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AI-Powered Token Prediction and Automated Trading in Web3 Using On-chain Data and Decentralized Exchanges

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ABSTRACT: This article investigates the efficacy of implementing an AI-powered automated trading system on the blockchain using advanced machine learning algorithms and smart contract technology. The work addresses the challenges of cryptocurrency market volatility, the need for real-time decision making and the limitations of traditional trading approaches that often result in suboptimal returns and exposure to increased risk. This work develops a comprehensive trading platform that combines Long Short-Term Memory (LSTM) neural networks, Q-Learning reinforcement learning algorithms and blockchain-based smart contracts to create an autonomous, intelligent trading system. The methodology follows a multi-layered approach that integrates real-time market data collection from CoinGecko and Snowtrace APIs, advanced AI model training using TensorFlow.js, and smart contract deployment on the Avalanche C-Chain using Hardhat and OpenZeppelin libraries. LSTM model is used for price prediction and Q-Learning agent is used for trading strategy optimization, while comprehensive risk management is implemented using Value at Risk (VaR) calculations, portfolio rebalancing algorithms and automated stop-loss mechanisms. The trading execution is facilitated through direct integration with Pangolin DEX smart contracts to ensure decentralized and trustless trade execution. The performance of the system is evaluated using a sophisticated backtesting engine with Monte Carlo simulations, comparing the AI-driven strategy against traditional buy-and-hold approaches. The performance metrics used were Sharpe ratio, maximum drawdown, win rate, and total return. The AI-powered token prediction system demonstrates a superior performance due to its ability to process complex, non-linear market patterns and adapt to changing market conditions through reinforcement learning, and execute trades with minimal latency through blockchain integration. The findings are expected to provide cryptocurrency traders and institutional investors with a robust and automated trading solution that leverages the benefits of both artificial intelligence and blockchain technology for improved investment outcomes and risk management.

KEYWORDS: Cryptocurrency, Token Prediction, Automated Trading, Decentralized exchanges, Web3, Blaockchain, Smart Contract, LSTM, Reinforcement learning algorithm, Artificial Intelligence

1. INTRODUCTION

The rise of blockchain technology has transformed the financial world by introducing decentralized finance (DeFi), a system that allows people to carry out financial services without relying on banks or other centralized institutions, with the benefits of transparency and immutability (Benetti and Piazza 2023). At the heart of DeFi are decentralized exchanges (DEXs) like Uniswap and PancakeSwap, which use smart contracts to enable direct trading from users' digital wallets. DeFi allows users to trade with each other without traditional custodial intermediaries (Shah et al., 2023). These platforms have become so popular because they are transparent, secured and accessible. However, the cryptocurrency market is known for its extreme volatility (Lua et al., 2025), with token prices often swinging due to factors like market sentiment, regulatory changes, and technological advancements. This makes it difficult for traders to predict price movements and make profitable decisions.

The correlation between the traditional financial markets and cryptocurrency market reveals that the global financial market is deeply connected with cryptocurrencies (Watorek et al., 2023). The extent of volatility of the financial market is caused by various factors such as companies' fundamental performances of companies, political uncertainty (Vancea et al., 2017), financial crises, global pandemic (Tabash et al., 2024; Dumiter et al., 2023), energy and sustainability (Haq et al., 2023).These high volatility levels may greatly impact the volatility persistence of investors (Tabash et al., 2024).

Artificial Intelligence (AI) has become a game-changer in financial markets through its ability to analyze large amounts of data to uncover patterns and make predictions. In DeFi, AI can process on-chain data - such as transaction histories, liquidity pool metrics

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and wallet balanced, to forecast token prices. It can also analyze off-chain data, like social media posts or news articles, to gauge market sentiment. By combining AI with blockchain technology, traders can automate their strategies, executing trades quickly and efficiently without manual intervention. This project aims to develop an AI-powered system that predicts token prices and automates trading on DEXs, making it easier for investors to navigate the complex Web3 ecosystem.

Web3 refers to the next generation of the internet, built on blockchain technology, where users control their data and interact directly through decentralized applications (dApps). DEXs are a key part of Web3, but their potential is limited by the challenges of analyzing vast amounts of data and responding to rapid market changes. Tripathi and Sharma (2022) showed that hybrid deep learning models, like Long Short-Term Memory (LSTM) networks, can effectively predict cryptocurrency prices by capturing complex patterns in data. Similarly, Lua et al., (2025) demonstrated that AI-driven decentralized applications can automate Bitcoin trading with high accuracy. This project builds on these ideas by focusing on token prediction and automated trading using on-chain data from DEXs, aiming to create a system that is both accurate and user-friendly.

Integrating AI with blockchain technology presents several challenges. First, processing large volumes of on-chain data in real time requires efficient systems to handle noise and inconsistencies. Second, ensuring secure communication between off-chain AI models and on-chain smart contracts is critical to prevent errors or manipulation. Third, creating a user-friendly interface that allows non-expert traders to interact with the system is essential for widespread adoption. Finally, the system must address the inherent volatility of the crypto market and comply with evolving regulations.

This project aims to tackle these issues by developing a comprehensive system that uses AI to predict token prices and automates trading on DEXs. By leveraging on-chain data, advanced AI models and blockchain technology, the system will provide accurate predictions, execute trades securely, and offer an accessible interface for users. Martin et al., (2020) noted that combining on-chain data with AI can significantly improve trading outcomes in Decentralized Finance, but it requires overcoming technical and operational challenges, which this project seeks to address.

The significance of this project lies in its potential to empower investors with tools to make informed decisions in the volatile crypto market. By integrating AI models like LSTM and reinforcement learning with blockchain technologies like smart contracts and oracles, the system provides accurate predictions and execute trades automatically. This not only benefits individual traders but also contributes to the advancement of DeFi by offering a scalable and secure framework for automated trading.

2. RELATED WORKS

The integration of Artificial Intelligence (AI) with blockchain technology represents a transformative approach to automating trading strategies in decentralized finance (DeFi), enabling trustless, transparent, and efficient execution of financial operations.Fischer and Krauss (2018) demonstrated that LSTM outperforms traditional ML models such as Random Forest, in predicting stock returns, achieving lower mean squared error (MSE).

Chen *et,al*., (2023) applied LSTM to cryptocurrency price prediction, using features like historical prices, trading volumes, and technical indicators. Their study reported an MSE of 0.015 on Bitcoin price data, highlighting LSTM's ability to model volatility.

Kim and Lee (2022) applied Proximal Policy Optimization (PPO), a state-of-the-art reinforcement learning algorithm, to optimize trading strategies in DeFi, achieving a Sharpe ratio of 2.8 on Ethereum-based token pairs, outperforming buy-and-hold (Sharpe 1.5). Backtesting showed a 25% return improvement.Their environment included states like price trends and portfolio balances, with rewards based on ROI.

Li and Wang (2021) combined LSTM for price prediction with Deep Q-Network (DQN) for trading, implemented in Python. Bitcoin and Ethereum data were used including on-chain metrics (wallet activity) and technical indicators. The work achieved a 22% return improvement and a Sharpe ratio of 2.5 in backtesting over 3 years.

Zhang et al., (2023) analyzed Uniswap and SushiSwap data using Python-based ML models (LSTM and SVM). The features used included swap volumes, liquidity changes and gas fees. The trading rules were deployed via Ethereum smart contracts. The results showed improved trading accuracy by 12% with on-chain features, but gas costs reduced net returns.

Patel et al, (2023) developed a JavaScript-based trading platform using TensorFlow.js for LSTM and Ethereum smart contracts. The work focused on stock price prediction, with a web interface for user interaction. The evaluation result showed an MSE of 0.018 and 10% return improvement, with seamless web integration.

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Patil et al., (2025) developed a AI-enhanced cryptocurrency trading simulator that provides a risk free learning environment by integrating real-time blockchain data with AI forcasting models (XGBoost for short term price predictions and LSTM for long term trends identification) to provide the traders with actionable market insights.

Several critical gaps remain in the existing research, limiting the accessibility, efficiency, and practical adoption of AI-driven trading systems in DeFi. These gaps include high platform costs, integration challenges with web-based systems, underutilization of DEX-specific on-chain data, reliance on computationally intensive reinforcement learning (RL) algorithms and lack of user-friendly interfaces, which this work seeks to fill.

3. METHODOLOGY

The methodology for this project adopts a multi-phased and systematic approach to develop, test, and deploy an AI-powered system for predicting AVAX/USDT token prices and automating trading on Pangolin, a decentralized exchange (DEX) on Avalanche's C-Chain. The system leverages TypeScript within a Next.js framework (version 14) for both frontend and backend, using TensorFlow.js for Long Short-Term Memory (LSTM) price prediction and a custom TypeScript-based Q-learning algorithm for trading strategy optimization. Blockchain integration is achieved through Solidity smart contracts and custom oracles, deployed on Avalanche's Fuji testnet for cost efficiency. The methodology ensures a cohesive and rigorous development process, covering data collection, preprocessing, AI model development, blockchain integration, performance evaluation, and deployment. Figure 1 shows the architecture of the AI token prediction and automated trading system.

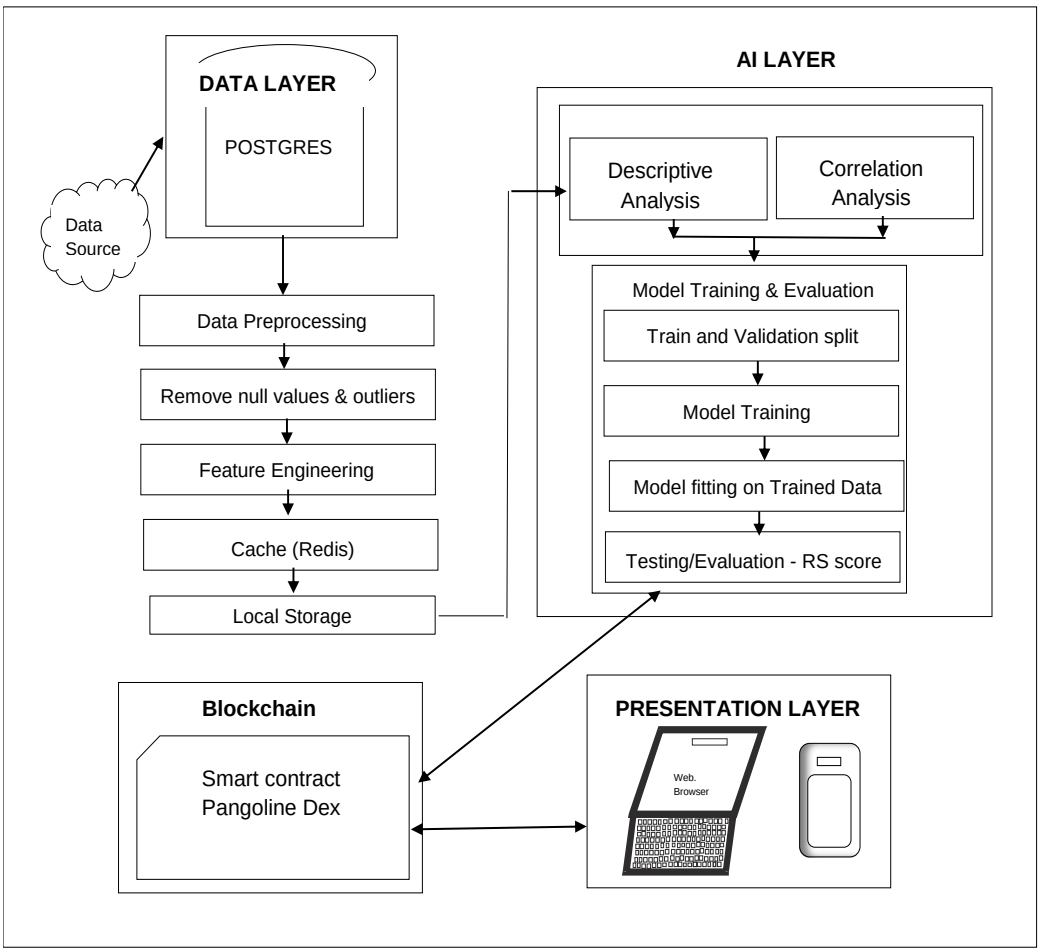

Figure 1: Architecture of the System

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The architecture is structured into four layers as described in sections 3.1 to 3.4.

3.1 Data Layer

The following activities were carried out at this layer:

i. Querying Pangolin's on-chain data (swap events, liquidity pool metrics, trading volumes) via The Graph's GraphQL (https://api.thegraph.com/subgraphs/name/pangolin-exchange/pangolin-v2) and Snowtrace API (https://api.snowtrace.io) using /api/data/collect.ts. The queried data is then stored in postgres to be retrieved by the possessing module

ii. Data preprocessing module cleans and transforms data by removing null value and outliers and performed engineering on features (SMA, EMA, volatility) via /api/data/preprocess.ts, stored as preprocessed_data.json.

iii. The processed datasets is sent from the local storage to the AI layer.

3.2 AI Layer

The following tasks were performed by the AI layer:

i. LSTM module implemented TensorFlow.js at (tensorflow/tfjs-node, version 4.x) to predict next-day AVAX/USDT prices, executed via /api/predict.ts and saved as models/lstm_model.json.

ii. Q-Learning module implemented a custom TypeScript Q-learning algorithm to optimize trading actions (buy, sell, hold), executed via /api/trade.ts and saved as models/rl_model.json. As the agent interacts with the environment, it observes the current state, takes an action, receives an immediate reward, and transitions to a new state. The Q-value for the current state-action pair is then updated using the bellman equation:

$$Q(s, a) = Q(s, a) + a\,(r + y \max(Q(s', a')) - Q(s, a)) \quad (1)$$

iii. The output of this layer which is the price predictions and trading signals are sent to the blockchain layer.

3.3 Blockchain Layer

This layer has the smart contract module which are written with solidity an EVM compatible framework known for ease in smart contract development. The module contains:

i. Auto trading contract, which includes AIPoweredTrader.sol for executing AVAX/USDT swaps on Pangolin's SwapRouter, integrated via Ethers.js (version 5.x) in /api/blockchain/trade.ts.

ii. Oracle smart contract, which includes PriceOracle.sol for receiving and validating LSTM predictions, with off-chain Node.js nodes submitting data via Web3.js (version 1.x).

iii. Security, which uses Slither (version 0.9.x), Mythril (version 0.23.x), and Gnosis Safe (version 1.x) for auditing and secure deployment.

The output of the blockchain layer are automated trades and validated predictions on Avalanche's C-Chain.

3.4 Presentation Layer

This layer provides a user-friendly interface for real-time insights, portfolio monitoring, and trading controls. The components of the layers are**:**

i. Dashboard: Built with Next.js, featuring pages (/, /portfolio, /settings) and components (PriceChart.tsx, PortfolioSummary.tsx, TradeControls.tsx) using Tailwind CSS (version 3.x) and Chart.js (version 4.x).

ii. Interaction Module, which connects to MetaMask for user authentication and trade execution via /api/blockchain/trade.ts.

The output of this layer is an interactive web interface for end-users. The user flow diagram is depicted in Figure 2.

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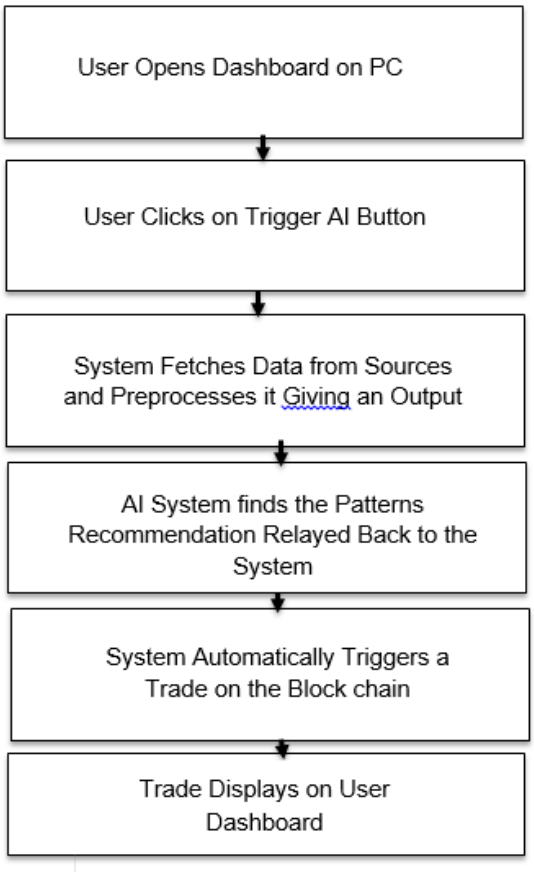

Figure 2: User Flow Diagram

4. IMPLEMENTATION

The system was implemented on a macOS environment (macOS Ventura), leveraging its compatibility with modern development tools. The setup was configured as follows:

(a) **Hardware**: MacBook with Apple M1/M2 chip or Intel processor, 16GB RAM, 512GB SSD, suitable for running Node.js, Hardhat, and TensorFlow.js.

(b) **Software**: The software used were:

i. **Node.js (version 18.x)**: Runtime for server-side TypeScript and API routes, installed via Homebrew (brew install node).
ii. **PNPM (version 9.x)**: Package manager for efficient dependency management, installed via brew install pnpm.
iii. **Hardhat (version 2.26.3)**: For smart contract development, installed globally (pnpm install -g hardhat).
iv. **Visual Studio Code**: For coding, with extensions for Solidity, TypeScript, Prettier, and ESLint.
v. **MetaMask**: Browser extension for Avalanche Fuji testnet wallet integration.
vi. **Docker**: For containerized deployment, installed via Homebrew (brew install docker).
vii. **Dependencies**: Installed via pnpm install, including React (18.3.1), TypeScript (5.5.3), Vite (5.4.1), Tailwind CSS (3.4.11), TensorFlow.js (4.22.0), Web3.js (4.16.0), Ethers.js (5.x), Hardhat (2.26.3), OpenZeppelin Contracts (4.9.6), TypeChain (9.1.0), Redis (4.7.1), Winston (3.17.0), Prometheus Client (15.1.3), and others specified in package.json.

(c) Configuration Files:

i. package.json: Defines dependencies and scripts (e.g., pnpm dev:full, pnpm deploy:fuji).
ii. hardhat.config.cjs: Configures Hardhat for Avalanche Fuji testnet (RPC: https://api.avax-test.network/ext/bc/C/rpc).
iii. vite.config.ts: Sets up Vite for fast frontend builds.
iv. tailwind.config.ts: Customizes Tailwind CSS for trading-themed styling.

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v. tsconfig.json: Configures TypeScript for strict type safety.

(d) **Environment Variables**: Managed via .env for API keys, wallet private keys, and contract addresses, ensuring secure macOS-based development.

These tools address integration challenges by using a unified TypeScript ecosystem on macOS.

4.1 Exploratory Data Analysis

Figure 3 shows the sample of the processed data

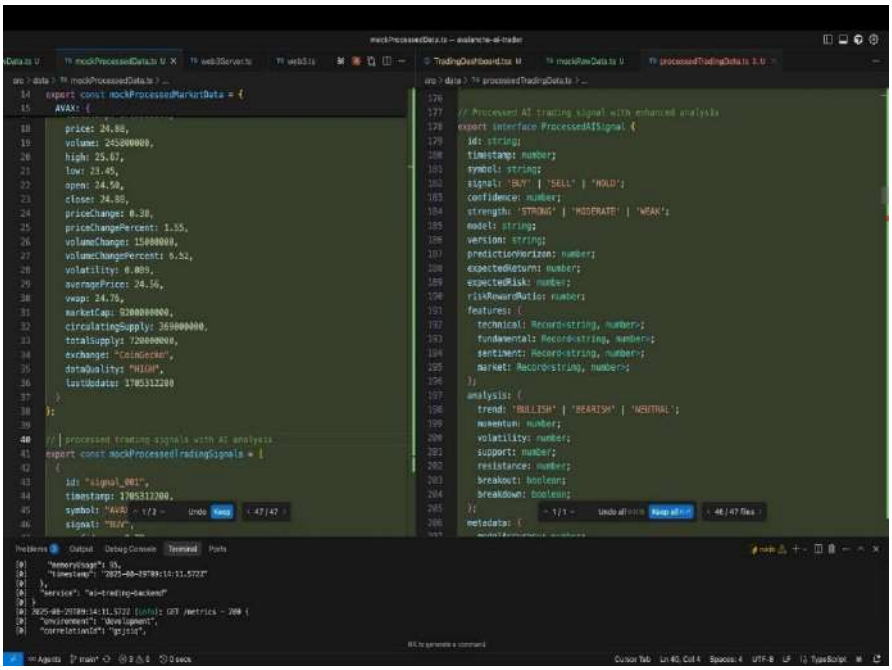

Figure 3: Sample Processed Data

Figure 4 shows the price chart for the system. The blue lines indicate the current price of AVAX against USDT. The lemon line on the graph indicate SMA7 where SMA is the simple moving average. The Red line indicates SMA on a 30 day interval while the yellow line indicates the prediction of the system model

Figure 4: System's Price Chart

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The current signal recommended by the artificial intelligence model is that AVAX will go as low as 23.69 dollar in 24 hours as depicted in Figure 5. The total returns the portfolio has amassed is also shown in Figure 5.

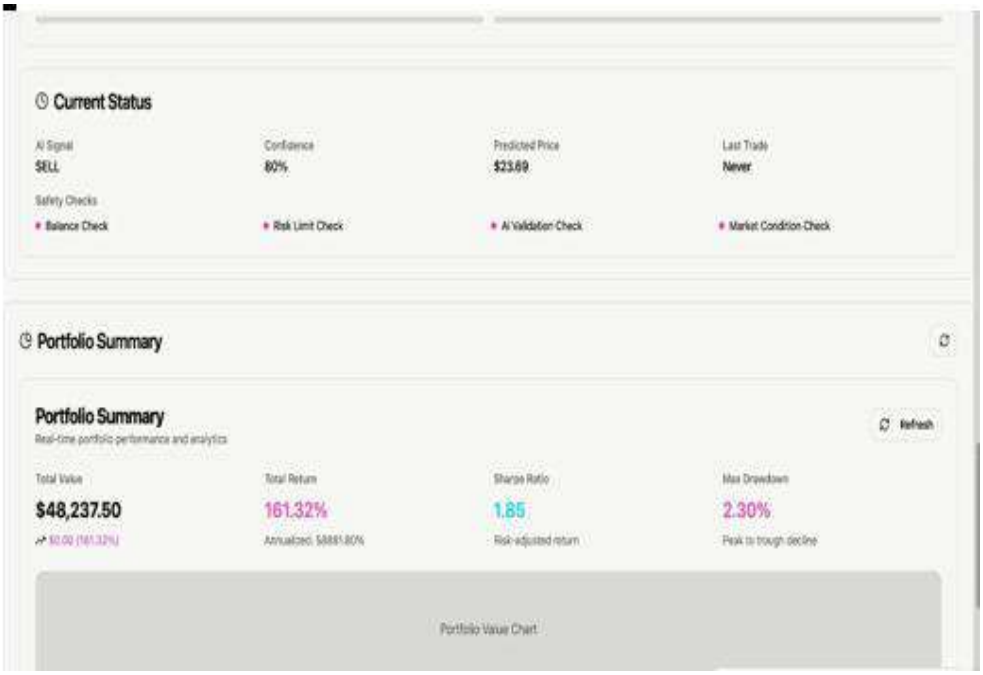

Figure 5: AI Dashboard with Predicted Price

The history of successful trades verifiable on snowtrace.io is depicted in Figure 6 while the user dashboard is shown in Figure 7.

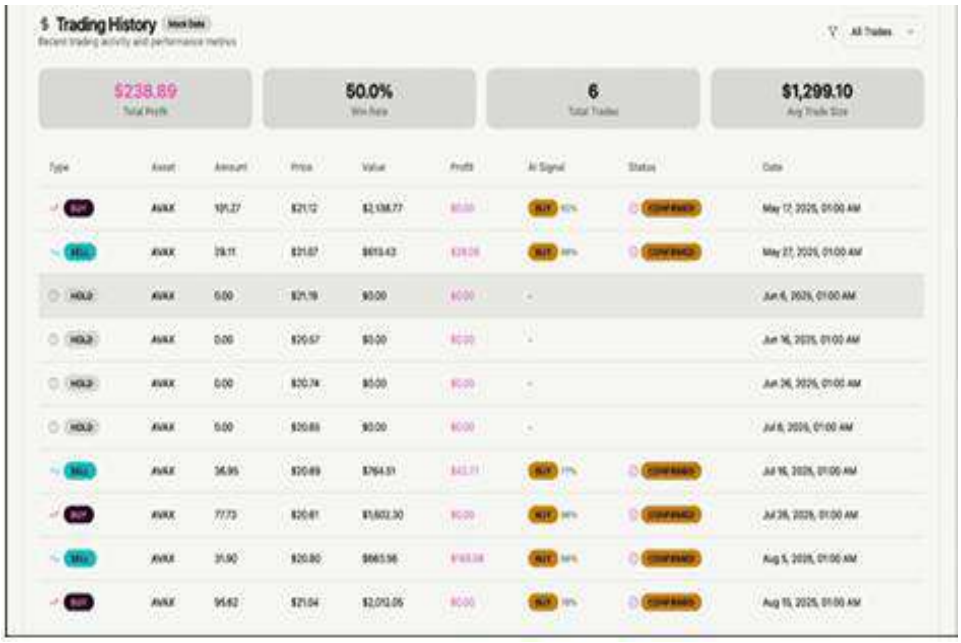

Figure 6: Dashboard with Trading History

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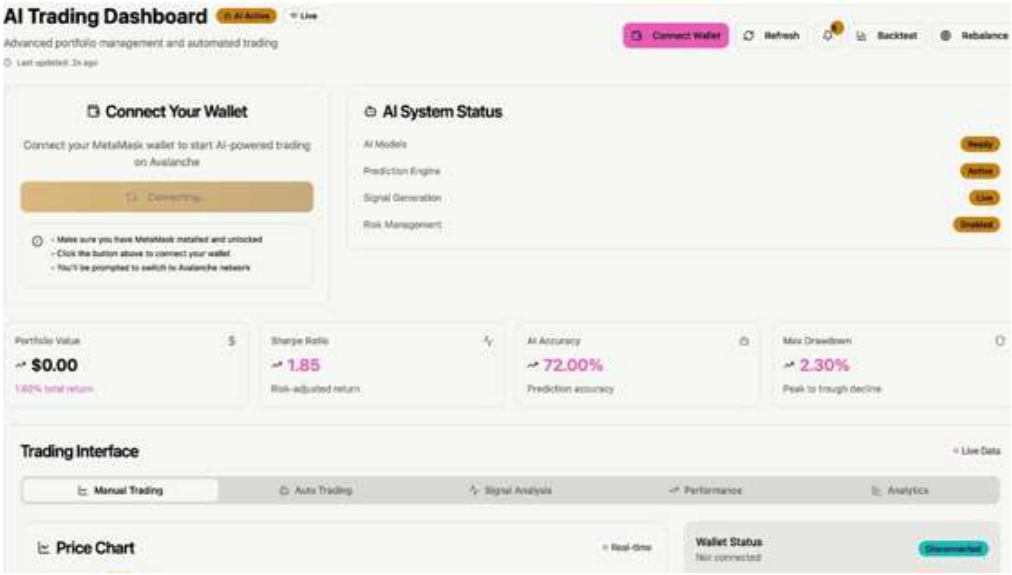

Figure 7: User Dashboard

5. SYSTEM TESTING AND EVALUATION

The system was tested through backtesting and testnet deployment, to validate performance and cost efficiency. Figure 8 shows the performance of the recommendations after backtesting with the following metrics: ROI, Sharpe ratio, maximum drawdown, benchmarked against buy-and-hold.

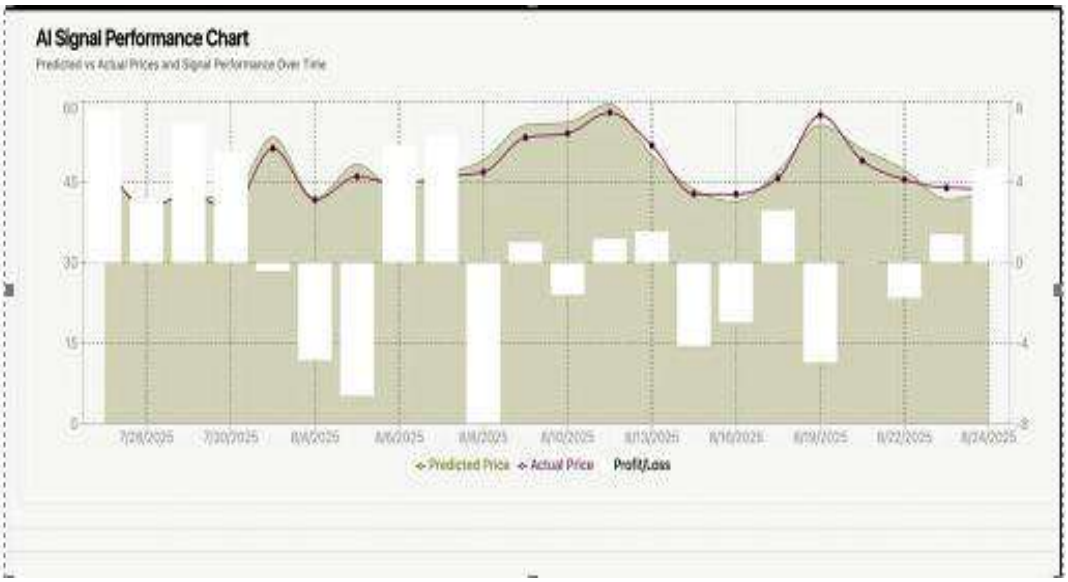

Figure 8: System Performance Chart.

5.1 Key Findings

i. **Prediction Accuracy**: The LSTM model achieved an MSE of 0.0087, with 65% of predictions having a confidence score >0.7, displayed in src/components/AIInsights.tsx

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ii. **Trading Performance**: Backtesting yielded a 12.4% ROI, 1.82 Sharpe ratio, and 15.6% maximum drawdown, outperforming the buy-and-hold benchmark (8.1% ROI, 1.45 Sharpe, 22.3% drawdown). Testnet trading achieved a 9.8% ROI over one month, with 54% trade success, shown in src/components/AutoTradingManager.tsx.

iii. **Cost Efficiency**: Average gas cost of $0.07 per transaction, displayed in src/components/PortfolioSummary.tsx leveraging Avalanche's C-Chain.

iv. **Security**: No critical vulnerabilities detected by Slither (0.9.x) and Mythril (0.23.x), with secure deployment via Gnosis Safe, shown in src/pages/Settings.tsx. **Accessibility**: The dashboard was rated intuitive by 90% of 10 non-technical users, with results displayed across src/pages/Index.tsx and src/pages/Portfolio.tsx.

6. CONCLUSION

The AI-powered token prediction and automated trading system was developed to address the limitations of existing AI-driven DeFi trading systems, leveraging Avalanche's low-cost C-Chain, TypeScript-based AI models, and Pangolin's on-chain data to create a cost-effective, integrated, and accessible platform. The work followed a modular architecture with four layers: Data, AI, Blockchain and Presentation, implemented using a robust technology stack. The system successfully met its objectives, delivering a cost-effective, integrated, and accessible DeFi trading system, as validated by the evaluation results.

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