident.

The rapid price swings in the cryptocurrency markets pose significant risks to investors. Currently, users are confronted with time loss and additional transaction costs during the crypto asset transfers to their accounts on different exchanges. Therefore, it has become a need to accurately predict the price change in the markets and make appropriate transfer strategies by taking early measures. Current solutions require users to gather information about market changes from different platforms, which reduces transaction speed and decision-making efficiency. All these challenges which come with the transfer processes highlight the need for a fast and easy-to-use solution that allows investors to manage their entire portfolio on a single platform.

The aim of this study is to provide a solution for users to manage their crypto assets more effectively and minimize the risks inherent in the complexity of the market. To this end, a system has been developed where users can evaluate price differences between different exchanges and choose the most suitable trading options, providing instant access to price fluctuations in the cryptocurrency market, and through the machine learning–based recommendation system, the most profitable crypto asset to be sold can be recommended to users by evaluating current market data.

This study is organized as follows: Section 2 includes relevant literature. Details of the platform are presented in Section 3. Results of the study are given in Section 4. Section 5 concludes the paper.

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2. Literature Review

(Bahram Alidaee et al., 2025) examined Modern Portfolio Theory models in the U.S. stock and cryptocurrency markets. Analyses show that Markowitz Portfolio Selection and the Optimal Dynamic portfolio models provide better returns and work much faster than other models. Furthermore, these models have been found to mitigate risks and outperform both exchange-traded funds and other models. The result of the study, it has been concluded that the frequency of data collection did not make a difference on portfolio selection.

(Mehrdad Heydarpour et al., 2025) presented a portfolio optimization model based on short-term Moving Average (MA) techniques using LSTM forecasts to reduce uncertainties in algorithmic trading. The study applied the algorithms Variable Length MA, Flexible Length MA, Exponential MA, and Simple Moving Average (SMA) to stock and cryptocurrency portfolios. The results revealed that these algorithmic strategies outperformed the "buy and hold" method. However, it has been noted that some strategies are not appropriate in certain situations. In general, it is concluded that portfolios in which all strategies and assets are used outperform traditional approaches, even in uncertain markets.

(Xinran Huang, Linzhi Tan et al., 2025) introduced a new approach for portfolio optimization based on a deep learning Conditional Value-at-Risk (CVaR) utility function which is a measure of tail risks. The performance of this approach has been assessed in comparison to other portfolio construction techniques, including the Naïve, Minimum Variance and Mean-Variance portfolios. Findings showed that the suggested approach performs better than traditional optimization methods.

(Taufeeq Hussain and M. Ramamoorthy, 2025) aimed to provide cryptocurrency portfolio management by applying LSTM networks and compare its effectiveness with Deep Reinforcement Learning (DRL) method. To this end, an LSTM-based model has been developed using historical cryptocurrency price data for optimal portfolio management. It has been seen that the LSTM model can capture long-term market dependencies and market patterns, also it improves portfolio performance in backtesting results. However, with the comparative analysis of LSTM and DRL-based models, it has been observed that DRL algorithm outperformed the LSTM model with a higher value of Accuracy, confirmed by an independent sample test.

(Dailin Song, 2025) aimed to forecast the bitcoin prices using machine learning algorithms Gradient Boosting and LSTM algorithms. In the first step of the study, Bitcoin prices have been forecasted by LSTM-based model and other models. The performances of models were evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) error metrics. After that, four major cryptocurrencies have been forecasted using LSTM algorithm. The forecasted prices have been used in portfolio optimization through Monte Carlo simulation and the Efficient Frontier method. This study demonstrated that machine learning techniques can be used to enhance investment methods, ensuring optimal portfolio allocation, as well as the prediction of cryptocurrency values.

(Zhongyuan Xu, 2025) Presented an approach using Reinforcement Learning (RL) algorithm for dynamic portfolio optimization. With the DRL model developed, it was enabled to interact with the cryptocurrency market, continuously optimizing asset allocation and control volatility. After the evaluation of the model, a cumulative return rate of 85.12%, annual volatility of 45.76% and a maximum drawdown rate of 22.34% were achieved. Findings show that the RL model has a strong capability of revenue generation and risk management.

(Rüya Kaplan Yıldırım et al., 2025) introduced a hybrid portfolio optimization model that combines the Markowitz optimization method with the Ridge Regression algorithm. The model is trained with a dataset divided into 80% training and 20% testing. Cross-validation has been implemented to the model to prevent overfitting. The findings showed that this integrated approach significantly improved portfolio stability and achieved the maximum Sharpe ratio.

(Habib ZOUAOUI & Maryam-Nadjat NAAS, 2025), aimed to explore advanced portfolio management techniques in cryptocurrency markets. For this purpose, return and risk-dependent behavioral finance models and deep learning methods such as Artificial Neural Networks and LSTM were developed. A random portfolio of 25 cryptocurrencies was selected from the Yahoo Finance database and the 5-day portfolio weights of the investment portfolio were estimated. Deep learning models achieved a level of %0,0218 Mean Squared Error (MSE). The study demonstrated that deep learning algorithms are effective in predicting optimal portfolio weights, excelling in performance indicators such as the Sharpe ratio over the Markowitz return-risk model.

(Mariam Elkhechafi and Jihane Aayale, 2024) presented a new portfolio management system based on DRL which can use 5 parameters for a comprenshive market analysis, also can evaluate multiple data sources simultaneously. Additionally, deep concolution has been used to assess each parameter separately. For the better understanding of high-potential assets, a five-dimensional attention gating network has been proposed. According to the simulation results, this approach outperformed traditional methods by providing outstanding returns and reduced short-term risks.

(Rihab Bedoui et al., 2023) explored the potential advantages of utilizing the CVA/R optimization approach, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, Extreme Value Theory (EVT) and Vine Copula together to make optimal allocation decisions for a portfolio consisting of Bitcoin, gold, oil, and stock indices. In the first step of the study, a suitable GARCH model has been applied to each entity. Then, Generalized Pareto Distribution has been used for modelling of innovation tails. Vine Copula-GARCH-EVT model has been created to catch the interdependency structure between the assets. This model was integrated with Monte Carlo simulation to improve risk assessment. This study offered valuable insights for portfolio managers looking to optimize multi-asset portfolios.

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(Prashnatita Pal et al., 2024) addressed the scalability issues in the implementation of micropayments on cryptocurrency networks. To this end, a payment method that uses the Polygon distributed ledger network has been proposed for fast and low-cost transactions. MetaMask electronic wallet which provides secure and independent data transaction has been used in the proposed approach. Findings showed that, proposed method offered advantages for retailers.

(Dendej Sawarnkatat and Sucha Smanchat, 2022) presented a payment system architecture where buyers can make payment in one currency and sellers receive the payment with their choosing, for a payment system called NAGA which works with several cryptocurrencies. With this structure of payment, complexity and inconvenience has been reduced and also, payments could be processed with their real-time exchange rates.

(Valery Titov et al., 2021) addressed the implementation of a cryptocurrency financial system based on open innovation over transactions per second using a statistical approach. In the study, a comprhensive approach has been presented to select the optimum crypto payment finance system. Additionally, the social factors which might have effect on implementation of the cryptocurrency financial system have been analyzed. According to the results of this study, the cryptocurrency finance system is being adopted due to its practicality and convenience, as well as the provision of efficient transaction time.

3. Details of the Platform

The platform has been structured in microservices architecture to offer scalability and modularity. For the basic data flow of the system, a layered structure consisting of user interaction, exchange integrations, and an artificial intelligence engine has been designed. Spring Security has been used to ensure system security. AES-256 algorithm has been chosen in services for encryption of the data, and JWT method has been used for user verification.

The system architecture includes 4 main layers as follows:

1) User Layer: This layer involves web and mobile applications developed with React and Flutter frames.
2) API Gateway Layer: This layer is the place where all requests are first met and routed to the relevant microservice.
3) Microservice Layer: It consists of independent services such as "User Service", "Portfolio Management Service", "Crypto Gateway" and "AI Recommendation Service".
4) Data and External Services Layer: Includes PostgreSQL database, Redis, Kafka and external exchange APIs such as Binance, Kraken and Coinbase.

The AI service works by retrieving data from both the database and the stock exchange service. The system architecture and data flow diagram of the platform is presented in Figure 1.

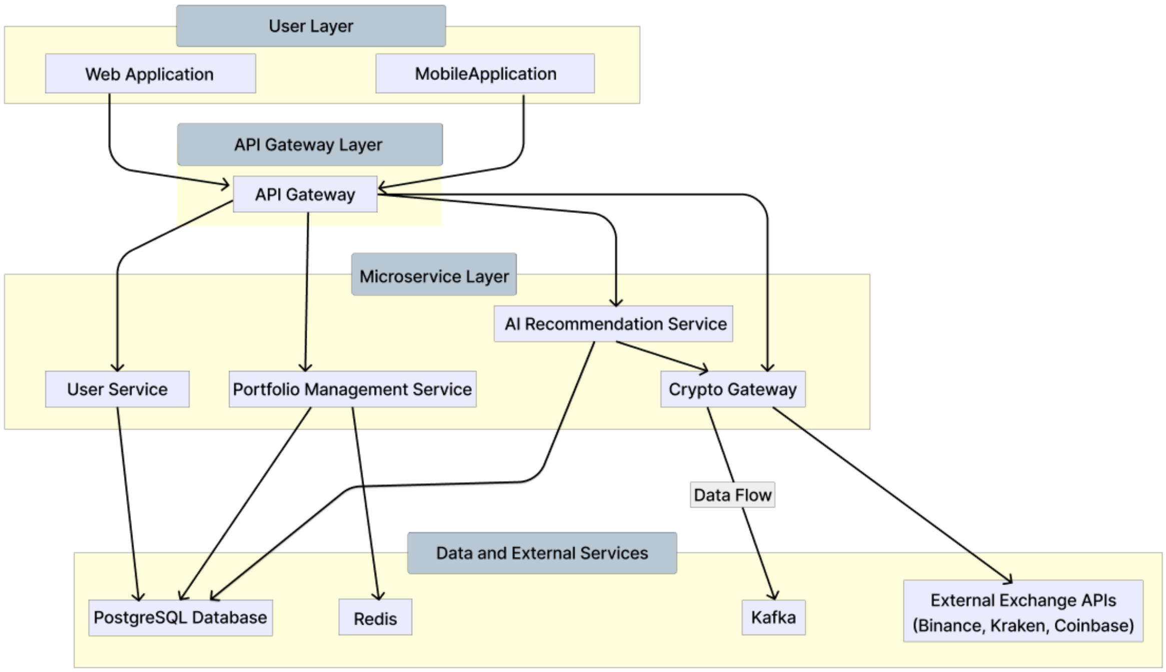

Figure 1. System architecture and data flow diagram

The front end of the platform has been developed using React.js 18.2, Flutter 3.10, TypeScript and Redux. Technologies such as Java 17, Spring Boot 3.1, and WebFlux (Reactive Programming) have been used on the backend. PostgreSQL 15.2 database has been used for relational data, and Redis 7.0 database has been used for session and cache management.

Model training has been conducted on a server equipped with 64 GB of Random Access Memory (RAM) and NVIDIA RTX 4090 GPU. The training lasted approximately 8 hours with 100 epochs and a batch size of 64. The best model is recorded based on the lowest loss value in the validation set.

For model training, a dataset named "BTC / USDT Price Dataset with Technical Indicators" obtained from the Huggingface (Huggingface.co, 29.09.2025). The data covers the period from 18.08.2017 to 19.03.2025. Hourly OHLCV data for BTC/USDT, ETH/USDT, and SOL/USDT pairs obtained from Binance, Coinbase Pro, and Kraken exchanges have been used. A total of 26,280 hours of data for the three major pairs has been combined, yielding approximately 78,000 data points. Missing values in the dataset have been filled using forward-fill, and all attributes have been scaled to 0–1 using Min-Max normalization to ensure model stability. The attributes used in the dataset and their descriptions are provided in
Table 1.

Table 1. The attributes and their descriptions

Attributes	Description
Timestamp	The data point's timestamp in UTC is a standard time reference unaffected by seasons or time zones.
Open	The opening price of Bitcoin at the given timestamp.
High	The highest price of Bitcoin during the period.
Low	The lowest price of Bitcoin during the period.
Close	The closing price of Bitcoin at the given timestamp.
Volume	The trading volume of Bitcoin during the period.
MA_20	20-period MA.
MA_50	50-period MA.
MA_200	200-period MA.
RSI	Relative Strength Index.
%K	Stochastic Oscillator %K.
%D	Stochastic Oscillator %D.
ADX	Average Directional Index.
ATR	Average True Range.
Trendline	Calculated trendline value.
MACD	MA Convergence Divergence.
Signal	Signal line for MACD.
Histogram	MACD histogram.
BL_Upper	Bollinger Bands Upper.
BL_Lower	Bollinger Bands Lower.
MN_Upper	Minopy Bands Upper.
MN_Lower	Minopy Bands Lower.

LSTM architecture has been chosen to capture long-term dependencies in time series data. The model uses a 48-hour data window (48 steps) for the input layer, and the hidden layers contain two consecutive LSTM layers, each consisting of 128 neurons. A 20% dropout has been applied after each layer to prevent overfitting. The output layer consists of a single-neuron Dense structure that predicts the next hour's closing price. The model has been compiled with the 'Adam' optimization algorithm, and MSE has been used as the loss function.

The Pay with Smart Sale function, which optimizes the selection of the most suitable cryptocurrency for payments, is triggered when the user initiates a transaction. Firstly, the user asks if the balance is sufficient. If the answer is “yes”, the payment is directly completed. If it is “no”, the process continues with the Artificial Intelligence Suggestion Service. In this step, the processes of withdrawing instant stock market prices, analyzing portfolio assets and obtaining LSTM price forecasts are carried out in parallel. After that, the most profitable sales asset is determined. Then, the recommendation is presented to the user and approval is expected. If the user confirms, the sell order is transmitted through Crypto Gateway, then the balance is updated, and finally the payment is completed. Figure 2 presents the "Pay with Smart Sale" flow.

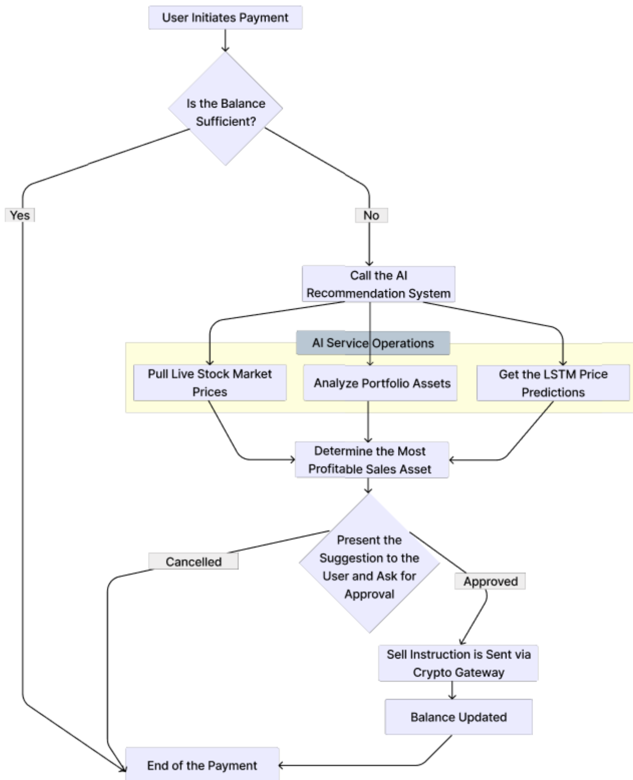

Figure 2. Flow diagram of payment with smart sale

The mobile app interface and Artificial Intelligence suggestion screen are modelled with an example in Figure 3. According to this, the user's portfolio is displayed on the mobile phone screen. On the screen, a notification appears under the title "500 TL Coffee Payment". Notification text is as follows: "Insufficient balance. Optimal recommendation: Based on current market valuation and a 1-hour positive trend forecast, it is advised to execute a sell order of 0.005 ETH. (Projected profit: +8.5 TL). Approve." Thus, the Artificial Intelligence suggestion is submitted for user approval.

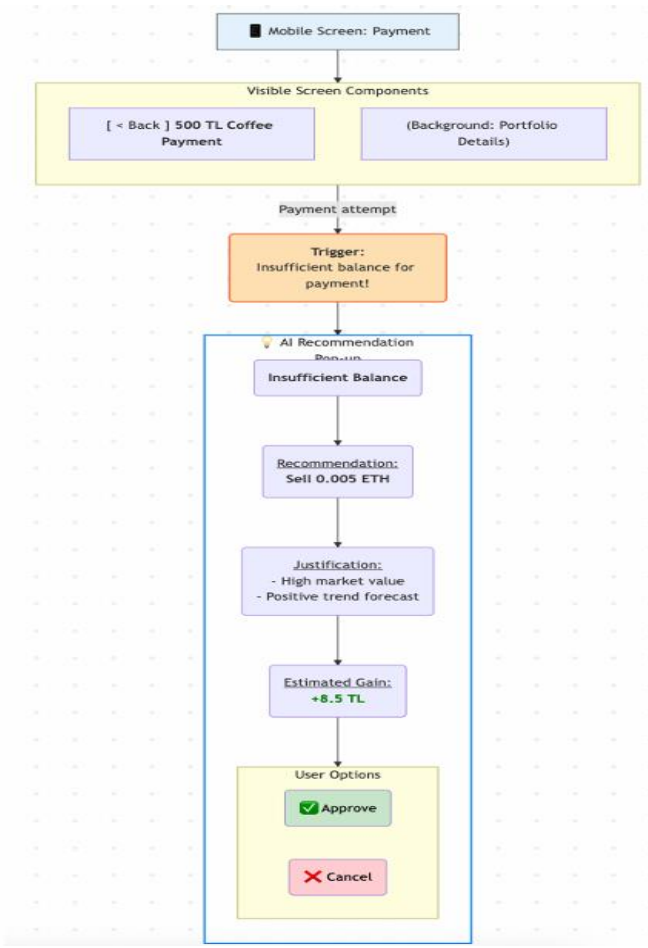

Figure 3. Modelling of mobile app interface and artificial intelligence suggestion screen

4. Results and Discussion

The performance of the platform and the benefits it provides to the user have been evaluated on three main axes: the predictive success of the machine learning model, the financial and operational impact of the platform, and the user experience. During the evaluation, standard and accepted metrics have been used to measure different aspects of the study.

Machine Learning Model Performance Metrics:

- MAE: It represents the average absolute difference between the predicted price and the actual price. It shows the model's margin of error in dollars.
- RMSE: It is a more precise error metric than MAE, which penalises large errors more.

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- Coefficient of Determination (R^2): It indicates the extent to which the independent variables, namely the historical data and account for the variability in the dependent variable, such as the future price. A value close to 1 indicates that the model has higher explanatory power.

Platform Impact Metrics:
- Average Earnings Per Trade (%): It refers to the percentage of the average financial advantage of a trade made with the recommendation of the platform over manual trade.
- Average Transaction Time (seconds): It refers to the average time the user initiates the payment request to the successful completion of the transaction on the exchange.
- System Usability Scale Score (SUS): It refers to an industry-standard metric that measures the usability of the platform with a standard 10-question questionnaire and produces a score between 0-100.

In order to compare the forecasting performance of the developed LSTM-based model, the SMA and ARIMA algorithms have been employed on the test dataset covering the period from 01.01.2025 to 31.03.2025. The results obtained are presented in Table 2.

Table 2. Performance comparison of forecasting models

Model	**RMSE ($)**	**MAE ($)**	**R^2**
SMA	530.25	415.80	0.58
ARIMA (5,1,0)	385.60	291.52	0.72
LSTM	175.43	132.50	0.91

The results show that in tests conducted on the BTC/USDT pair, the LSTM model is more successful in understanding the complex and volatile structure of the market than other models and produces more accurate forecasts. It provided significantly lower error and high accuracy compared to other traditional SMA and ARIMA-based models.

To analyze whether the platform's technical success turns into user benefit, 1,245 "pay by smart sell" transactions have been analyzed during the 90-day test with 50 beta users. In the manual method, the user obtains the target amount by randomly selling the asset with the highest balance in his portfolio at the time of need. In the machine learning-supported method, the platform's LSTM-based recommendation system recommends selling the asset that has a short-term positive trend and instant price advantage. Manual trading vs. proposed system trading performance comparison is given in Table 3.

Table 3. Comparison of manual trading vs. proposed system trading

Metrics	Manual Trading	Proposed System	Margin and Profit
Average Processing Time	215 sec	28 sec	187 sec savings
Average Cost on a $500 Transaction	$500.00	$493.85	$6.15 savings

After 90 days of testing, it has been observed that the platform's recommendation system allowed users to execute trades on average 7.7 times faster than when performing the same trades manually. This increased speed led to cost savings of approximately $6.15 per $500 trade, which corresponds to about 1.23% profit.

The platform had an average rating of 85.5 SUS score out of 100. This score indicates an "Excellent" and "Class A" usability level according to industry standards. It showed that users not only find the platform powerful but also use it with an extremely easy and satisfying experience.

5. Conclusion

Cryptocurrencies distributed over the internet are frequently used in commercial activities nowadays. However, this growth brings challenges: the rapidly increasing transaction volume and the high volatility of digital currencies make investors' decision-making processes increasingly complex. Sudden price changes in the cryptocurrency markets pose great risks to investors. There is an increased need for solutions where investors can manage their entire portfolios from a single platform and trade quickly and easily. In response to this need, a platform has been developed where users can choose the most optimal trading options. Various machine learning-based models such as ARIMA, SMA, and LSTM, have been tested for the asset transfer suggestions that the platform will offer to the user, and as a result, an LSTM-based model has been developed that makes the most accurate predictions. The results showed that in tests conducted on the BTC/USDT pair, the LSTM model provided significantly lower error and high accuracy compared to other traditional SMA and ARIMA-based models. According to the results of the performance tests applied on the developed platform, the processing time has been accelerated by an average of 7.7 times compared to the manual scenario. An average SUS score of 85.5 out of 100 based on user reviews indicates an "Excellent" and "A-Class" usability level according to industry standards. An examination of academic literature reveals that a significant portion of existing studies typically focus on price predictions for a single currency pair. This study, however, combines different cryptocurrency pairs, allowing investors to manage their portfolios on a single platform. Furthermore, the developed platform distinguishes itself from other studies in literature in terms of transaction efficiency. It has been observed that user experience is often secondary in most academic studies. In this study, usability has been measured using the System Usability Scale (SUS), achieving an average score of 85.5 out of 100. All these elements highlight the significant differences of the study.

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