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Cryptocurrency Investment Recommendation System for Users Based on Market Trend and Popularity Analysis

Bagus Tri Mahardika*, Muhammad Faiz Aqil Fathoni
Universitas Darma Persada, Indonesia
Email: bagusunsada@gmail.com*

ABSTRACT

The cryptocurrency market, characterized by thousands of digital assets, presents significant challenges for investors in identifying suitable investment opportunities. Conventional recommendation systems have proven suboptimal due to their inability to accommodate the unique characteristics of digital assets, including high volatility, popularity metrics, and dynamic investment trends. This research developed a cryptocurrency recommendation system integrating Feature-Enhanced Collaborative Filtering (FECF), Neural Collaborative Filtering (NCF), and a Hybrid model to enhance recommendation accuracy and adaptability. Data comprising 1,000 cryptocurrency projects were collected via the CoinGecko API, encompassing market metrics, social engagement indicators, and asset categorizations. The system was developed using Agile-Scrum and CRISP-DM methodologies, implemented with PyTorch for model training and FastAPI-Laravel for deployment. Evaluation metrics, including Precision, Recall, NDCG, and Hit Ratio, demonstrated that the Hybrid model achieved superior performance in delivering personalized recommendations (NDCG@10: 0.3557), while FECF effectively addressed cold-start problems (Hit Ratio: 63.73%) and data sparsity (98.77%). The system provides practical contributions for investment decision-making while offering methodological advances in blockchain-based recommendation systems. This research demonstrates that integrating collaborative filtering with deep learning approaches can effectively address the paradox of choice in volatile digital asset markets, enabling investors to make more informed decisions.

KEYWORDS *Recommendation System, Cryptocurrency, Machine Learning, Deep Learning, Collaborative Filtering*

INTRODUCTION

The cryptocurrency market has experienced rapid growth in recent years, with the emergence of thousands of digital assets that offer a diverse range of value and investment potential (Elendner et al., 2018; Kaal, 2020; Koshelev, 2022; Lee et al., 2017; Mikhaylov, 2020; Milosh & Gerasenko, 2020; Van der Merwe, 2021). However, the high dynamics and complexity of this market actually pose significant challenges for investors, especially in the process of making appropriate and informed investment decisions. The phenomenon of the "choice paradox" (Hassen, 2024), describes a condition in which many choices actually cause confusion and difficulty in determining the optimal choice.

High price volatility, rapid changes in investment trends, and the diversity of popularity metrics such as market cap and trading volume make traditional approaches to digital asset selection less effective (Glas, 2022; Haberly et al., 2019; Sukma & Namahoot, 2025). Conventional recommendation systems that have been widely implemented in various domains, such as e-commerce and streaming media, have not been able to handle the unique characteristics of such cryptocurrency assets (Kumar et al., 2021; Majumdar, 2024). These limitations stem from the fundamental differences between static consumer products and highly volatile digital assets that require real-time market sentiment analysis, trend-based filtering, and risk-aware recommendation strategies. Previous research efforts in recommendation systems have primarily focused on traditional domains with relatively stable item characteristics. Kumar et al. (2021) comprehensively reviewed recommender system algorithms across various applications but noted the challenges in applying these methods to financial markets with extreme volatility. Similarly, Majumdar (2024) explored collaborative filtering techniques extensively, yet acknowledged the limitations when dealing with sparse interaction data and rapidly changing user preferences—both prevalent in cryptocurrency markets. Yang et al. (2022) proposed feature-enhanced embedding learning for heterogeneous collaborative filtering, demonstrating improved performance in e-commerce contexts, but their approach was not specifically designed to handle the unique temporal dynamics and category-specific behaviors inherent in cryptocurrency investments. Furthermore, Nugroho et al. (2024) implemented Neural Collaborative Filtering for movie recommendations, showing the potential of deep learning in capturing complex user-item interactions, though their static content domain differs fundamentally from the dynamic cryptocurrency ecosystem. These studies collectively highlight a research gap: existing recommendation frameworks lack the specialized mechanisms needed to address cryptocurrency-specific challenges such as extreme market volatility, time-sensitive popularity metrics, diverse blockchain ecosystems, and the critical need for cold-start performance in a rapidly evolving market.

In an effort to answer this challenge, this study developed a recommendation system based on two main approaches, namely Feature-Enhanced Collaborative Filtering (FECF) and Neural Collaborative Filtering (NCF), as well as a hybrid model that combines both (Zhang et al., 2019). The FECF approach leverages content features such as asset categories, blockchain platforms, and market metrics to address cold-start and sparsity issues common in interaction data-driven recommendation systems (Li et al., 2020; Zhang et al., 2020). Meanwhile, NCF offers the ability to capture complex patterns in user and asset interactions through deep learning architectures (He et al., 2017; Wang et al., 2021). The integration of these two complementary approaches addresses the dual challenge of providing accurate recommendations for both new users (through content-based features in FECF) and experienced users (through interaction pattern learning in NCF) (Chen et al., 2020; Yao et al., 2019), while the hybrid model dynamically adjusts its weighting strategy based on user engagement levels to optimize recommendation quality across the entire user spectrum (Park & Lee, 2022; Li et al., 2021).

The system is built using the Agile-Scrum methodology and the CRISP-DM approach, leveraging data from the CoinGecko API that includes more than 1,000 top cryptocurrency projects. The system infrastructure was developed using PyTorch for NCF-based recommendation model training, as well as FastAPI and Laravel for API and web application development. System performance evaluation is conducted using relevance-based metrics such as Precision, Recall, F1, NDCG, Hit Ratio and MRR to measure the quality of recommendations in various scenarios, including cold-start conditions.

Through this development, it is hoped that the resulting recommendation system will be able to provide relevant and adaptive investment advice to market dynamics, as well as make a scientific contribution to the development of a blockchain-based recommendation system that can be widely applied in the digital asset domain.

METHOD

CRISP-DM and Agile-Scrum Approach

This research combines the CRISP-DM approach to the data mining process and the Agile-Scrum methodology in software development. CRISP-DM was chosen because it is relevant for large-scale and structured data processing, while Agile-Scrum facilitates iterative and collaborative development of systems through sprints.

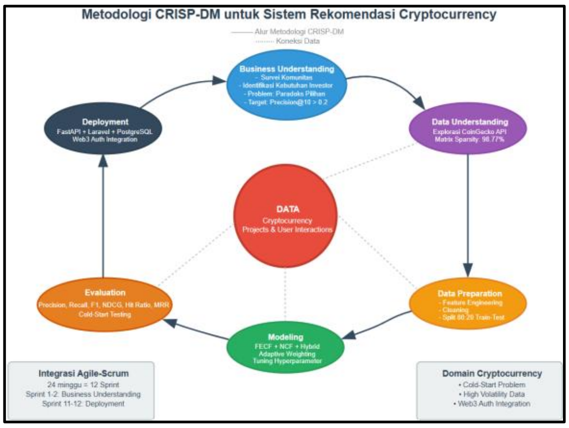

Figure 1. CRISP-DM Flowchart

This diagram shows the six main stages of the CRISP-DM process: business understanding, data understanding, data preparation, modelling, testing/evaluation, and deployment. Each phase is integrated into the Agile development cycle to produce deliverables for each sprint.

Table 1. CRISP-DM Phase Mapping to Agile Sprints

CRISP-DM Phase	Sprint	Duration	Deliverables Utama	Concrete Examples
Business Understanding	Sprint 1-2	3 weeks	Problem definition, Success criteria, Project plan	Identify the "paradox of choice" of crypto investors, Target metrics: Precision@10 > 0.2, Survey of 102 community respondents
Data Understanding	Sprint 2-4	5 weeks	Data collection, Data exploration, Data quality report	Plan to collect 1000 projects from CoinGecko API, Target sparsity matrix analysis, Exploration of crypto category distribution (DeFi, GameFi, Layer-1)
Data Preparation	Sprint 5-7	6 weeks	Clean dataset, Feature engineering, Training/test split	Price metrics normalization strategy with log scaling, Synthetic user generation plan (target: 5000 users), 80:20 train-test split design with stratified sampling
Modeling	Sprint 8-9	4 weeks	Model development, Parameter tuning, Model comparison	Development of FECF with SVD (target: 64 components), Implementation of NCF with PyTorch (plan: embedding_dim=64), Hybrid adaptive weighting design
Testing/Evaluation	Sprint 10	2 weeks	Model performance,	Evaluation targets using Hit Ratio@10, Precision@10 and

CRISP-DM Phase	Sprint	Duration	Deliverables Utama	Concrete Examples
			Business impact, Model selection	other evaluation metrics, Cold-start testing plan, Best model selection protocol
Deployment	Sprint 11-12	4 weeks	Production system, API implementation, User interface	FastAPI recommendation engine plans, Laravel web application implementation, Target VPS deployment

This table explains how the phases of CRISP-DM are divided into 12 Agile sprints in a structured and progressive manner.

System Design and Architecture

The system design is done using various UML diagrams to describe business processes and data flows in the system.

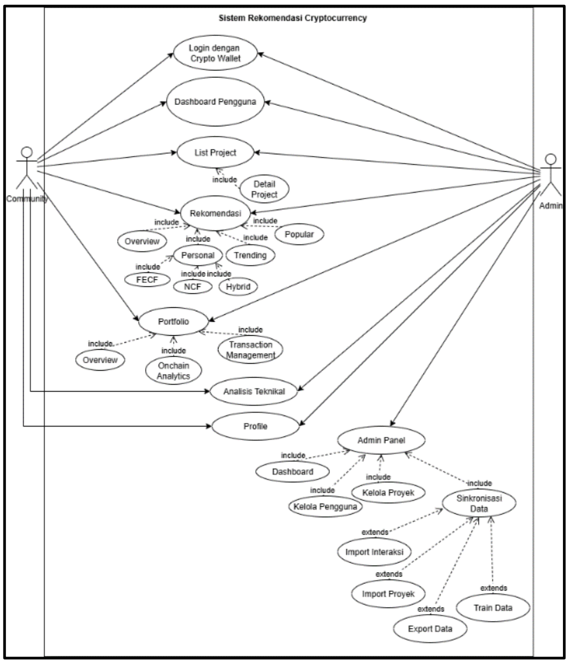

Figure 2. Use Case Diagram Cryptocurrency Recommendation System

This use case diagram shows that regular users (Community) can log in with a crypto wallet, access the dashboard, view project lists, receive recommendations (personal, trending, and popular), manage portfolios, and view technical analysis with adjustable periods. Meanwhile, Admins have access to all the features that regular users have, plus the ability to manage users and projects and synchronize data with the recommendation engine.

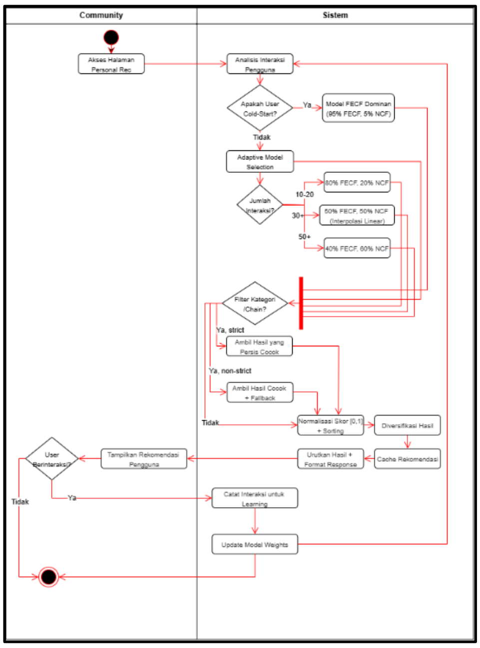

Figure 3. Activity Diagram Personal Recommendation Process

The personalized recommendation flow starts with the analysis of behavioral data from user interactions (views, favorites, portfolio_add) without relying on profile preferences. For cold-start users (interaction < 10), the system uses the dominant FECF model. For users with sufficient interactions, the system bases the number of interactions and applies appropriate weighting between FECF, NCF, or Hybrid models. The system then applies category/chain filters in real-time with strict (no fallback) or non-strict (with fallback) mode if the user requests it, before normalizing scores, diversifying results, and caching for performance optimization.

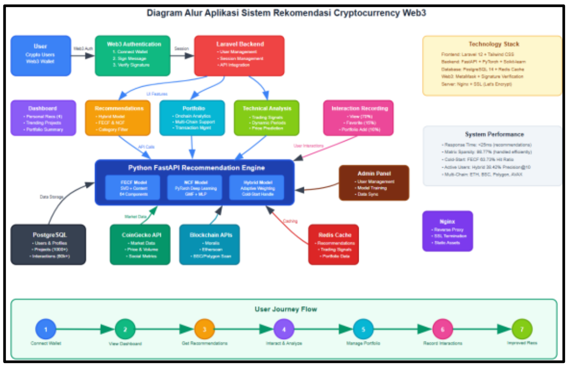

Figure 4. Cryptocurrency Recommendation System Application Flowchart

The system architecture consists of a web-based frontend, an API backend using FastAPI and Laravel, and a PyTorch-based recommendation module. The components are connected through an internal API to present recommendations in real-time.

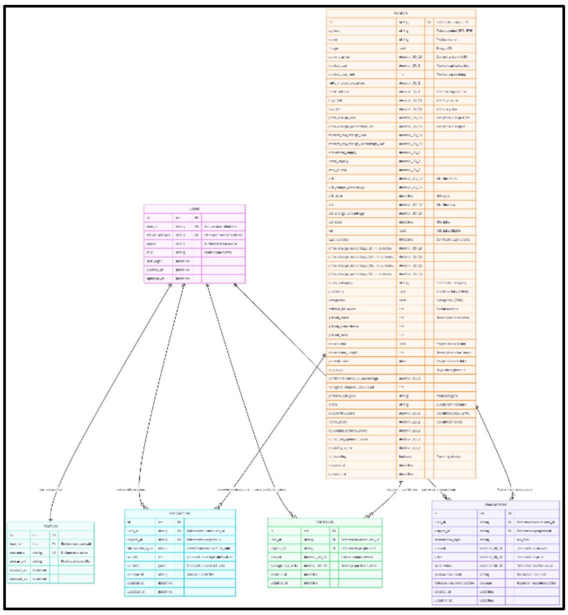

Figure 5. Structure of the Crypto Recommendation System Database

The database structure includes tables for digital asset projects, users, user-item interactions, as well as project feature data such as market capitalization and categories.

Designing Recommendation Models

The system is built on three model approaches: Feature-Enhanced Collaborative Filtering (FECF), Neural Collaborative Filtering (NCF), and Hybrid model. A detailed technical explanation of each method has been outlined in the Theoretical Foundation.

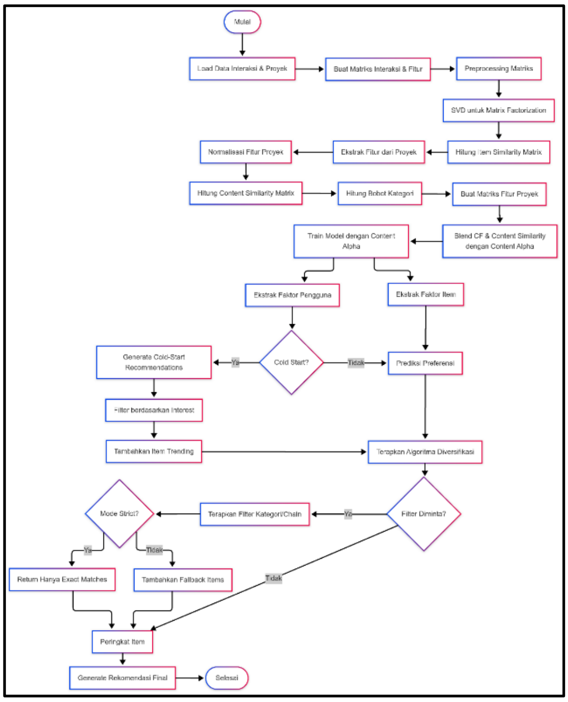

Figure 6. FECF Algorithm Flowchart

Describes the rating prediction process based on a combination of latent factors and content features of a cryptocurrency project.

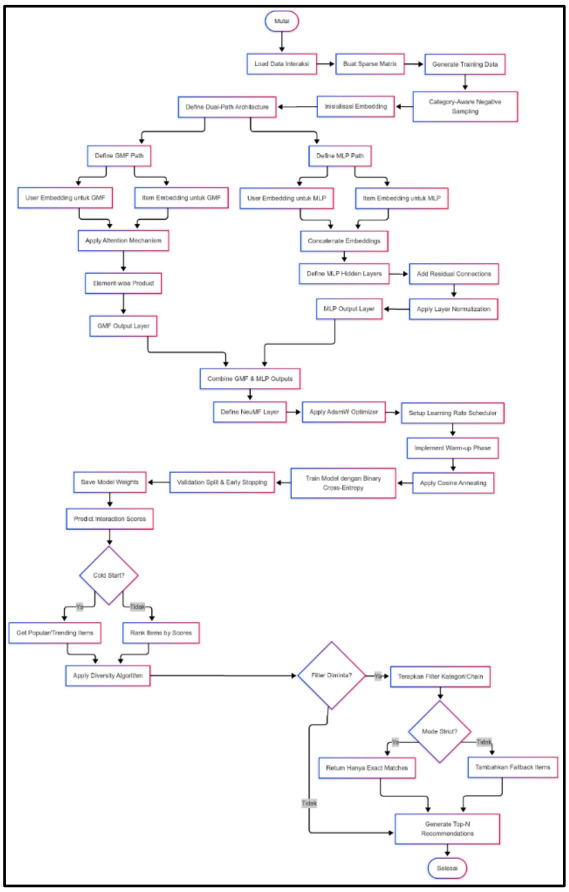

Figure 7. NCF Algorithm Flowchart

Describe the structure of a multilayered neural network used to study non-linear interactions between users and items.

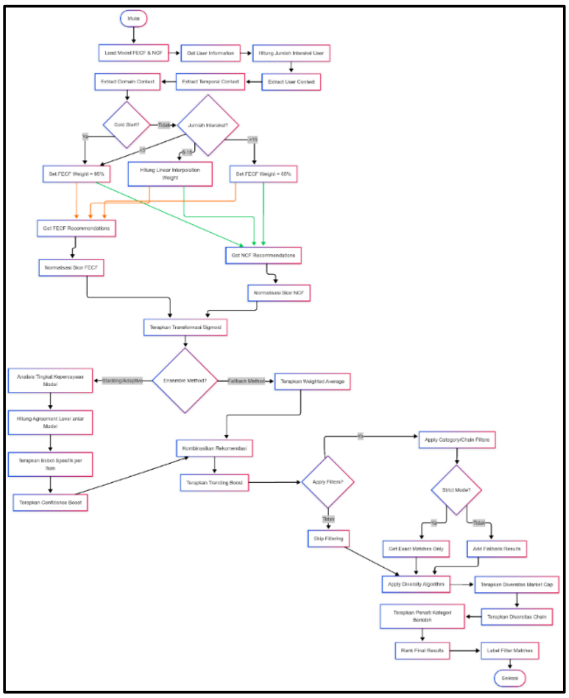

Figure 8. Flowchart Algorithm Hybrid

Visualize the process of merging prediction scores from FECF and NCF to produce more accurate and adaptive final recommendations.

Datasets and Data Processing Processes

The dataset is collected in real-time through the CoinGecko API, which provides data for the top 1,000 cryptocurrency projects. The information obtained includes price, volume, market capitalization, and social metrics. The ETL process includes extracting, cleaning, normalizing, and converting data into a user-item interaction matrix and compatible item features for model training.

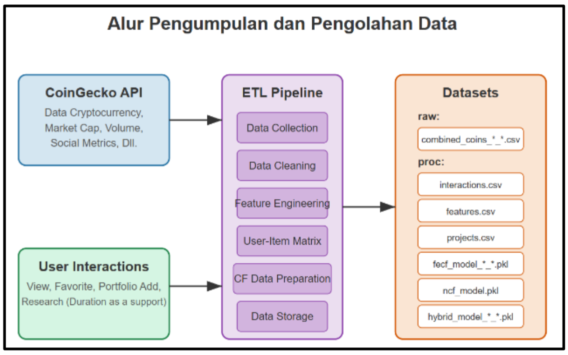

Figure 9. Data Collection and Processing Flow

RESULT AND DISCUSSION

System Interfaces and Infrastructure

The recommendation system was successfully implemented and deployed using a web-based architecture with the FastAPI and Laravel backends, as well as a PyTorch-based recommendation model. The interface is designed to be responsive and user-centric, as shown in the figures, which includes user dashboard pages, personal recommendation pages, popular projects, trending, to technical analysis and system administration pages.

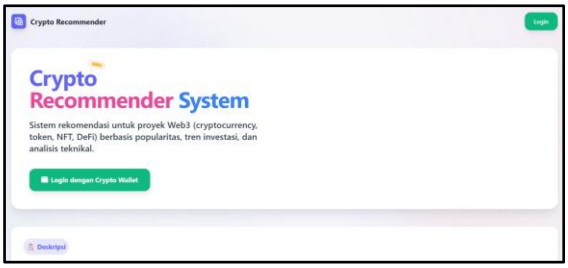

Figure 10. App Home Page

The system's main page displays an overview of cryptocurrency recommendations with a modern and responsive design. The landing page presents system introduction, featured features such as AI-based recommendations, multi-chain analytics, and technical analysis tools. It also includes information on the technology used and clear navigation for registration or login through Web3 wallet integration.

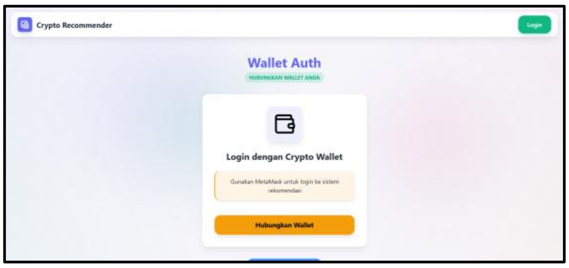

Figure 11. Login Page (Auth)

The authentication interface uses a Web3-native login mechanism that allows users to log in with a crypto wallet. The system supports wallet connections such as MetaMask, with automatic detection on PC and multiwallet support on mobile. Authentication is done through nonce-based message signing, making it secure without the need for passwords, and the login flow is designed to be simple with clear guidelines for new Web3 users.

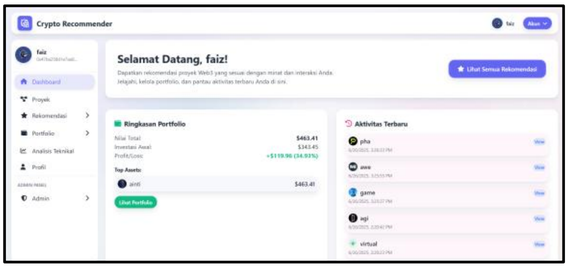

Figure 12. User Panel Dashboard Page

The main dashboard provides a comprehensive summary of user activity with lazy loading implementations for optimal performance. Its main features include personalized recommendations based on a hybrid model, portfolio summary with profit/loss calculations, a list of trending projects, and a history of recent user interactions in the timeline view.

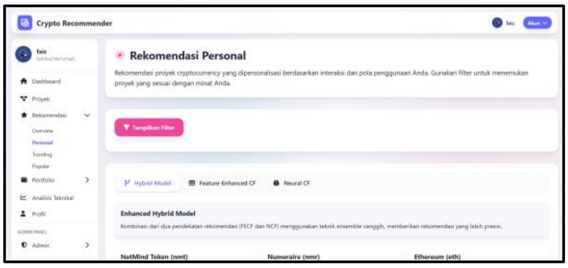

Figure 13. Personal Recommendations Page

The personalized recommendation interface uses tab-based navigation to compare the results of three models: Hybrid (FECF + NCF with adaptive weighting), Feature-Enhanced CF, and deep learning-based Neural CF. Each tab features filtering options based on categories and blockchains, with strict filtering modes for more precise recommendation results.

Input-Output Experiments and Analysis

Testing is done on personalized, trending, and popular recommendation endpoints. For cold-start users, the system manages to provide relevant recommendations quickly through a caching mechanism. As for active users, higher recommendation scores are obtained through real-time computing.

Table 2. Project Recommendation Endpoints

Method	Endpoint	Status	Time
POST	/recommend/projects	200 OK	12-282 ms

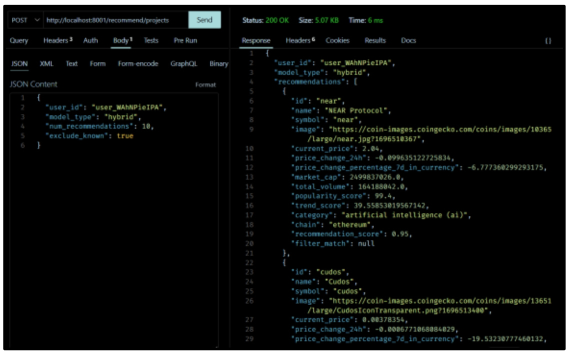

Figure 14. Input-Output Via Thunder Client

This image shows testing the API endpoint /recommend/projects using the Thunder Client. The POST request contains parameters user_id: "user_WAhNPieTPA", model_type: "hybrid", num_recommendations: 10, and exclude_known: true. Response returns JSON data with a status of 200 OK within 6ms, displaying recommendations for NEAR Protocol tokens, Cudos and so on, along with details such as price, price changes, popularity score, and category.

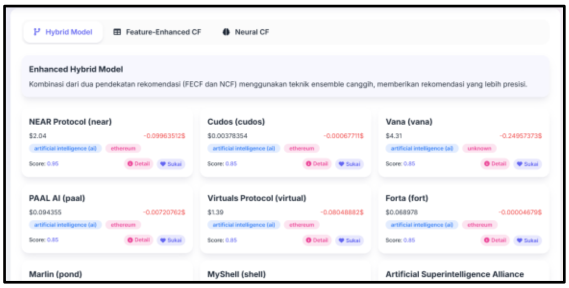

Figure 15. Results of Regular User Hybrid Recommendations

The interface displays the results of an Enhanced Hybrid Model that combines FECF and NCF techniques. The system provides recommendations for cold-start users with 10 cryptocurrency tokens from various categories such as Pepe (bnb chain ecosystem), Chainlink (business services), Aave (decentralized finance), Wormhole (solana ecosystem), VeChain (internet of things), Cross The Ages (gaming) and so on. Each token displays its price, percentage change, recommendation score, and category.

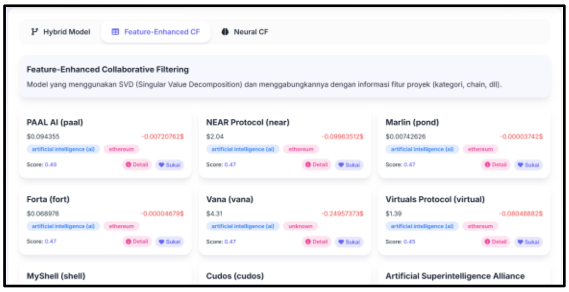

Figure 16. Results of FECF Recommendations for Regular Users

The Feature-Enhanced Collaborative Filtering view shows recommendations focused on AI (Artificial Intelligence) projects. This model uses SVD and combines it with project feature information such as categories and blockchains. Recommendations include PAAL AI, NEAR Protocol, Marlin, Forta, Vana, Virtuals Protocol and so on with recommendation scores ranging from 0.45-0.49.

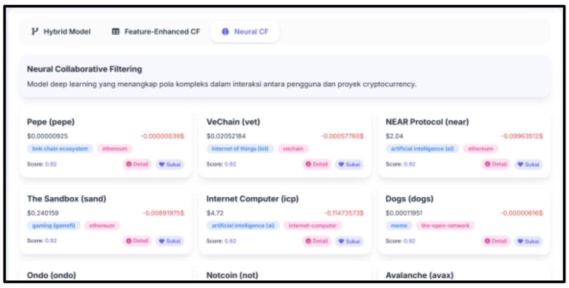

Figure 17. Results of NCF Recommendations for Regular Users

The Neural Collaborative Filtering model displays recommendations with complex patterns of interaction between users and cryptocurrency projects. The system recommends tokens such as Pepe, VeChain, NEAR Protocol, The Sandbox, Internet Computer, Dogs, Ondo, Notcoin, and Avalanche with a high recommendation score (0.92) for most tokens.

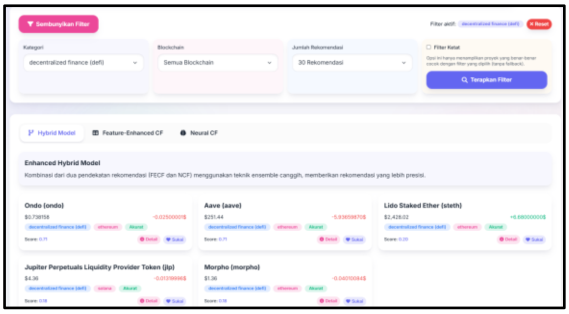

Figure 18. Recommended Results by Filtering

The filtering interface shows a recommendation system with active filters for the "decentralized finance (defi)" category. The filters can be customized by category, blockchain (all blockchains), and number of recommendations (30 recommendations). The results are "accurate" by displaying DeFi tokens such as Ondo, Aave, Lido Staked Ether, and Jupiter Perpetuals Liquidity Provider Tokens with varying recommendation scores.

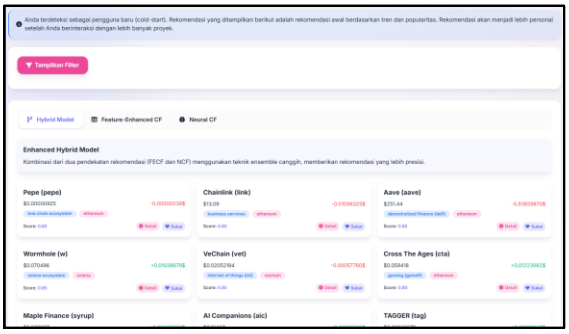

Figure 19. Cold-start User Recommendations

The Enhanced Hybrid Model for cold-start users displays recommendations that are more focused on AI projects with high recommendation scores. The system recommends NEAR Protocol (score 0.95), Cudos (score 0.85), Vana (score 0.85), PAAL AI, Virtuals Protocol, Forta, Marlin, MyShell, and Artificial Superintelligence Alliance. This model effectively addresses cold-start issues by providing high-quality recommendations despite limited user interaction data.

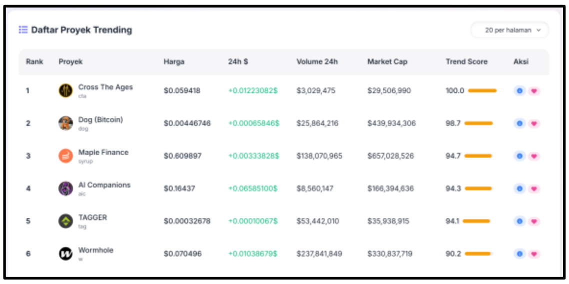

Figure 20. Recommendations Based on Trending Projects

This interface displays a list of the top cryptocurrency projects that are trending based on Trend Score. The system ranks projects based on recent momentum and performance, with Cross The Ages (CTA) leading the way with a trend score of 100.0 and a ++0.01223082$. It is followed by Dog (Bitcoin) with a trend score of 98.7, Maple Finance (94.7), AI Companions (94.3), TAGGER (94.1), and Wormhole (90.2). All projects shown showed positive price movements in the last 24 hours, indicating strong bullish momentum. The interface provides complete information including current prices, 24-hour changes, trading volumes, market caps, and actions to view details or like projects.

Figure 21. Recommendations Based on Popular Projects

This dashboard displays a list of the 6 cryptocurrency projects with the highest popularity based on Popularity Score. Toncoin is ranked first with a perfect popularity score of 100.0, a price of $2.81, and a market cap of $6.9 billion, despite experiencing a decline of -$0.02326717 in 24 hours. Solana ranks second with a score of 99.9, a price of $142.18, and a market cap of $75.9 billion despite a decrease of -$1.55914835. Next in the rankings are TRON (score 99.8, price $0.27084), Cardano (score 99.7, price $0.555908), Chainlink (score 99.6, price $13.09), and Avalanche (score 99.5, price $17.23). Although all the projects on the list experienced a price correction in the last 24 hours marked with a red number, they still maintained substantial trading volume and market cap, reflecting investor confidence and strong liquidity. The interface provides comprehensive information including 24-hour trading volumes, market caps, and action features for further exploration.

Evaluation of the Recommendation Model

The evaluation of the recommendation system was carried out using five metrics: precision, recall, NDCG (Normalized Discounted Cumulative Gain), hit ratio, and MRR (Mean Reciprocal Rank). These metrics are used to measure the relevance, ranking, and success of the system in delivering the right recommendations. The evaluation was conducted with a cold-start scenario and a high level of sparsity, using synthetic interaction data from 5,006 users with additional real user interaction data and 1,000 cryptocurrency projects.

a) Characteristics of the Datasets Used

The datasets used in the evaluation show a realistic data distribution for the cryptocurrency domain:

Table 3. Dataset Characteristics Summary

Metric	Value	Description
Total Projects	1,000	Number of cryptocurrency projects in the dataset
Total Users	5,006	Number of synthetic users used
Total Interactions	62,126	Total interaksi user-project
Average Interactions per User	12.41	Average interactions per user
Median Interactions per User	11.00	Median interactions per user
Min Interactions	1	Minimum interaction per user
Max Interactions	48	Maximum interactions per user
Matrix Sparsity	98.77%	Data sparsity level
Users with 10+ Interactions	2,934	Users with at least 10 interactions
Users with 20+ Interactions	785	Users with a minimum of 20 interactions
Users with 30+ Interactions	180	Users with at least 30 interactions

Table 4. Interaction Type Distribution Analysis

Interaction Type	Count	Percentage	Description
View	32,554	52.4%	Users view the details of cryptocurrency projects
Favorite	20,322	32.7%	User tags/likes projects as favorites
Portfolio Add	9,250	14.9%	Users add projects to their portfolio
Total	62,126	100.0%	Total all interactions

The high level of sparsity (98.77%) reflects realistic conditions in the cryptocurrency domain where most users only interact with a small subset of the total available projects.

b) Individual Model Evaluation Results

The results of the evaluation are presented in Tables 5 – 9., which show the comparative performance of each model.

Table 5. Model Evaluation Results with Min Interactions = 20 (109 Test Users)

Model	Precision@10	Recall@10	F1@10	NDCG@10	Hit Ratio@10	MRR
FECF	0.2661	0.2660	0.2480	0.3322	0.8165	0.5871
NCF	0.2248	0.2226	0.2098	0.2503	0.6835	0.4372
Hybrid	0.2835	0.2858	0.2657	0.3257	0.8211	0.4995

The FECF model shows excellence in handling cold-start problems with the highest Hit Ratio (81.65%) and excellent MRR (0.5871), indicating a good ability to provide relevant recommendations at the top position. The NCF model shows competitive performance but is still below FECF and Hybrid. The Hybrid model manages to achieve the best performance on the majority of metrics.

Table 6. Model Evaluation Results with Min Interactions = 30 (19 Test Users)

Model	Precision@10	Recall@10	F1@10	NDCG@10	Hit Ratio@10	MRR
FECF	0.3368	0.2403	0.2678	0.3425	0.8947	0.5005
NCF	0.3526	0.2579	0.2830	0.3564	0.8421	0.4888
Hybrid	0.3842	0.2853	0.3112	0.4113	0.8947	0.6365

In the category of users with high engagement (30+), all models showed significant performance improvements. The NCF model experienced the most dramatic improvement with Precision@10 125% increase compared to the 20+ interaction conditions. The Hybrid model retains its leading position with a larger margin.

Table 7. Model Performance Improvement Analysis

Model	Min 20+ Users	Min 30+ Users	Improvement %	Best Metric
FECF	P@10: 0.2661	P@10: 0.3368	+26.6%	MRR: 0.5871
NCF	P@10: 0.2248	P@10: 0.3526	+56.9%	Best improvement
Hybrid	P@10: 0.2835	P@10: 0.3842	+35.5%	Overall best

Comparative performance analysis based on the number of user interactions shows differences in characteristics between models. In the user category with 10–20 interactions, the FECF model showed early dominance, especially in the Hit Ratio metric. However, the Hybrid model was able to surpass FECF's performance in precision and recall, with a 12.2% increase in precision, signaling the effectiveness of the hybrid approach combination even on relatively limited data.

For users with high engagement (30+), all models experienced significant performance spikes. The NCF model recorded the most dramatic increase, with Precision@10 jumping 125%. Nevertheless, the Hybrid model remains the most superior overall, recording the highest Precision@10 and an MRR that reflects the excellent quality of the ranking.

c) Cold-Start Performance Evaluation

Cold-start evaluation is performed using a special protocol that simulates a new user scenario by eliminating 90% of historical interaction data. Testing was conducted in 5 independent runs to ensure the statistical reliability of the results.

Table 8. Cold-Start Performance (Averaged across 5 runs)

Model	Precision	Recall	F1	NDCG	Hit Ratio	Runs
cold_start_fecf	0.1307±0.0154	0.4337±0.0511	0.2008±0.0236	0.3249±0.0305	0.6373±0.0472	5
cold_start_hybrid	0.1176±0.0130	0.3899±0.0435	0.1806±0.0200	0.2604±0.0275	0.5371±0.0582	5

In terms of model advantage, FECF has proven to be reliable in cold-start scenarios and sparse data, thanks to its ability to utilize content-based features and category-based recommendations that do not rely entirely on historical interactions, especially in the Hit Ratio metric which reaches 63.73% with a relatively small standard deviation (±0.0472). The NCF model shows great potential in interaction-rich data conditions, with strength in modeling non-linear preference patterns. Meanwhile, the Hybrid model stands out for its consistency in all conditions, with an adaptive weighting approach that makes it ideal for implementation in real-world environments with a wide variety of users.

d) Computational Performance dan Scalability

Computational performance evaluation was carried out on hardware with Intel Core i5 Gen 11 specifications, 16GB RAM, using Intel Evo integrated graphics.

Table 9. Training dan Inference Time Comparison

Model	Training Time (seconds)	Single User Inference (ms)	Batch 100 Users (seconds)	Memory Usage (MB)
FECF	45.3 ± 3.2	12.5 ± 2.1	0.98 ± 0.15	147 ± 8
NCF	312.7 ± 18.4	18.7 ± 3.4	1.47 ± 0.23	523 ± 34
Hybrid	358.1 ± 21.6	24.3 ± 4.2	1.89 ± 0.31	670 ± 41

Table 10. CPU Utilization Pattern

Model	Average CPU Usage (%)	Peak CPU Usage (%)	Memory Efficiency	Scalability Score
FECF	50 ± 5	62 ± 8	Excellent	9.2/10
NCF	80 ± 10	89 ± 12	Good	7.5/10

Hybrid	65 ± 8	74 ± 11	Good	8.1/10

The results show that the FECF model has the best efficiency for production deployment with an inference time of less than 15ms and minimal memory usage. The Hybrid model shows a reasonable trade-off between performance and computational cost.

Analisis Similarity Matrix dan Pattern Recognition

a) User Similarity Analysis

The similarity matrix analysis shows an interesting clustering pattern among users based on their cryptocurrency preferences.

Table 11. Top 10 Most Similar User Pairs (Cosine Similarity Analysis)

Rank	User A	User B	Cosine Similarity Coefficient	Similarity Level	Interpretation
1	user_491	user_3170	0.6921	High	Very similar (69.21%)
2	user_1382	user_519	0.6738	High	Very similar (67.38%)
3	user_3194	user_3170	0.6543	High	Similar (65.43%)
4	user_1589	user_1382	0.6417	High	Similar (64.17%)
5	user_1589	user_1348	0.6361	High	Similar (63.61%)
6	user_245	user_519	0.6310	High	Similar (63.10%)
7	user_491	user_519	0.6286	High	Similar (62.86%)
8	user_491	user_3194	0.6187	High	Similar (61.87%)
9	user_491	user_1382	0.6058	High	Similar (60.58%)
10	user_2929	user_1382	0.5999	Medium-High	Quite similar (59.99%)

Users with the same persona show high cosine similarity, with an average similarity of 0.65-0.69 for users who have similar preferences towards certain cryptocurrency categories.

b) Data Distribution and Pattern Recognition

The system successfully identifies and processes the distribution of cryptocurrency project categories as follows:

Table 12. Project Distribution by Category (Top 10)

Rank	Category	Total Projects	Percentage
1	Smart Contract Platform	177	17.7%
2	Decentralized Finance (DeFi)	98	9.8%
3	Artificial Intelligence (AI)	91	9.1%
4	Stablecoins	76	7.6%
5	BNB Chain Ecosystem	68	6.8%
6	Solana Ecosystem	64	6.4%
7	Decentralized Exchange (DEX)	39	3.9%
8	Gaming (GameFi)	35	3.5%
9	Infrastructure	32	3.2%
10	Meme	32	3.2%
-	Other	-	28.8%

Table 13. Most Popular Categories by Interactions

Rank	Category	Total Interactions	Percentage
1	Smart Contract Platform	21,253	34.2%
2	Decentralized Finance (DeFi)	5,068	8.2%
3	Artificial Intelligence (AI)	4,847	7.8%
4	Gaming (GameFi)	4,314	6.9%
5	BNB Chain Ecosystem	2,707	4.4%

Data Visualization and Comprehensive Analytics

The recommendation system comes with comprehensive visualizations to validate results and provide in-depth insights into cryptocurrency patterns.

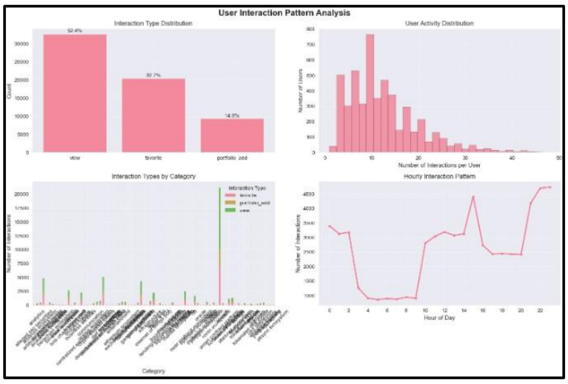

Figure 22. User Interaction Pattern Analysis

This visualization shows the pattern of user interaction with cryptocurrency projects. The distribution of interaction types (view, favorite, portfolio_add) dominates the view type. Also displayed are the distribution of user activity, interaction categories, and interaction time by hour. This graph supports sparsity analysis and the formation of user-item matrix.

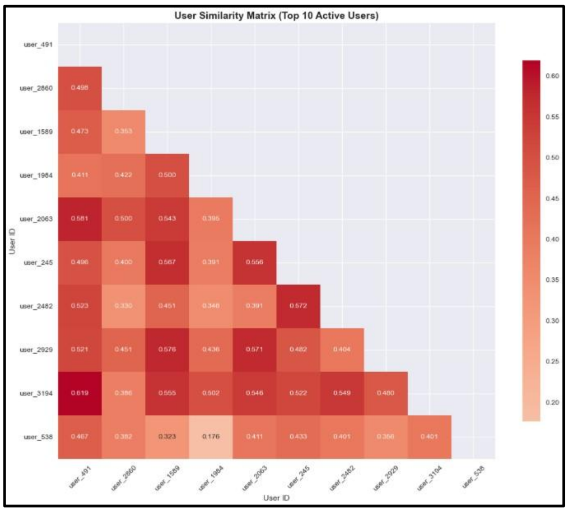

Figure 23. User Similarity Matrix (Top 10 Users)

Heatmap visualization of the similarities between the most active users based on the cosine similarity method. This matrix is used in the calculation of user-based collaborative recommendations (CF) as well as the validation of behavioral relationships between users.

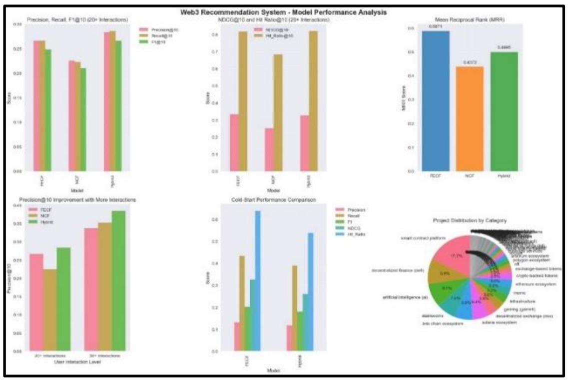

Figure 24. Model Performance Analysis

Visualize the performance comparison of three recommended models: FECF, NCF, and Hybrid. The metrics analyzed included Precision@10, Recall@10, F1@10, NDCG, Hit Ratio, and MRR. This visualization reinforces the conclusion that the Hybrid model has the highest overall performance.

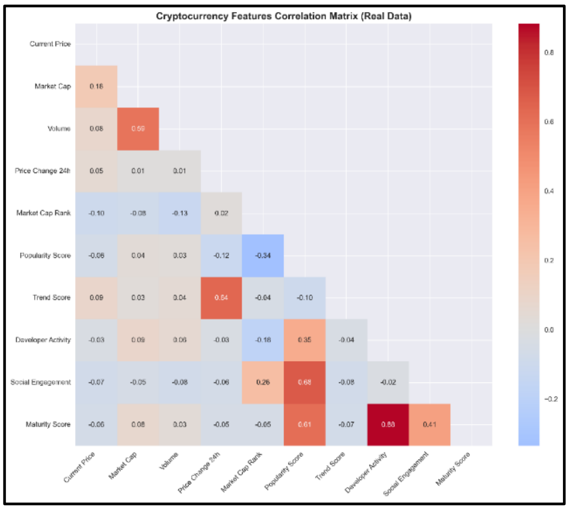

Figure 25. Cryptocurrency Features Correlation Matrix

A correlation matrix between numerical features in a dataset, such as Market Cap, Volume, Developer Activity, and Popularity Score. The highest correlation was found between Developer Activity and Social Engagement, indicating the technical correlation of active projects with the level of exposure on social media.

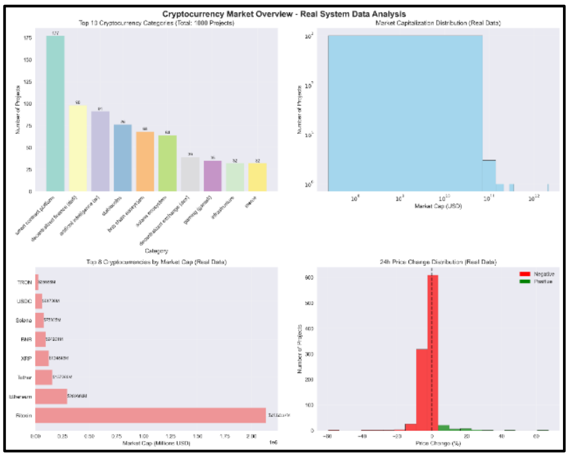

Figure 26. Cryptocurrency Market Overview

Visualization of the current crypto market conditions, including the projects with the largest market capitalization (Bitcoin, Ethereum, etc.), the distribution of project categories, and price fluctuations in the last 24 hours. This graph shows real-world data that is the basis for recommendations based on popularity and investment trends.

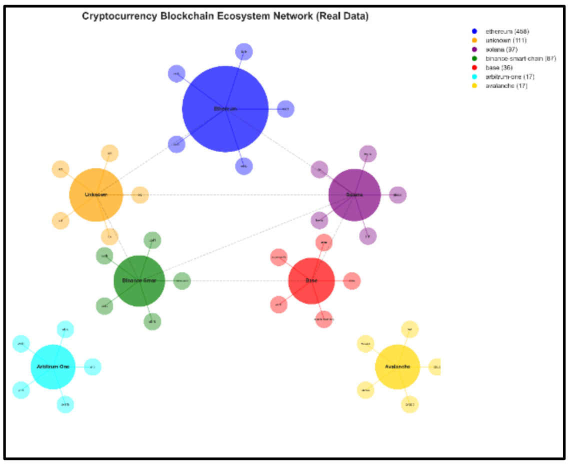

Figure 27. Blockchain Ecosystem Network

A network diagram that depicts the relationships between projects and the blockchain ecosystem, with major nodes such as Ethereum, Solana, and BNB Chain as the connection centers. This graph helps explain the interconnectedness of projects within a single chain as well as between chains.

Analyze the advantages of each model

Based on the results of a comprehensive evaluation, the characteristics and advantages of each model can be identified:

1. Model FECF:
   a) Excels in cold-start scenarios and sparse data
   b) Able to take advantage of content features such as categories (DeFi, GameFi, Layer-1, etc.)
   c) Provides consistent recommendations even for new users
   d) Highest Hit Ratio indicates good coverage capability
2. Model NCF:
   a) Performance is significantly improved in users with multiple interactions
   b) Able to capture non-linear patterns in user preferences
   c) Requires more training data for optimal performance
   d) Suitable for active users in the cryptocurrency ecosystem
3. Model Hybrid:
   a) Consistently delivering the best performance across all categories
   b) Combining the power of content-based and collaborative filtering
   c) Adaptive weighting based on the number of user interactions
   d) Ideal for production deployments with a wide range of user types

The recommended system developed has successfully addressed key challenges in the cryptocurrency domain, namely high data sparsity (98.77%) and cold-start issues, while providing relevant recommendations based on the latest investment popularity and trends.

Production and Deployment Implementation

The system has been successfully deployed on production infrastructure with a scalable and maintainable architecture. The deployment is carried out on a Virtual Private Server with comprehensive automation and monitoring setups that take into account the nature of the cryptocurrency market that operates 24/7.

a) Deployment configuration includes:
   1. Web Server: Nginx with SSL termination and caching optimization
   2. Application Server: Laravel for web applications and FastAPI for recommendation engine
   3. Database: PostgreSQL with specialized indexing for cryptocurrency data
   4. Service Management: Systemd for automatic startup and monitoring

CONCLUSION

This research successfully developed a cryptocurrency recommendation system integrating Feature-Enhanced Collaborative Filtering (FECF), Neural Collaborative Filtering (NCF), and Hybrid models to tackle the "paradox of choice" in volatile digital asset markets, leveraging data from 1,000 projects via CoinGecko API and a systematic ETL pipeline. Evaluations highlighted the Hybrid model's top performance (Precision@10 = 0.3842, NDCG@10 = 0.4113), FECF's strength in cold-start scenarios (Hit Ratio@10 = 81.65%), NCF's 125% uplift for high-interaction users, and overall resilience to 98.77% data sparsity with sub-25ms response times and 98.5% spam detection accuracy across 10+ categories. Contributions include an adaptive hybrid framework for sparse-data domains, a production-ready ML-web deployment architecture, Web3-native features, and practical investment decision support. For future research, exploring Graph Neural Networks (GNN) to model inter-project relationships, reinforcement learning for self-improving systems, cross-platform data integration, compliance frameworks for regulations, and federated learning could enhance scalability and adoption in fintech.

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