Improved Intelligent Model for Cryptocurrency Trading in Blockchain Platform

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ABSTRACT

In studying Blockchain Technology, one of its predominant applications that have provided a massive growth in their recent global acceptance and market capitalization in the past few years is cryptocurrencies. Individual investors, notable institutions and corporate firms are readily investing in it. Predicting cryptocurrency prices owing to their volatile nature has been a challenging decision for researchers owing to social and psychological factors that affect price of cryptocurrency. Substantively, the crypto market is highly volatile when compared to the traditional commodity markets and may be affected by factors like sentimental, legal and other technical indicators. The uncertainty and unpredictable nature of cryptocurrency necessitated this study on Improved Intelligent Model for Cryptocurrency Trading in Blockchain Platform. The five cryptocurrencies utilized in this work were Bitcoin (BTC), Ethereum (ETH), XRP, Cadona (ADA), Solana (SOL). This study incorporated Bi-LSTM and Attention Mechanism techniques with trading strategies like buy, sell or hold depending on the choice of the investors. It is depicted that our model yields more accurate and reliable predictions when confirmed alongside with the Live price time-based model. This work provided with guarantee an interface that can be used by investors especially those in cryptocurrency trade for accurate predictions as it will go a long way in extenuating investment risk. This research adopts Object-Oriented Programming (OOP) methodology to design and implement an intelligent cryptocurrency trading system. This study was implemented using C# Programming Language with incorporation of python.NET. The system can be used in real-time scenarios as it is well trained and evaluated using standard data sets. The result depicted that this new system predicts cryptocurrency prices with high accuracy compared to the existing system. The outcome of this study assured us that our approach enhances the necessary assurance on the new system and offers customers a more reliable financial service in cryptocurrency trade.

Keywords: Blockchain Technology, Cryptocurrency, Predicting, Attention Mechanism and investment risk.

INTRODUCTION

Artificial intelligence has increasingly been applied in diverse fields in the past ten years. This has contributed greatly to improved results. One of the interesting applications is in the financial markets where it has been used to refine market strategies and operations to great measures. The commonly accepted applications of AI in finance are loan credit scoring, credit evaluation, mortgage choice decisions, portfolio management, predicting of financial performance, and predicting of the market direction (Bahrammirzaee, 2010).

On the other hand, the blockchain is, in essence, a distributed data structure that makes a digital ledger of transactions shared across a distributed network of computers, maintained by a continuously expanding list of records (blocks) that are secured from tampering and revision of the content. Blockchain technology is made up of two components: blocks and transactions, (Sanjana et al., 2016). Each block is time-stamped and linked to a previous block using a secured hash algorithm. The most important feature of blockchain is that it is based on the use of cryptography, and therefore, multiple users can alter transactions of the same system in a secure network where everyone accesses his/her own node of data. This new block, added to the chain, is the result of a majority of nodes agreeing that the transaction corresponds with history matching information that the chain is composed of. The configurations of blockchain vary according to the size and type of the network and are mainly customized according to the business need of a specific company. Depending on the design and available control mechanisms, there could be great differences in the ways blockchains allow users to access and manage data (Fernández-Caramés and Fraga-Lamas, 2018).

Public blockchains are open to participation without requiring permission from a central authority. In contrast, a private blockchain requires permission to join and is very controlled by the owners. On the other hand, federated or consortium blockchains are controlled by a coalition of owners and there is limited access to the network and its participants. The explosion of research regarding blockchain and its applications had great implications within the field of government services, finance, and energy, as well as many others. (Alketbi et al., 2018), The blockchain architecture is a peer-to-peer network with its transactions not dominated by a single central entity. The transactions are stored in a chain of blocks, generally accessible to all nodes, in a trusted manner. The consensus algorithms and cryptography are employed by blockchain to make the validation of transaction data possible and the linked blocks resistant to modification. (Tschorsch and Scheuermann, 2016), Among the most important decisions to be made concerning the effective operation of a blockchain is the consensus algorithm. Most importantly, it should not use the idealistic consensus mechanism, in which each miner has equal weight in voting. This can lead to a Sybil attack in which a single entity might control the whole blockchain. Besides the traditional Proof of Work consensus used in Bitcoin, there are other mechanisms like Proof of Stake, Proof of Activity, Proof of Space, and Practical Byzantine Fault Tolerance. Cryptocurrencies, having been recently introduced into the market, have received a very fast rate of acceptance and development. According to some hedge funds and asset managers, the inclusion of the cryptocurrency assets within an investment portfolio and trading strategy is now becoming apparent. There has been significant work within the academic environment to understand the dynamics of cryptocurrency trading. This work thoroughly reviews research on cryptocurrency trading, including studies that support and develop strategies for trading cryptocurrencies. Cryptocurrency trading has evolved significantly with great interest and increased activities. (Farell, 2015), Cryptocurrency is a decentralized digital medium of exchange which uses cryptography to accomplish a transaction or to transfer funds.

The market thus constitutes the whole environment in which purchasing, selling, and exchanging currencies are performed at prevailing or at preset prices. It is blockchain technology that brings about decentralization, immutability, and transparency into the workings of cryptocurrencies, (Meunier, 2018). A cryptocurrency trading system can be defined as a service or platform that allows the exchange of cryptocurrencies and digital assets for fiat currency. A cryptocurrency exchange, just like a traditional monetary exchange, facilitates the buying and selling of such digital assets. It can also be referred to as a digital currency exchange (DCE). This is not an amazing thing to find in a market that has an average daily trading volume in trillions of dollars. Its total market capitalization now goes over half a trillion dollars for the entire market, and the market is not up to a decade old yet. This makes the choice of the best cryptocurrency trading platform tough. I really believe there is no 'best' exchange, but a few act as the 'best' solution for several users' needs and preferences.

So, growing investments, growing popularity of cryptocurrencies. It is necessary to emphasize the fact that in the beginning of 2018, over 1,500 actively traded cryptocurrencies had been already created, with overall market capitalization exceeding $300 billion. In the best days of January 2018, it reached $800 billion. Today, access to the market is surprisingly easy for almost 2.9 to 5.8 million private investors and institutions participating in numerous networks. Blockchain is the technology backing cryptocurrencies and is popularly known as an immutable distributed ledger. It is the fundamental technology on which cryptocurrencies are based (Shermin, 2017).

Cryptocurrency is an electronic cash system that is purely electronic. In a total opposite, cryptocurrencies are found on a decentralized peer-to-peer mechanism and remain peripheral to a regulatory central bank system. The basis of this work is to enable direct transfers among the users. Meanwhile, since the emergence of cryptocurrencies, several cryptocurrencies have gained dominance among different diverse groups of users, such as Bitcoin, Ethereum, Bitcoin Cash, and Litecoin. Some certain attributes, such as lower fees, faster payment processing, the ability to conduct transactions from anywhere, and superior fraud detection capability, have facilitated the fast lane toward adoption and popularity (McIntosh, 2018).

Cryptocurrency transactions have many types and undergo many processes before finally being confirmed. When an initiated transaction is shown in the main pool, miners can choose this transaction to build a new block

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and to put into the blockchain. (Reiff, 2020), A block can be reversed even after mining and confirming a block. The security of transaction increases when more blocks are part of the chain, and if the block is later added to the chain, it makes the security of the transaction more robust. Most cryptocurrencies are bought and sold in online exchange. The average daily exchange in online exchange counts about $15 billion. As 170 hedge funds have mushroomed that concentrate solely on cryptocurrencies, the demand to trade and hedge Bitcoin has increased considerably.

Theories that underlie cryptocurrency price volatility and which are also used to refine prediction models, majorly in the context of Bitcoin. (Reshma et al., 2020), They developed a recurrent neural network model based on algorithmic trading to predict future prices for cryptocurrencies based on historical data. An RNN, specifically its long short-term memory variation, takes in a full sequence of data and is thus especially well-suited for time series data analysis. Intelligent algorithms have drawn an increasing limelight because of their potential in making decisions based on available information. These enable computers to be intelligent data interpreters through the processing, understanding, and use of data for automated knowledge. The algorithms are created in a way that enables a computer to learn on its own; it is trained so that it can set its rules through automatic data analysis. The rules later serve as a prediction based on data that was initially unknown.

Deep learning was developed as a part of machine learning but differs, because of its multi-layered artificial neural networks (Erickson et al., 2017). Machine learning is a subpart of artificial intelligence that equips a system with the ability to learn and improve using experience-based paradigms, as opposed to the use of explicit programs. Deep learning has a much wider coverage than what the traditional machine learning techniques had in store since it has discarded manual feature engineering for it, hence a great enhancement in its performance. It also enables the execution of very complex applications, for example, sophisticated sensing.

Deep learning algorithms are designed to construct mappings from raw inputs to desired outputs, and they differ from more classical machine learning methods based on manual feature extraction. Instead, deep learning learns to identify such features from data. More frequently, the architecture for deep learning most often contains under one roof a coalition of learning and adaptation techniques that overcome each other's individual deficiency and achieve synergistic effects from the hybridization or fusion of these techniques. People engage in blockchain trading for business and speculative purposes. The key to assimilating artificial intelligence in robots was due to automation. (Edwards et al., 2019).

A trading robot is an informal name for a program that carries out algorithmic trading and that uses some market signals to decide at a particular moment whether to buy, hold, or sell a currency pair. The typical automated variety would be integrated with an online or global trading platform. Trading for speculative reasons focuses solely on profit-making, driven by fluctuations in price. This type of trading involves both individuals and institutions and occurs daily. It revolves around comparing the values of currencies to determine which one offers better value, guiding decisions on whether to make an exchange. Using fundamental data to identify the relationship between market behavior and external information. (Arman et al., 2011).

Blockchain trading is inherently complicated because of the multitudes of factors coming from both economic and psychological backgrounds. Trading Robots (TRs) can lower capital costs for traders through improved risk sharing, liquidity enhancement, hedging, and the promotion of better competitive exchanges. These robots are developed to mimic human functions, requiring in-depth research on human decision-making and manipulation mechanisms. Just like the way humans can interact with and manipulate their environment, similar expectations are placed on robotic capabilities.

Consistently making profits in Forex trading has always been a challenge, as the sector is influenced by numerous price-determining factors. (Kuepper, 2021). Successful traders must be able to predict the signals emanating from the market correctly and, at the same time, practice good risk management techniques to minimize losses in case the markets move against their expectations (Billard and Kragic, 2019).

Much of the research conducted has been on the machine learning techniques in blockchain pricing model development, and it has largely been focused on the accuracy of the models; results on profitability have been quite sparse. However, profitability is core to why traders go to the exchanges on the blockchain.

This research integrates current intelligent algorithms and to achieve the desired system that will provide support for profit generation in the blockchain exchange through strategic trading decisions. The developed strategies will aim to capture the expected market signals; the trading system will combine the output from each strategy to maximize profits. Optimization in blockchain market trading can be achieved with respect to traditional rule-based trading models, a fact that could help trading houses add another dimension to their optimization strategies. Moreover, to succeed, traders should focus not only on right market signal prediction but also on management strategies in the blockchain to help at least keep losses at bay. With the aim of developing an effective and optimal system, this will enhance the efficiency of blockchain transaction markets. It will be designed with easy training, testing of strategies, and observation of the performance before actual deployment.

A cryptocurrency digital wallet is a software program that stores private and public keys and interacts with various blockchain to enable the owner to transact in multiple cryptocurrencies. In easy terms, it is a digital wallet used to store, receive, and send many different cryptocurrencies. A cryptocurrency wallet is an application that stores your cryptocurrency under its possession. Whereas a physical wallet stores money and cards inside it, a cryptocurrency wallet stores keys to sign cryptocurrency transactions and gives access to your cryptocurrency. Real money is not stored, but it records all transactions on the blockchain. Because any person in possession of private keys becomes an owner of the coins associated with the key, you must take care of them.

Review Of Related Works

Vasukidevi and Sethukarasi (2020), systematically examined the application of blockchain in securing cryptographic keys, marking its evolution into a robust method for data storage and transfer within decentralized systems. Their review sheds light on the maturity of blockchain technology and emphasizes the need for further development to enhance its readiness for broader adoption. The study also points out the increasing reliance on encryption for regular communications, suggesting an ongoing need to advance cryptographic and key management schemes.

Rajashree and Girish (2020), focused on how blockchain's inherent security features can be integrated into cloud computing environments, crucial for the evolving landscape of financial technology that attracts numerous business enterprises. They highlighted how blockchain could bolster data security through mechanisms like peer authentication, encryption, and hash value generation. The recommendation for companies to conduct strategic evaluations on blockchain's feasibility reflects the necessity to align new technologies with business models and strategic objectives.

Sarvesh and Shriti (2020), discussed the specific challenges faced by cryptocurrencies, particularly Bitcoin, which dominates the cryptocurrency market. While acknowledging blockchain's potential to revolutionize payment infrastructures, they pointed out issues like cost-effectiveness, efficiency, price volatility, and scalability. Their analysis suggests that despite these hurdles, blockchain has a significant role to play in international trade, trade finance, and social benefit transfers, particularly in low-income countries.

Dendej and Sucha (2022), proposed a novel decentralized multi-blockchain platform architecture aimed at facilitating cryptocurrency payments in e-commerce. Their NAGA platform is designed to support cross-cryptocurrency payments, addressing the inconvenience faced by buyers and sellers who prefer different cryptocurrencies. This initiative could potentially increase e-commerce sales and revenues by reducing transactional friction. The study underscores the necessity for more robust error-handling mechanisms to accommodate multiple simultaneous errors and new scenarios.

Chittala and Sri (2022) conducted a comparative analysis of different AI models, namely Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTM) networks, to predict cryptocurrency prices. Their research highlights the adaptability of LSTMs in handling the short-term dynamics crucial for forecasting rapid changes in cryptocurrency prices, owing to their ability to utilize historical data effectively. Although ANNs also showed promise, LSTMs were noted for their superior precision in predictions due to their advanced memory capabilities.

Reshma et al. (2020) focused specifically on Bitcoin, using LSTM models to predict its price movements. Their study underscores the LSTM's effectiveness in dealing with complex datasets, which are common in the cryptocurrency market. The LSTM's ability to manage and learn from large, noisy data without overfitting makes it a preferred choice over other machine learning models, thereby providing a potentially lucrative tool for traders and investors looking to capitalize on market trends.

Amit et al. (2019) ,explored the operational aspects of real-time cryptocurrency trading platforms. They emphasized the role of mining in verifying transactions and generating new currency, noting the absence of a central authority as a defining characteristic of cryptocurrencies. The research also pointed out the gaps in current trading platforms, such as the need for faster withdrawals and better user interface designs, suggesting that improvements in these areas could enhance user satisfaction and platform reliability.

Constance and McIntyre (2015) and Danda et al. (2020) delve into the technical and practical aspects of cryptocurrencies and blockchain technology, offering valuable insights into their potential impact across various sectors. They explored the underlying computer science and information systems (CS/IS) of cryptocurrencies such as Bitcoin, Litecoin, and Dogecoin. Their research serves as a foundational text for understanding how these digital currencies function without borders and are sustained through a combination of CS/IS principles. The study categorizes the cryptocurrency world into four main areas: trading, use, mining and regulation. The researchers suggest that the technology underpinning these digital currencies might eventually integrate with traditional banking systems, potentially revolutionizing transaction fees and infrastructure in much the same way VoIP disrupted long-distance communication.

Danda et al. (2020), provide an in-depth look at how blockchain technology, the backbone of cryptocurrencies like Bitcoin, can be utilized beyond its original financial context. They described blockchain as a distributed ledger technology that enhances the integrity, accountability, and confidentiality of data without the need for centralized oversight. This technology is particularly potent in developing secure and trustworthy smart systems due to its features: Decentralization, Encryption and key Immutability.

Deepa, et al. (2022) and Aboosaleh et al. (2022) showcase innovative applications of blockchain and machine learning technologies in different domains: energy trading and financial forecasting, respectively. Each study exemplifies how integrating advanced technologies can solve complex problems and optimize systems in dynamic environments. They focused on the development of a blockchain-based peer-to-peer energy trading platform. Their approach leverages blockchain's inherent strengths—decentralization, security, and transparency to facilitate energy transactions directly between individuals without the need for traditional intermediaries. This system architecture comprises several key elements: Integration with IoT, Decentralized Network, Real Time Transaction. This innovative application of blockchain technology in energy sectors underscores its potential to revolutionize traditional industries by improving efficiency, reducing costs, and enhancing sustainability.

Aboosaleh et al. (2022), explored a hybrid approach to predicting Bitcoin prices, combining the capabilities of LSTM neural networks with the CDSA (Cuckoo Search Differential Algorithm), a metaheuristic algorithm.

Iresha and De-Zoysa (2017), addressed a critical challenge in the realm of cryptocurrency transactions double spending. Double spending is a significant security risk where the same digital tokens are spent more than once, undermining the integrity of the payment system. Here's a breakdown of their research approach, the proposed solution, and its implications for digital currency transactions.

The research by Iresha and De-Zoysa provides a comprehensive solution to one of the most pressing issues in digital payment systems. Their proposed model demonstrates a viable pathway to securing cryptocurrency transactions against double spending, offering a blueprint that could influence future developments in digital payment security. This study underscores the ongoing need to evolve and adapt security measures in line with technological advancements to safeguard the integrity and reliability of digital financial transactions.

Sanjana et al. (2016), explored the extensive capabilities of blockchain technology, detailing its structure and the broad spectrum of its applications. This deep dive into blockchain highlights its pivotal role in redefining how data is handled across numerous sectors, particularly in enhancing security and decentralization in digital transactions and beyond. Blockchain technology represents a groundbreaking shift in how information is shared and stored.

Haritha and Shyma (2010), highlighted the transformative potential of blockchain technology in these areas, recognizing its growing influence across multiple sectors. Here's a deeper dive into the expanded utility of blockchain beyond its initial application in cryptocurrencies: Blockchain's architecture makes it exceptionally secure against tampering and fraud. Each block contains a cryptographic hash of the previous block, a timestamp, and transaction data, making it virtually impossible to alter any aspect of the blockchain without the network consensus. This security feature is critical in fields like healthcare, where patient data privacy and integrity are paramount.

MATERIALS AND METHODS

The proposed intelligent cryptocurrency trading system employs a sophisticated multi-layered architecture designed to predict cryptocurrency prices accurately using historical data and real-time signals. The system integrates a Bi-directional Long Short-Term (Bi-LSTM) model with an intelligent attention mechanism that ensures predictions are only triggered when the market exhibits significant behavioral patterns. This approach maintains computational efficiency while avoiding unnecessary processing during low-volatility periods.

System Objective and Core Functionality

The primary objective of the proposed system is to provide reliable cryptocurrency price predictions while maintaining computational efficiency. The system achieves this through an intelligent filtering mechanism that distinguishes between meaningful market movements and regular market noise. Unlike traditional prediction systems that continuously process every minor price fluctuation, our system employs selective prediction activation based on market volatility thresholds.

The core functionality incorporates several key components working in coordination. The data collection and processing component connects to the CryptoCompare public API to collect both historical and live market data, including precise timestamps, OHLC (Open, High, Low, Close) prices, trading volumes, and additional market indicators such as moving averages and relative strength index (RSI). The dual-model architecture maintains two complementary models - a long-term model trained on two years of historical data to capture fundamental market patterns, and a short-term adaptive model using a two-month look-back window to reflect current market dynamics.

The intelligent prediction triggering mechanism continuously monitors market conditions and only activates the prediction engine when significant market movements occur, typically defined as price changes beyond established volatility thresholds. This is complemented by adaptive learning capabilities that continuously update models based on new market data, ensuring predictions remain relevant to current market conditions.

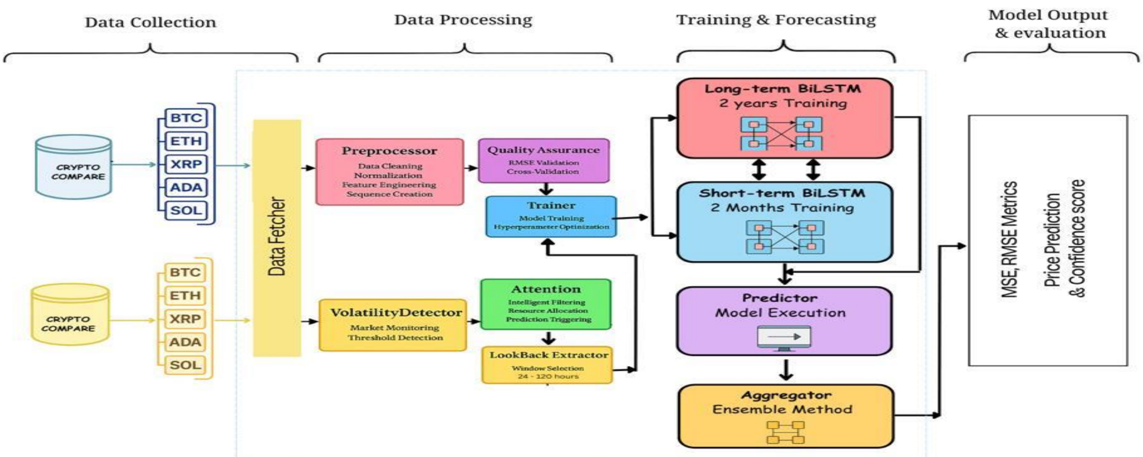

Figure 1: Architecture of the Proposed System

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Technical Architecture Components of the Proposed System

The technical architecture of the proposed system comprises several interconnected components that work in a coordinated manner to ensure seamless data flow from collection to prediction generation. These components are designed to handle the complete data lifecycle, from initial acquisition through the CryptoCompare API to final model training and prediction output.

Data Collection Module (CryptoCompare API Integration)

The system establishes connections to the CryptoCompare public API using standard HTTP requests for historical data and WebSocket connections for real-time streaming data. The data collection process operates at regular intervals, typically every minute for real-time data, storing information in a structured time-series database.

Data Types Collected:

1. **Timestamps** with precise time markers for chronological order 2025-01-28T14:30:00Z" (UTC timestamp format)
2. **OHLC prices** that define market movement within each period Open: $102,065.72, High: $103,787.72, Low: $100,221.08, Close: $101,284.47
3. **Trading volumes** indicating market activity and liquidity Sample: Volume From: 44,096.37 BTC, Volume To: $4,510,250,877.49 USD
4. **Technical indicators** including moving averages, RSI, and market sentiment metrics MA(20): $101,500.23, RSI: 45.67, Sentiment Score: 0.72

Data Foundation and Model Preparation

The DataFetcher module establishes connections to the CryptoCompare API and initiates continuous data collection. Raw market data flows through validation and quality checks before being processed by the Preprocessor module for cleaning, normalization, and structuring. Simultaneously, the Trainer module utilizes cleaned historical data to train the primary Bi-LSTM model on two years of market data while maintaining a secondary model trained on recent two-month data windows. This dual-model approach captures both long-term patterns and short-term market dynamics.

The DataFetcher module serves as the primary responsibility for managing all data acquisition from CryptoCompare API.

Detailed Functions:

i. Establishes and maintains API connections with automatic retry logic

ii. Handles rate limiting and implements connection pooling

iii. Manages both historical data retrieval and real-time streaming

iv. Ensures data continuity and implements failover mechanisms

v. Validates incoming data integrity and format compliance

Preprocessor Module

The Preprocessor module transforms raw data into model-ready sequences through comprehensive data processing capabilities. This module implements comprehensive data cleaning algorithms, performs feature engineering and normalization, and creates sliding window sequences for LSTM input. The module handles missing value imputation and outlier detection while generating training, validation, and testing datasets with proper temporal ordering.

Trainer Module

The Trainer module manages model training and optimization processes for both long-term and short-term prediction models. This module implements Bi-LSTM training algorithms, manages hyperparameter optimization and model checkpointing, and handles overfitting prevention through regularization techniques. The module implements early stopping and learning rate scheduling while maintaining model versioning and performance tracking capabilities.

Intelligent Monitoring and Prediction Generation

The Volatility Detector continuously monitors live market data, calculating various volatility measures and market activity indicators. The Attention Mechanism evaluates these measurements against predefined thresholds to determine when market conditions warrant prediction activation. Upon trigger activation, the LookBack Extractor gathers appropriate historical data windows and formats them for model input. The Predictor module runs both long-term and short-term models, generating individual predictions that are processed by the Aggregator to produce comprehensive final predictions.

VolatilityDetector Module

The VolatilityDetector module monitors real-time market conditions to determine when prediction activation is warranted. This module calculates multiple volatility metrics across different timeframes, compares current conditions against dynamic thresholds, and filters false signals and noise from genuine market movements. The module tracks market momentum and trend strength while providing market context for prediction decisions.

Attention Mechanism Module

The Attention Mechanism module provides intelligent resource allocation and prediction triggering capabilities. This module evaluates market significance using multiple criteria, manages computational resource allocation, and prevents unnecessary predictions during low-volatility periods. The module optimizes system efficiency through selective activation and maintains prediction queue and priority management.

With both models trained and ready for deployment, the attention mechanism serves as an intelligent filter that triggers predictions only when market conditions warrant analysis. This component continuously monitors the processed data streams to identify significant market movements that justify computational resource allocation.

Implementation Details

i. Continuous monitoring of live market data with real-time volatility calculations
ii. Multi-timeframe analysis considering volatility patterns across various temporal windows
iii. Dynamic threshold adjustment based on recent market volatility characteristics
iv. Cross-validation comparing movements with other major cryptocurrencies for context Filtering Logic
i. Primary triggers based on significant price movements beyond established statistical thresholds.
ii. Volume confirmation ensuring price movements are accompanied by adequate trading activity.
iii. Persistence checks requiring movement duration minimums to filter temporary fluctuations.
iv. Market-wide versus asset-specific event differentiation for appropriate response calibration

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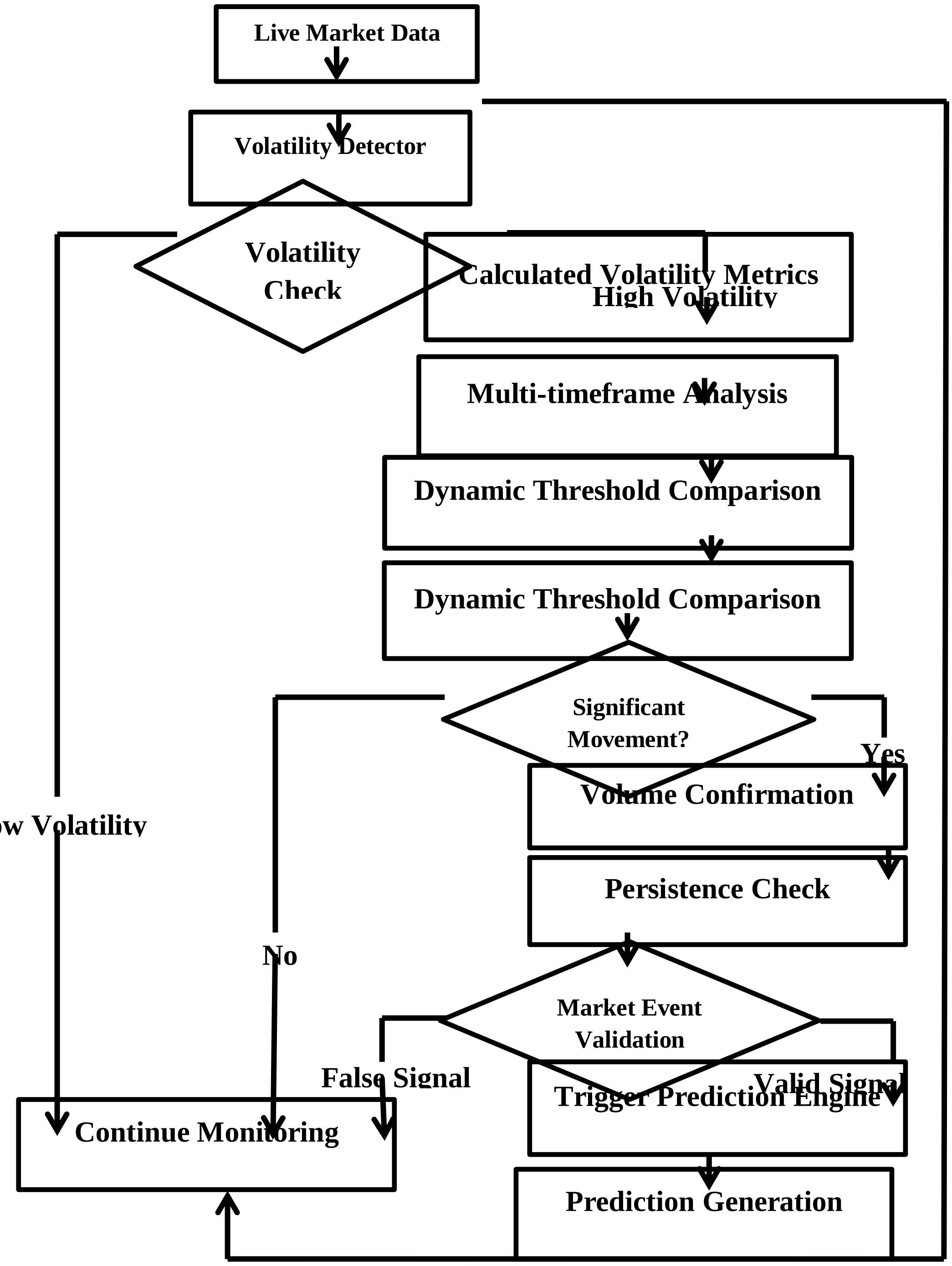
Figure 2. illustrates the attention mechanism workflow and its integration with the prediction engine.



Look Back Extractor Module

Upon attention mechanism activation, the prediction engine initiates analysis using variable look-back windows (24-120 hours) selected based on current market conditions figure 3.4. This engine coordinates with all previously processed data and trained models to generate comprehensive market predictions through pattern recognition, trend analysis, support/resistance calculation, and momentum assessment. The Look Back Extractor module prepares historical data for prediction by selecting appropriate time windows (24-120 hours) based on current market conditions. This module formats data according to model input requirements, ensures temporal consistency and data quality, and handles edge cases and missing data points while optimizing data structure for efficient model processing.

Figure 2: Attention mechanism's decision-making process with conditional flows

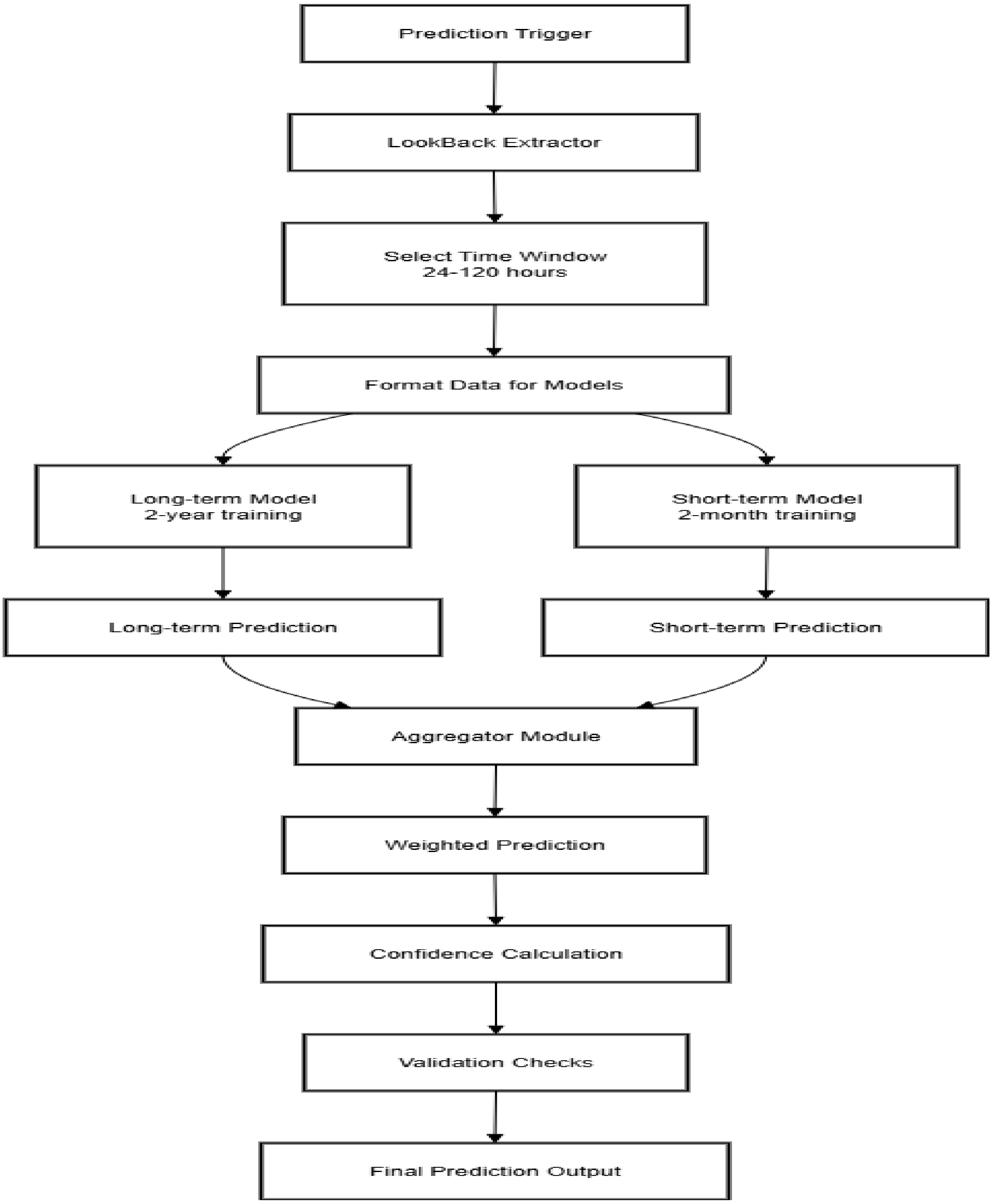


Figure 3: Real-time prediction engine with dual models

Predictor Module

The Predictor module executes trained models and generates predictions through coordinated model inference processes. This module runs Bi-LSTM model inference on prepared data, calculates confidence scores and prediction intervals, and validates reasonableness and consistency output. The module generates comprehensive prediction packages and handles model ensemble and voting mechanisms.

Aggregator Module

The Aggregator module combines multiple model outputs to produce final consensus predictions as depicted in figure 4. This module weighs predictions from long-term and short-term models, resolves conflicting signals using intelligent algorithms, and produces final consensus predictions with confidence metrics. The module manages model ensemble strategies and provides uncertainty quantification and risk assessment capabilities.

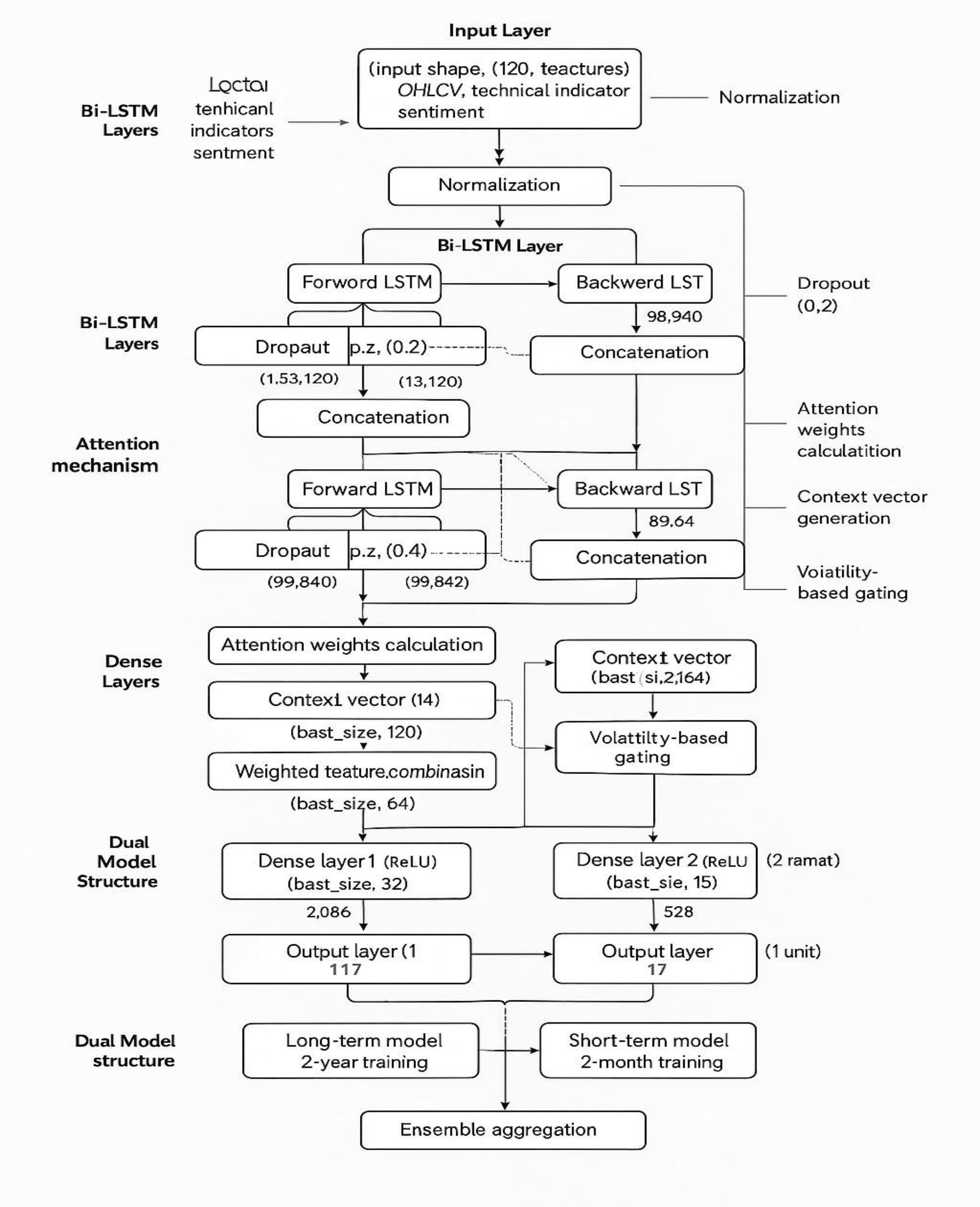


Figure 4: Detailed BiLSTM model architecture with attention mechanism

EXPERIMENT AND RESULTS

The system was organized into two main components namely the backend Application Program Interface as depicted in figure 5. and the Angular frontend as shown in figure 6. The backend API, built with ASP.NET Core 8.0, provided endpoints to load historical data, fetch live prices, train the model, generate predictions, and apply an attention mechanism. The Angular UI featured five main functions: Load Historical Data, Live Price, Train, Get Predictions, and an ongoing Attention Mechanism.

Historical data was first fetched and normalized before being used to train the model via ML.NET. Live price data was continuously retrieved and fed into the trained model to generate future price predictions. The attention mechanism compared the live and predicted prices, issuing recommendations when the difference exceeded the present threshold (±$1 or ±0.5%).

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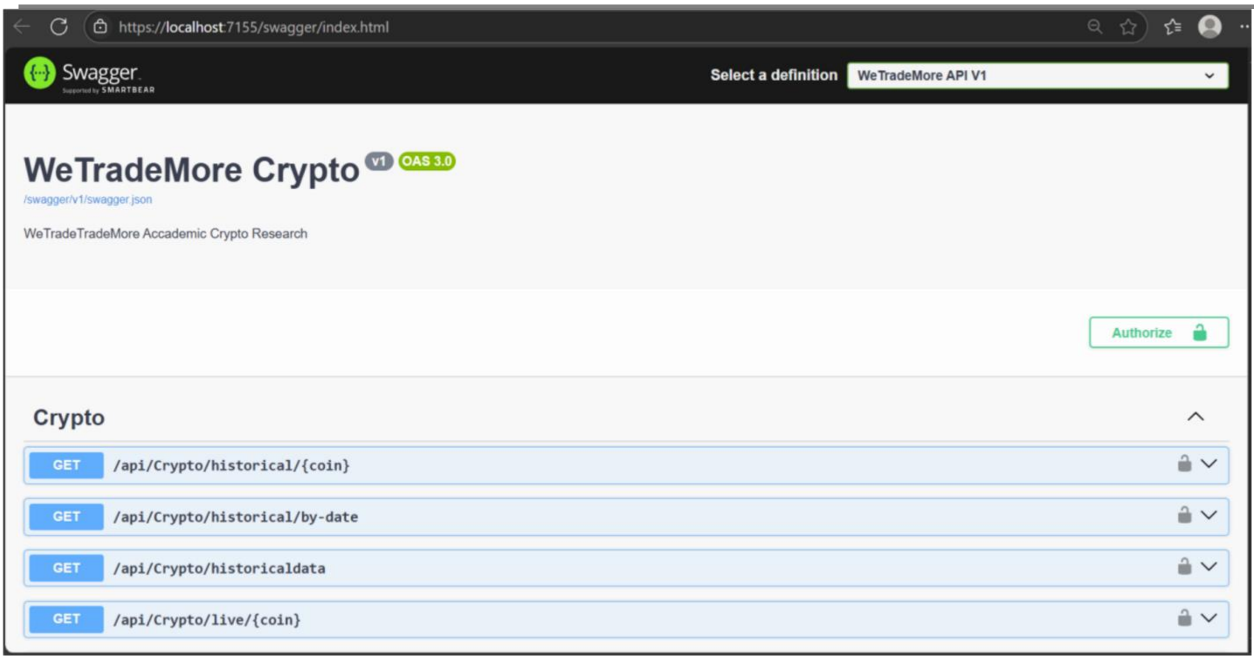


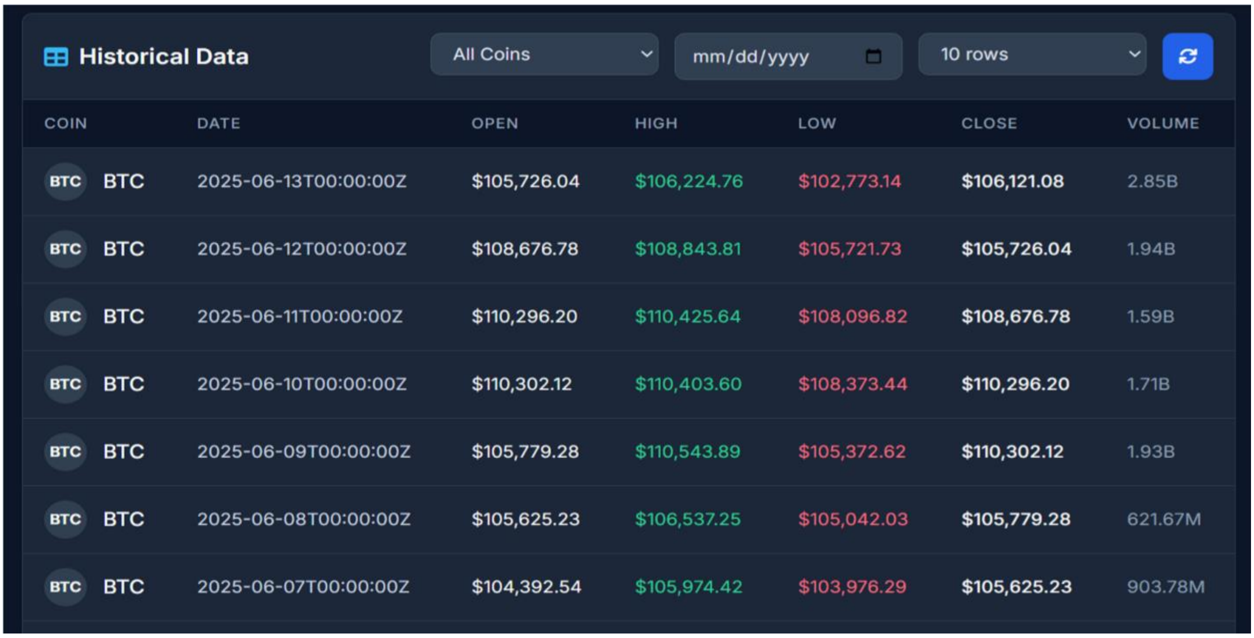
Fig. 5. Backend API

The entire architecture was modular, ensuring that each component could be updated or replaced independently as needed.

Load Historical Data Endpoint

The Load Historical Data endpoint retrieved historical OHLC data from external APIs for model training and visualization as shown in figure 6. Implemented as an **HTTP GET** at **/api/crypto/historical/{coin}**, it accepted parameters for currency, start date, and end date. It fetched data from sources such as Binance, encapsulated it into Crypto Price Data objects (containing timestamps and closing prices), and normalized the data using Min-Max scaling.

This endpoint supplies essential training data for the model and enables visualization of historical trends on the front end, reducing overfitting by ensuring a diverse temporal dataset. Figure 6. shows the endpoint in action.



COIN	DATE	OPEN	HIGH	LOW	CLOSE	VOLUME
BTC BTC	2025-06-13T00:00:00Z	$105,726.04	$106,224.76	$102,773.14	$106,121.08	2.85B
BTC BTC	2025-06-12T00:00:00Z	$108,676.78	$108,843.81	$105,721.73	$105,726.04	1.94B
BTC BTC	2025-06-11T00:00:00Z	$110,296.20	$110,425.64	$108,096.82	$108,676.78	1.59B
BTC BTC	2025-06-10T00:00:00Z	$110,302.12	$110,403.60	$108,373.44	$110,296.20	1.71B
BTC BTC	2025-06-09T00:00:00Z	$105,779.28	$110,543.89	$105,372.62	$110,302.12	1.93B
BTC BTC	2025-06-08T00:00:00Z	$105,625.23	$106,537.25	$105,042.03	$105,779.28	621.67M
BTC BTC	2025-06-07T00:00:00Z	$104,392.54	$105,974.42	$103,976.29	$105,625.23	903.78M

Fig. 6: Historical Data Endpoint for Bitcoin

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Historical Data — All Coins — 06/21/2025 — 10 rows

COIN	DATE	OPEN	HIGH	LOW	CLOSE	VOLUME
BTC	2025-06-21T00:00:00Z	$103,313.31	$104,021.01	$100,925.53	$102,165.68	1.15B
ETH	2025-06-21T00:00:00Z	$2,407.22	$2,449.16	$2,217.69	$2,296.94	705.75M
XRP	2025-06-21T00:00:00Z	$2.12	$2.15	$2.00	$2.06	210.24M
ADA	2025-06-21T00:00:00Z	$0.58	$0.59	$0.54	$0.56	23.75M
SOL	2025-06-21T00:00:00Z	$140.15	$142.61	$131.03	$135.47	171.09M

Showing 1-5 of 5 records — Previous 1 Next

Fig. 7. Historical Data Endpoint for the Five Cryptocurrency

Live Price Endpoint

The Live Price endpoint provided real-time price data to support trading decisions. Using an HTTP GET at /api/cryptocompare/live/{coin}, with a query parameter for currency, it polled the external API every 30 seconds for up-to-date prices. This live data will be used as input for the prediction engine and to trigger the attention mechanism when deviations exceeded the threshold. The endpoint ensured that the system's forecasts were always based on the latest market conditions, and its results were displayed dynamically on the front-end dashboard.

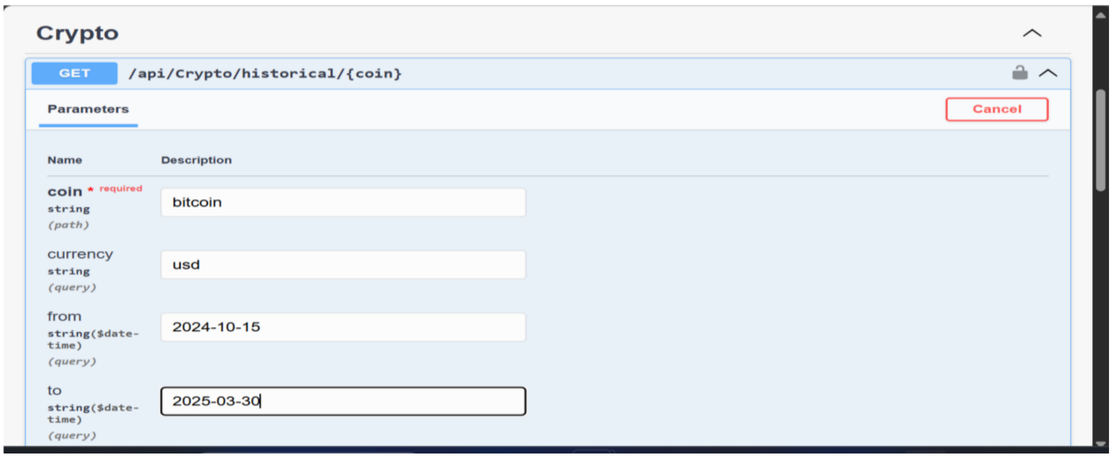

Fig. 8. Historical Data Endpoint

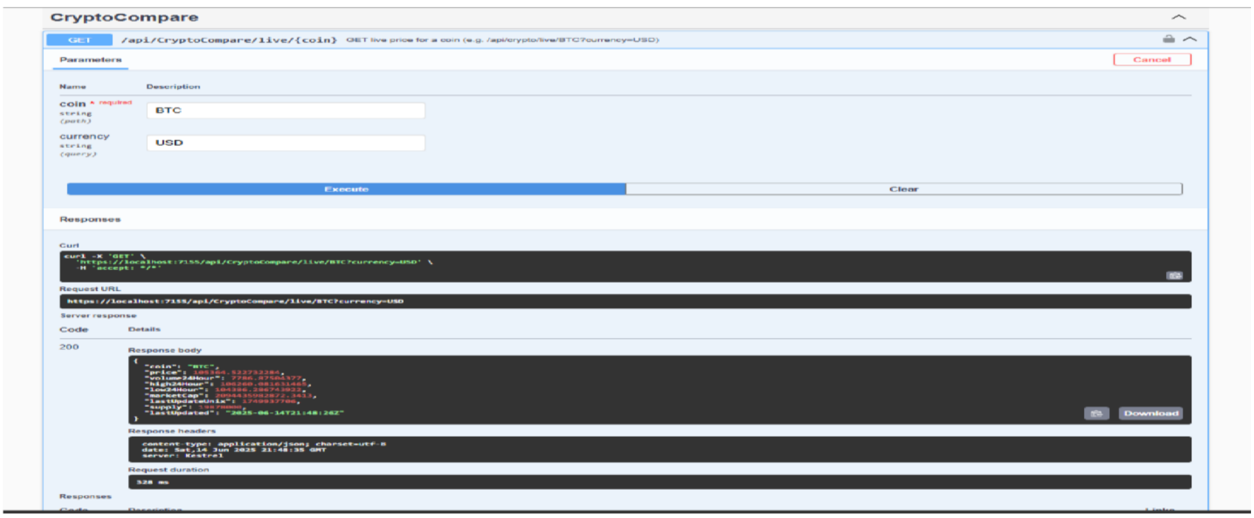

Fig. 9. Live Price of Bitcoin and other live market information

The Train functionality was responsible for building the predictive model using historical data. Although not exposed as a standalone HTTP endpoint, it was triggered within the BiLSTM Model Service. Historical data was loaded into an ML.NET I DataView, transformed (e.g., feature concatenation), and used to train the model with an SDCA regression trainer using L2 regularization. This dynamic training reduced RMSE significantly compared to earlier methods and mitigated overfitting. The trained model formed the foundation for subsequent predictions and was critical to the system's performance as depicted in figures 9 and 10.

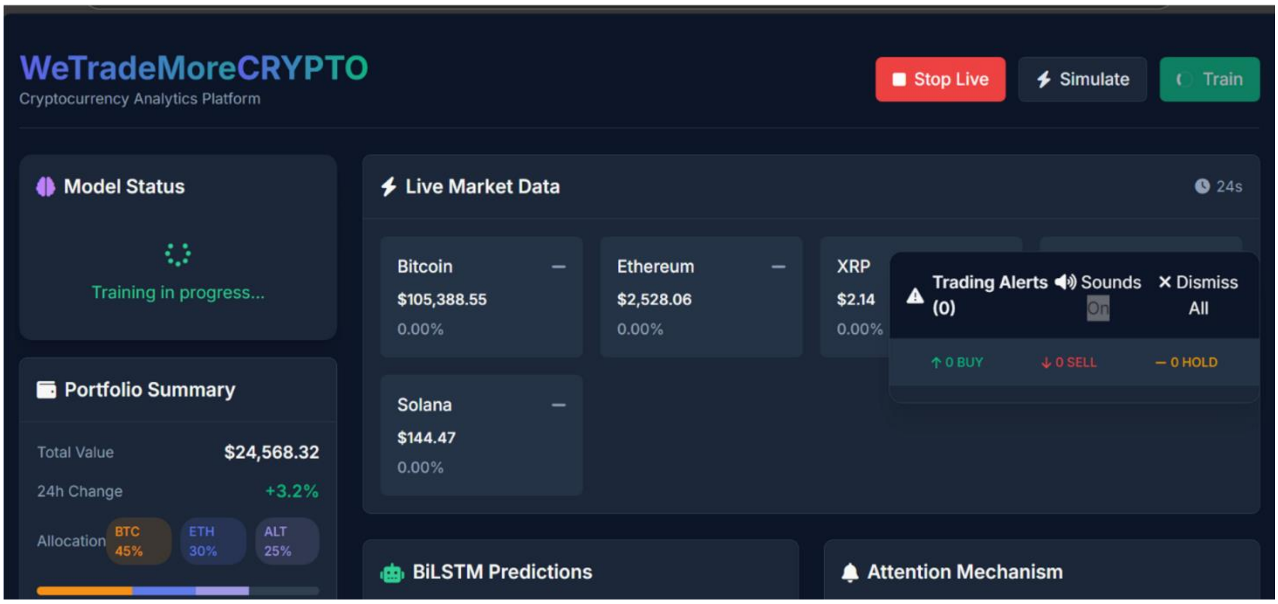

Fig. 10 Frontend Model Training

Get Predictions Endpoint

The Get Predictions endpoint generated forecasts using the trained model. It was implemented as an HTTP POST at **/api/crypto/predict/{coin},** accepting a JSON body with the live price. Upon receiving the live price, the system used the trained model to predict the future closing price and returned a JSON response containing both the live and predicted prices. This endpoint was crucial as it provided the quantitative basis for trading recommendations. Its accuracy depended on the quality of the historical data used in training and the reliability of the live price input.

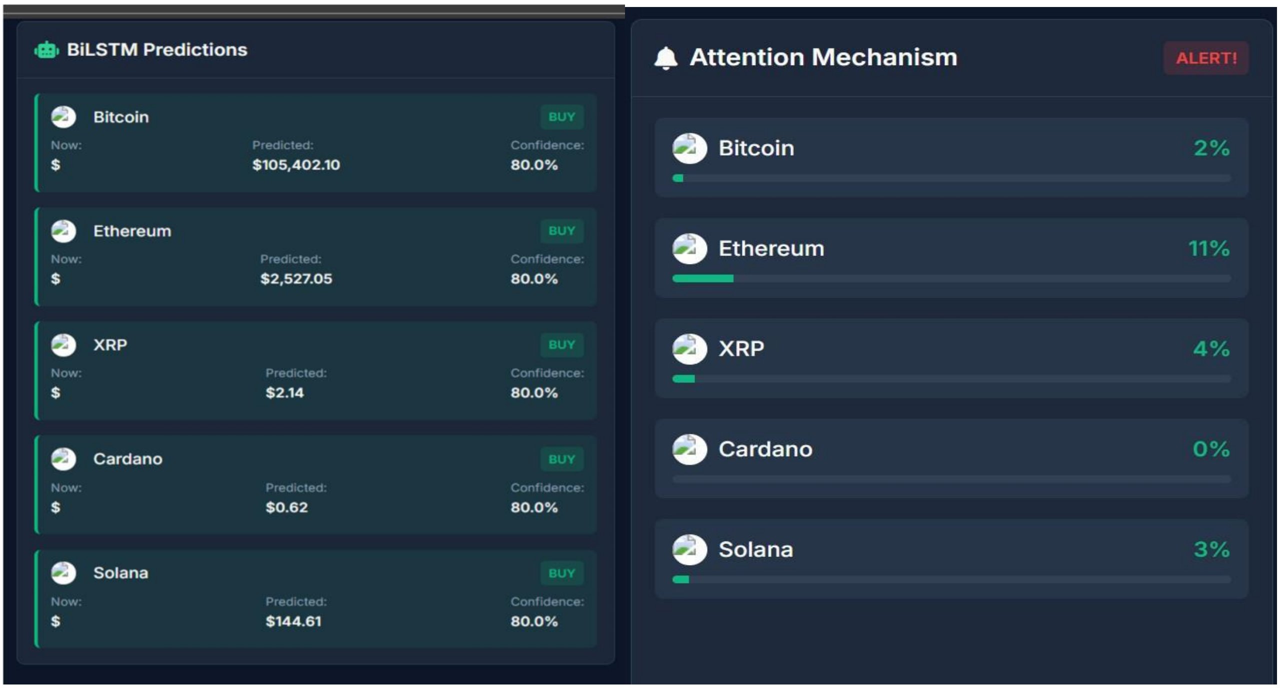

Figure 11 Showing Attention Mechanism Alert System

Mechanism endpoint evaluated the difference between live and predicted prices to generate trading recommendations. Implemented as an HTTP POST at **/api/crypto/attention**, it accepted a JSON payload with live Price and predicted Price. The mechanism compared the two values, and if the difference met or exceeded a predefined threshold (±$1 or ±0.5%), it issued a recommendation: "Buy" if the predicted price was higher, "Sell" if lower, and "Hold" if the deviation was minimal. This endpoint was vital in filtering out noise and ensuring that only significant market changes triggered trading actions. Figure 11. provides the console view of the Attention Mechanism endpoint and Attention Mechanism Alert System . It relied on accurate outputs from both the live price and prediction endpoints.

CONCLUSION

This study has drawn the approach of designing an improved intelligent model for cryptocurrency trading in blockchain platform. Predicting cryptocurrency trade focuses on requirements, specification applicable to the detailed, exhaustive studying and analysis of the existing systems from the literature review. It also reviewed multiple strategies on the cryptocurrency trading.

Substantially, this work present a summary of an intelligent model for cryptocurrency trading in blockchain platform offering diverse strategies from prediction and profitability in this system. However, owing to the volatile, dynamic and unpredictable nature of this cryptocurrencies transactions, providing an appreciable environment for user interaction in the network is absolutely necessary, challenging and time consuming studying the market. In furtherance to this, designing an improved intelligent model for cryptocurrency trading is a worthy research area of interest for growth and profitability. The volatile and unpredictable nature of cryptocurrency market necessitates our incorporating BiLSTM with Attention Mechanism for optimal result in this study. Designing an improved intelligent model for cryptocurrency trading in blockchain platform will enhance investment, reliability, cost-efficiency and positively deepen assets in blockchain system.

Designing an improved intelligent model for cryptocurrency trading in blockchain platform. The volatile nature of cryptocurrencies and the need for an improved intelligent model for strategic trading blockchain platform. The BiLSTM and Attention Mechanism model in this work ameliorated some of the challenges in the existing system. The BiLSTM model aid in prediction for effectual trading direction in this study. The Attention Mechanism introduced in this work handles issues related/associated with time varying transactions like cryptocurrencies system. The hold, buy and sell strategies played a great role in accomplishing trade direction and anticipated optimal profitability our system.

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