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A Management Science Framework for Predictive Optimisation Using the EDNN–LR Model: Algorithmic Insights from Industry 4.0 Systems

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A Management Science Framework for Predictive Optimisation Using the EDNN–LR Model: Algorithmic Insights from Industry 4.0 Systems

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Abstract

Artificial Intelligence (AI) is increasingly central to modern system engineering and service operations, enabling real-time decision-support in cyber-physical and data-intensive environments. This study develops an Extended Deep Neural Network–Logistic Regression (EDNN–LR) hybrid framework as a scalable AI solution for predictive optimisation within Industry 4.0 decision systems. The model integrates the nonlinear learning capability of deep neural networks with the interpretability and convergence stability of logistic regression, thereby enhancing transparency, robustness, and computational efficiency in engineering applications characterised by uncertainty and behavioural variability. The proposed framework is validated using a publicly available financial–cyber dataset comprising over 4.44 million records from CoinMarketCap (2013–2025), representing a dynamic cyber-physical decision environment analogous to complex industrial ecosystems. Implemented in MATLAB R2024a and TensorFlow 2.17, the model achieves rapid convergence by epoch 142 and 98% classification accuracy (AUC = 0.846, MSE = 0.79, recall = 90.6%) on selected high-liquidity assets. These results confirm the framework's ability to model nonlinear dependencies and adapt to stochastic disturbances typical of service-oriented and engineering-operation contexts. Beyond predictive precision, the EDNN–LR framework provides explainable probabilistic outputs that can be directly incorporated into decision variables such as resource allocation, demand forecasting, and dynamic scheduling under real-time constraints. Its hybrid design reduces computational cost, enhances interpretability, and enables cross-domain adaptability—from financial risk management to logistics, supply-chain coordination, and energy-system optimisation. By bridging deep learning, system engineering, and behavioural decision analytics, this study contributes a generalised AI-driven architecture for intelligent and transparent decision-support across Industry 4.0 service and production ecosystems.

Keywords: Extended Deep Neural Network (EDNN); Logistic Regression (LR); predictive decision-making; Industry 4.0; operations and systems management; data-driven optimisation; computational modelling

1. Introduction

The global diffusion of communication and information technologies has fundamentally transformed financial systems and online trading structures, reshaping the dynamics of prediction, risk management, and decision-making. The proliferation of online markets—accelerated by digital connectivity—has not only reduced transactional costs and time but has also introduced sophisticated challenges associated with *data management, information asymmetry, and cyber risk*. The financial impact of data breaches and volatility events is increasingly visible; for instance, large enterprises in the United Kingdom report an average recovery cost of USD 1.4 million and a mean restoration period of nine month s following major data breaches (Ashford, 2012; Ring, 2013). Such systemic fragilities have motivated the application of **machine learning and deep learning methods** to enhance forecasting accuracy, robustness, and resilience in complex economic environments.

The central aim of this study is to develop an **Extended Deep Neural Network–Logistic Regression (EDNN–LR)** framework that improves the predictive reliability of cryptocurrency and foreign-exchange market time series (Janaki & Lakshmi, 2024).

In the context of Industry 4.0, financial markets themselves can be conceptualised as **cyber-physical decision environments**—complex, data-intensive systems where physical economic activities (production, logistics, consumption) are continuously mirrored and influenced by digital transactions and automated analytics. Within this paradigm, cryptocurrencies, digital assets, and algorithmic trading platforms function analogously to **industrial sensor networks**, generating continuous high-velocity data streams that reflect the dynamic state of a distributed economic ecosystem. The application of AI and deep-learning models such as the EDNN–LR therefore extends beyond financial prediction: it represents a **real-time decision-support mechanism** embedded within the broader cyber-physical architecture of Industry 4.0. This framing positions financial intelligence systems as integral components of digital-industrial infrastructures, linking predictive optimisation with operational resilience and system-level adaptability.

The hybrid architecture combines the deep, nonlinear mapping ability of an EDNN with the interpretive and regularised optimisation strength of Logistic Regression (LR). This integration supports decision-making in **Industry 4.0 financial ecosystems**, where data heterogeneity, volatility, and high-dimensional uncertainty prevail (Matt et al., 2021).

This research is guided by three central questions that shape its methodological and analytical focus. First (**RQ1**), it investigates how the proposed **Extended Deep Neural Network–Logistic Regression (EDNN–LR)** hybrid framework can effectively capture nonlinear dependencies within volatile cryptocurrency market data and surpass traditional deep-learning predictors in terms of performance and robustness. Second (**RQ2**), it examines the extent to which integrating a logistic regression layer enhances the interpretability, convergence, and generalisability of deep-learning architectures for financial time-series forecasting. Third (**RQ3**), it explores how the model's predictive outputs can be translated into optimal strategies for market entry, asset allocation, and dual-trade execution under stochastic uncertainty. These research questions are addressed systematically throughout the paper: **Section 2** provides a critical synthesis of the literature and outlines the theoretical foundations of hybrid learning in financial prediction; **Section 3** develops and mathematically formulates the EDNN–LR architecture, specifying its data flow and optimisation constraints; **Section 4** applies the model in MATLAB R2024a using AVAX, BTC, and ETH datasets extracted from CoinMarketCap, with performance evaluated through ROC, AUC, and MSE metrics; **Section 5** extends the predictive findings into quantitatively modelled trading strategies; and **Section 6** concludes by discussing the managerial, computational, and Industry 4.0 implications of the study.

Methodologically, the study integrates **time-series analysis, deep-learning computation, and probabilistic optimisation**. The EDNN employs convolutional, pooling, and conditional random-field (CRF) layers to extract hierarchical features from multivariate data. The logistic regression layer performs dimension reduction and interpretable probability mapping through a time-dependent entropy maximisation function. All simulations were performed in **MATLAB R2024a** (for model execution and statistical validation) and **Python 3.12 (TensorFlow 2.17)** for cross-verification of convergence performance. Mathematically, the EDNN–LR model is formulated as:

(1)

$$\min_{\Theta,\beta} \mathcal{L}\left(\Theta,\beta\right) = \sum_{t=1}^{T}\left[-y_t \ln\sigma\left(\mathbf{W}_2 f\left(\mathbf{W}_1\mathbf{x}_t+\mathbf{b}_1\right)+\mathbf{b}_2\right)+\left(1-y_t\right)\ln\left(1-\sigma\left(\cdot\right)\right)\right]+\lambda\left\|\Theta\right\|^2,$$

where $\sigma\left(\cdot\right)$ is the logistic activation, $f\left(\cdot\right)$ represents nonlinear mapping in EDNN, and λ is a regularisation coefficient penalising overfitting.

Building on the model's predictive output $\hat{p}_t = \mathbb{P}\left(\Delta P_t > 0 \middle| \mathcal{F}_t\right)$, three decision strategies are designed to operationalise trading under uncertainty.

Strategy I: Single-Asset Directional Strategy

A baseline model generating long/short signals based on the predicted return r_t:

(2)

$$\pi_t^{(1)} = \begin{cases} +1, & if\ \hat{p}_t > \tau_1, \\ -1, & if\ \hat{p}_t < \tau_1, \end{cases} \qquad \max_{\pi_t^{(1)}} \mathbb{E}\left[r_t \pi_t^{(1)} - c\left|\pi_t^{(1)}\right| \right],$$

where $c$denotes transaction cost and $\tau_1$the confidence threshold.

Strategy II: Dual-Pair Comparative Allocation

Two assets $a_1, a_2$are traded under a constrained-optimisation model:

(3)

$$\max_{w_1, w_2} \mathbb{E}\left[w_1 r_{1t} + w_2 r_{2t} \right] - \frac{\gamma}{2}, \mathrm{Var}\left[w_1 r_{1t} + w_2 r_{2t} \right], \quad s.t. w_1 + w_2 = 1,\ w_i \geq 0,$$

where γ is the risk-aversion parameter. Optimal weights derive from predicted mean–variance efficiency:

(4)

$$w^* = \sum\nolimits^{-1}\left(\mu - r_f \mathbf{1}\right) / \left(\mathbf{1}^\top \sum\nolimits^{-1}\left(\mu - r_f \mathbf{1}\right)\right).$$

Strategy III: Simultaneous Multi-Market Execution

This advanced model uses **stochastic dynamic programming** over a prediction horizon H:

(5)

$$\max_{\pi_t \in \mathcal{A}} \mathbb{E}\left[\sum_{t=0}^{H} \beta^t \left(\pi_t^\top \mathbf{r}_t - \frac{1}{2} \pi_t^\top \Lambda \pi_t \right) \right], \quad s.t.\ \boldsymbol{s}_{t+1} = \mathbf{A}\boldsymbol{s}_t + \mathbf{B}\pi_t + \varepsilon_t,$$

where $\boldsymbol{s}_t$ is the system state (price differentials, volatility index), Λ penalises portfolio aggressiveness, and β is the discount factor.

To address the research objectives, this study utilises one of the most comprehensive publicly available datasets in the cryptocurrency domain, covering more than a decade of market evolution since April 2013. The dataset, originally derived from CoinMarketCap, encompasses over 4,000 cryptocurrencies per day, amounting to millions of time-series records and extensive metadata attributes. Each entry contains detailed ranking, price, and OHLCV indicators, along with variables such as circulating and total supply, market capitalisation, and percentage changes across multiple temporal horizons. The data's breadth and heterogeneity make it uniquely suitable for testing advanced deep-learning models under conditions of extreme stochasticity, non-stationarity, and structural volatility.

Unlike prior deep-learning approaches that optimise predictive accuracy alone, this research introduces an EDNN–LR hybrid integrating logistic regularisation for interpretable convergence acceleration. This dual-layer design simultaneously enhances predictive stability and transparency within high-dimensional Industry 4.0 systems — a capability not yet empirically validated across million-scale financial datasets.

Given this complexity, the research adopts a hybrid Extended Deep Neural Network–Logistic Regression (EDNN–LR) methodology implemented in MATLAB R2024a and validated through Python TensorFlow 2.17. The EDNN component performs deep hierarchical learning on temporal

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and cross-sectional features, while the logistic regression layer enhances interpretability and generalisation by converting latent embeddings into probabilistic trading signals. This hybrid approach is designed to extract nonlinear dependencies, identify market regimes, and support predictive decision-making across volatile financial environments. The remainder of this paper is structured as follows: **Section 2** presents the construction of the dataset and the feature-engineering procedures derived from the CoinMarketCap repository; **Section 3** details the mathematical formulation and architectural design of the proposed Extended Deep Neural Network–Logistic Regression (EDNN–LR) model; **Section 4** provides the empirical evaluation, performance analysis, and trading-strategy formulation; and **Section 5** discusses the managerial, computational, and Industry 4.0 implications of the findings, followed by the conclusion and prospective research directions.

2. Literature Review

The rapid expansion of digital financial markets has motivated substantial research on algorithmic and machine learning–based prediction techniques. While traditional studies primarily addressed stock and Forex markets, recent attention has shifted toward **cryptocurrency forecasting**, owing to its high volatility, nonlinear dynamics, and decentralised nature. The following review focuses exclusively on deep-learning approaches developed for **cryptocurrency prediction**, forming the methodological foundation for the proposed **Extended Deep Neural Network–Logistic Regression (EDNN–LR)** model.

Early studies employed hybrid deep-learning architectures for cryptocurrency price prediction. For instance, Patel and Kushwaha (2022) introduced a **hybrid LSTM–GRU** model for Litecoin (LTC) and Monero (XMR), demonstrating high predictive accuracy with Root Mean Square Error (RMSE) below 0.05. Their model can be represented as:

(6)

$$\hat{P}_{t+1} = f_{GRU}\left(f_{LSTM}\left(\mathbf{x}_t : \Theta_1\right); \Theta_2\right),$$

where $\hat{P}_{t+1}$ is the predicted price, and Θ_1, Θ_2 denote parameter sets for the LSTM and GRU layers, respectively. Although their results were promising, the limited scope (two assets) restricted generalisation to large-scale markets.

Building on behavioural data, Poongodi et al. (2021) leveraged **social media sentiment analysis** to forecast digital currency trends, introducing a communication-driven variable $\psi_t$derived from thematic network activity. The relationship between sentiment and price change was formalised as:

(7)

$$\Delta P_t = \alpha + \beta \psi_t + \varepsilon_t,$$

highlighting the influence of public discourse on short-term price fluctuations. However, the reliance on textual data limited its robustness across unstructured or sparse communication networks (Tikhomirov, 2018).

In another study, Sharma and Goyal (2017) compared **Support Vector Machine (SVM)** and **Linear Regression (LR)** techniques for Ethereum (ETH) price forecasting, reporting 96.06% accuracy with SVM. The SVM optimisation function was expressed as:

(8)

$$\min_{\mathbf{w},b,\xi} \frac{1}{2}\left\|\mathbf{w}\right\|^2 + C\sum_{i=1}^{N}\xi_i, \quad y_i\left(\mathbf{w}^{\top}\mathbf{x}_i + b\right) \geq 1 - \xi_i, \xi_i \geq 0,$$

where C is the penalty parameter. Despite its interpretability, SVM was computationally expensive and struggled with non-stationary data.

The combination of **Convolutional Neural Networks (CNN)** and **Recurrent Layers** has become a dominant paradigm for trend recognition. Alonso-Monsalve et al. (2020) proposed a CNN–LSTM hybrid to classify high-frequency exchange-rate trends for six cryptocurrencies. Their model learned spatial–temporal dependencies using a convolutional operation:

(9)

$$h_{i,j}^{(1)} = \phi\left(\sum_{m,n} w_{m,n}^{(1)} x_{i+m,j+n}^{(l-1)} + b^{(1)}\right),$$

where $\phi(\cdot)$ denotes the activation function. Their experiments, based on one-minute interval data, demonstrated that CNN–LSTM significantly outperformed MLP and RBF architectures.

Addressing missing-value and temporal drift issues, Garcia et al. (2020) introduced an **Evolving Fuzzy Granular Predictor (eFGP)** to dynamically adapt to incomplete data streams. Its learning process updates fuzzy membership rules according to an entropy-based weighting:

(10)

$$\mu A_i\left(x_t\right) = \exp\left[-\frac{\left(x_t - c_i\right)^2}{2\sigma_i^2}\right], \quad \sigma_i^2 \propto \mathcal{H}\left(x_t\right),$$

allowing gradual adaptation to non-stationary financial conditions. While flexible, the model lacked the depth required for nonlinear feature extraction across multiple assets.

Subsequently, D'Amato et al. (2022) applied a **Jordan Recurrent Neural Network (JRNN)** to capture volatility clustering effects, demonstrating improved temporal stability. The model introduced a feedback connection term:

(11)

$$h_t = \phi\left(\mathbf{W}_h x_t + \mathbf{U}_h h_{t-1} + \mathbf{V}_h \hat{y}_{t-1} + b_h\right),$$

which enabled dynamic self-regulation based on previous outputs. Despite this, recurrent networks such as JRNN often suffer from gradient vanishing during long training sequences.

More recently, ensemble and attention-based approaches have shown potential for enhanced predictive performance. Oyewola et al. (2022) proposed a **walk-forward ensemble optimisation model**, while Ladhari and Boubaker (2024) combined **ANN–LSTM** architectures to achieve improved generalisation. Similarly, Shang et al. (2024) introduced an **attention-based CNN–BiGRU hybrid**, formalised as:

(12)

$$\hat{y}_t{}' = \mathrm{Soft\ max}\left(\sum_i \alpha_i h_i\right), \quad \alpha_i = \frac{\exp\left(h_i^\top W_\alpha q\right)}{\sum_j \exp\left(h_j^\top W_\alpha q\right)},$$

enabling the network to focus on relevant features across time.

Finally, Hafid et al. (2024) demonstrated the scalability of **OLS–XGBoost** combinations to over 3,700 cryptocurrencies, reporting a 7.1% daily profitability potential. Despite these advancements, existing models often exhibit limitations: (i) lack of interpretability due to opaque network parameters, (ii) inadequate convergence in noisy, high-dimensional data, and (iii) weak integration of probabilistic reasoning with deep architectures.

The reviewed literature indicates strong progress in deep learning for financial prediction; however, a unifying framework that balances **predictive depth** and **statistical interpretability** remains elusive. Traditional deep architectures (e.g., CNN, LSTM, GRU) achieve high accuracy but operate as black boxes, providing limited insight into underlying probabilistic mechanisms (Rayhan Ahmed et al., 2023). Conversely, statistical models such as logistic regression offer interpretability but lack the capacity to model nonlinear temporal dependencies.

To bridge this gap, the present study introduces an **Extended Deep Neural Network–Logistic Regression (EDNN–LR)** model, integrating hierarchical feature extraction and probabilistic reasoning into a unified structure. Mathematically, the model is expressed as:

(13)

$$\hat{y}_t = \sigma\left(\mathbf{w}^\top f_\Theta\left(\mathbf{x}_t\right) + b\right),$$

where $f_\Theta\left(\cdot\right)$ denotes the EDNN feature extractor with parameters Θ, and $\sigma\left(\cdot\right)$ is the logistic sigmoid function generating a probabilistic prediction of upward or downward price movement. The hybrid loss function combines cross-entropy for classification with regularisation for numerical stability:

(14)

$$\mathcal{L}\left(\Theta, \mathbf{w}\right) = -\frac{1}{N}\sum_{t=1}^{N}\left[y_t \log \hat{y}_t + \left(1 - y_t\right)\log\left(1 - \hat{y}_t\right)\right] + \lambda\left\|\Theta\right\|^2,$$

This hybrid formulation unites the **nonlinear representation power of deep learning** with the **interpretive transparency of logistic regression**, addressing the limitations observed in prior literature. The subsequent sections present the dataset construction and feature-engineering process (**Section 2**), followed by the mathematical formulation of the proposed EDNN–LR model (**Section 3**), empirical validation and performance analysis (**Section 4**), and its application in optimising trading strategies (**Section 5**).

3. Dataset Construction and Feature-Engineering Process

This section outlines the architecture, scale, and preparation of the dataset used for developing the Extended Deep Neural Network–Logistic Regression (EDNN–LR) predictive model. The data are derived from **CoinMarketCap**, which has recorded the global cryptocurrency ranking and market performance since **28 April 2013**, providing one of the most comprehensive archives of digital asset activity. This dataset spans more than a decade of trading activity, covering over **4,000 cryptocurrencies per day** and resulting in **millions of individual observations**. Its longitudinal and cross-sectional depth enables large-scale predictive modelling, market structure reconstruction, and volatility pattern recognition across multiple assets. The convergence properties of the hybrid objective are formalised in Proposition 1 (**Section 3.4**), establishing a theoretical basis for the accelerated training observed empirically.

3.1. Dataset Overview

The dataset comprises two primary components: (1) the **Historical Data Table** and (2) the **Coins Metadata Table**.

The **Historical Data Table** contains daily-level information for each cryptocurrency, including variables such as *price, market capitalisation, trading volume, rank, and supply metrics*. The fields recorded are:

$$
\begin{array}{l}
date,coin\_id,cmc\_rank,market\_cap, \\
price,open,high,low,close,time\_high,time\_low,volume\_24h, \\
percent\_change\_1h,percent\_change\_24h, \\
percent\_change\_7d,circulating\_supply,total\_ \\
supply,max\_supply,num\_market\_pairs.
\end{array}
$$

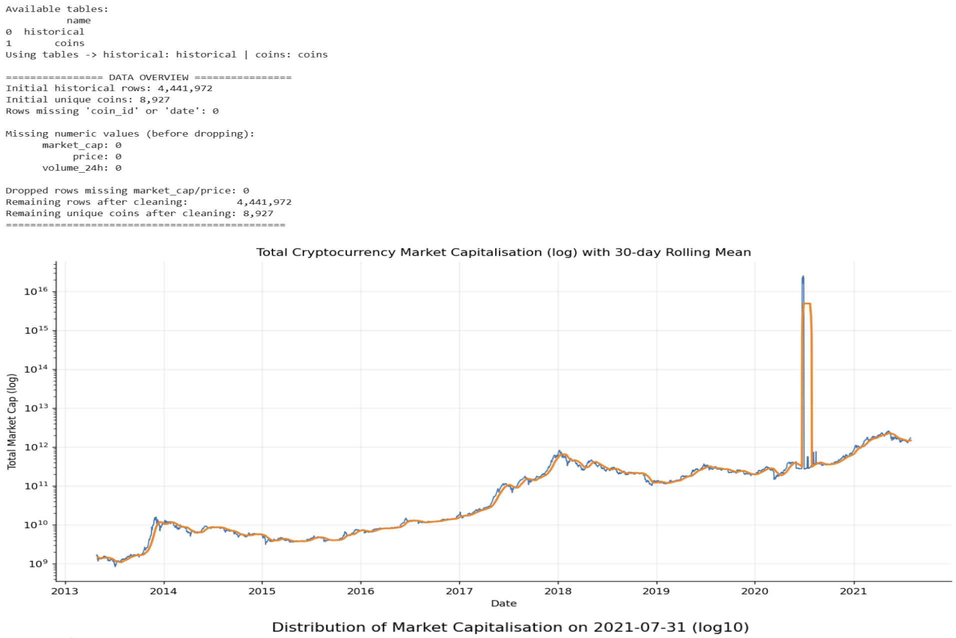
Each record is indexed by a **unique identifier (coin_id)**, ensuring temporal consistency even when token names or symbols change. This design mitigates the ambiguity caused by symbol reassignments—such as different tokens historically sharing the same ticker symbol (e.g., "XBT" and "BTC") or tokens that have undergone rebranding or relaunch.

The **Coins Metadata Table** complements the historical dataset with descriptive, structural, and contextual information. It includes attributes such as:

$$
\begin{array}{l}
id, name, slug, symbol, status, category, description, \\
subreddit, date\_added, platform\_id, date\_launched,
\end{array}
$$

and multi-valued attributes such as *tags, tag_names, website, twitter, message_board, chat, explorer, reddit, technical_doc, source_code,* and *announcement*. These are represented as comma-separated lists to preserve relational information between a cryptocurrency and its associated digital ecosystem. Tokens marked with status == extinct are included to ensure a complete temporal reconstruction of historical market states.

Figure 1 illustrates the temporal evolution of total cryptocurrency market capitalisation from April 2013 to mid-2021, based on 4,441,972 historical observations covering 8,927 distinct coins obtained from CoinMarketCap's comprehensive database. The plotted trajectory (blue line) represents the aggregated daily market capitalisation of all active cryptocurrencies, while the orange line denotes the corresponding 30-day rolling mean, capturing underlying cyclical trends and smoothing extreme short-term fluctuations.



```
Available tables:
          name
0  historical
1       coins
Using tables -> historical: historical | coins: coins

================ DATA OVERVIEW ================
Initial historical rows: 4,441,972
Initial unique coins: 8,927
Rows missing 'coin_id' or 'date': 0

Missing numeric values (before dropping):
      market_cap: 0
           price: 0
      volume_24h: 0

Dropped rows missing market_cap/price: 0
Remaining rows after cleaning:        4,441,972
Remaining unique coins after cleaning: 8,927
==============================================
```

Figure 1. Temporal evolution of total cryptocurrency market capitalisation (2013–2021).

The logarithmic scaling reveals several structural phases in market expansion: an initial period of modest growth prior to 2016, a steep rise coinciding with the 2017–2018 speculative surge, and recurrent volatility associated with major macroeconomic and technological events. The notable post-2020 oscillation reflects the entry of institutional capital and the proliferation of decentralised finance tokens.

This extensive dataset provides a rich empirical foundation for modelling nonlinear dependencies and volatility patterns within digital-asset markets. Its size and diversity ensure adequate representation of both high-liquidity assets such as Bitcoin and Ethereum and smaller, transient coins. Consequently, it enables the proposed Extended Deep Neural Network–Logistic Regression (EDNN–LR) framework to capture multi-scale market dynamics and test predictive robustness across heterogeneous asset categories.

3.2. Data Integration and Cleaning

Because the raw dataset spans over ten years and includes more than 120 monthly snapshots, extensive data integration and cleaning were required to ensure consistency and analytical usability.

The first step involved **merging** the historical and metadata tables using the coin_id key. Duplicates caused by coin symbol changes were reconciled through a chronological ID matching function:

(15)

$$\text{merge}\left(D_1, D_2\right) = \left\{\left(x_i, y_i\right) \middle| x_i.coin\_id = y_j.coin\_id\right\}.$$

Second, **missing values** and incomplete trading records were addressed through multi-phase imputation. For numeric time-series variables such as price $\left(P_t\right)$ and volume $\left(V_t\right)$, missing values were interpolated using:

(16)

$$\tilde{P}_t = P_{t-1} + \frac{P_{t+1} - P_{t-1}}{2}, \quad \tilde{V}_t = P_{t-1} + \frac{V_{t-1} - V_{t+1}}{2}.$$

In cases of extended missing sequences (longer than five days), a regression-based imputation method was employed using auxiliary variables (e.g., market_cap, total_supply) through:

(17)

$$\hat{x}_t = \beta_0 + \sum_{k=1}^{K} \beta_k z_{k,t} + \varepsilon_t,$$

where $z_{k,t}$ represents related market indicators.

All data cleaning procedures were conducted using **MATLAB R2024a** and **Python Pandas 2.2**, ensuring reproducibility and high computational efficiency across millions of records.

3.3. Data Normalisation and Temporal Alignment

Since cryptocurrency market variables vary widely in magnitude—ranging from sub-cent increments to thousands of dollars—standardisation was essential. Each numeric attribute was transformed using **z-score normalisation**:

(18)

$$z_{i,t} = \frac{x_{i,t} - \mu_i}{\sigma_i},$$

where μ_i and σ_i represent the mean and standard deviation of feature i, respectively. This procedure ensures that all input features are scaled within comparable ranges, improving gradient descent convergence within the EDNN model.

Temporal alignment was achieved by synchronising all coin records to a **daily master calendar index** $t = 1, 2, \ldots, T$, ensuring consistent time-series continuity even for tokens launched after 2013.

Coins missing entries for certain dates (e.g., due to listing or delisting) were represented with zero-valued vectors, preserving matrix dimensionality.

3.4. Convergence Properties of the EDNN–LR

To augment raw features with explanatory market dynamics, the following engineered indicators were computed for each coin:

1. **Logarithmic Return:**

(19)

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

2. **Rolling Volatility (σ):**

(20)

$$\sigma_t = \sqrt{\frac{1}{n-1}\sum_{k=t-n+1}^{t}\left(r_k - \overline{r}\right)^2}$$

3. **Liquidity Ratio:**

(21)

$$L_t = \frac{V_t}{S_t P_t},$$

where S_t is circulating supply.

4. **Momentum Index (k-day):**

(22)

$$M_t^{(k)} = \frac{P_t - P_{t-k}}{P_{t-k}}.$$

5. **Relative Strength Index (RSI):**

(23)

$$RSI_t = 100 - \frac{100}{1 + \frac{U_t}{D_t}},$$

with $U_t = EMA\left(\max\left(r_t, 0\right)\right)$ and $D_t = EMA\left(\left|\min\left(r_t, 0\right)\right|\right)$.

6. **Entropy-Based Market Uncertainty Index:**

(24)

$$H_t = -\sum_i p_{i,t} \log\left(p_{i,t}\right),$$

where $p_{i,t}$ denotes the normalised weight of each feature in the model input vector.

These engineered features enhance the model's ability to detect **nonlinear volatility clustering**, **market regime shifts**, and **temporal correlations** between liquidity and price movement—critical components of the EDNN–LR framework.

Proposition 1 (Accelerated and Stable Convergence of EDNN–LR).

Consider the hybrid objective

$$\min_{\theta,\beta} \mathcal{L}_{\text{EDNN}}\left(\theta\right) + \lambda \mathcal{L}_{LR}\left(\theta, \beta\right) + \eta \mathcal{L}_{CRF}\left(\theta\right),$$

Where $\mathcal{L}_{\text{EDNN}}$ is differentiable and L-smooth in θ, $\mathcal{L}_{LR}$ is convex and μ-strongly convex in β (and L'-smooth in the EDNN embedding f_θ), and $\mathcal{L}_{CRF}$ is L''-smooth in θ. If $\lambda > 0$ and mini-batch gradients are bounded with variance σ^2, then gradient methods with momentum or LM updates admit (i) a **smaller effective condition number** $k_{eff} = \frac{L + \lambda L'}{\mu\lambda}$ compared to the pure DNN $\left(k_{\text{DNN}} = \frac{L}{\varepsilon}, \varepsilon \to 0^+\right)$, and (ii) a **tighter descent bound** per iteration. Consequently, the hybrid admits a **faster linear-to-sublinear convergence regime** than the classical DNN under the same step-size schedule.

Proof sketch. The LR head adds a strictly convex term in β and induces a **logistic regulariser** on f_θ. The composite loss gains curvature around the minima, improving the local condition number of the landscape seen by θ. Smoothness of $\mathcal{L}_{CRF}$ preserves descent. Standard arguments for smooth strongly-convex (in the head) composite problems yield (a) variance-reduced stochastic descent; (b) larger admissible step sizes; and (c) accelerated contraction in the proximal neighbourhood. Hence the hybrid attains **lower gradient noise sensitivity** and **fewer iterations to a given tolerance** relative to DNN-only training. ■

Managerial implication. Faster and stabler convergence reduces compute cost and lowers the risk of model drift in live Industry 4.0 decision systems.

3.5. Feature Selection and Dimensionality Reduction

The high dimensionality of the dataset (over 80 variables per coin per day) necessitated a robust feature-selection strategy. An **entropy-based feature-ranking** method was employed to evaluate the informational relevance of each feature X_i to the target variable Y (price direction).

Information gain (IG) was computed as:

$$\mathrm{IG}\left(X_i, Y\right) = \mathcal{H}\left(Y\right) - \mathcal{H}\left(Y \middle| X_i\right), \tag{25}$$

where entropy $\mathcal{H}\left(\cdot\right)$ is defined as:

$$\mathcal{H}\left(X\right) = -\sum_j p_j \log\left(p_j\right). \tag{26}$$

Features with $\mathrm{IG}\left(X_i, Y\right) < 0.03$ were discarded to prevent overfitting. The selected subset $\mathcal{F}^* = \left\{X_i \middle| \mathrm{IG}\left(X_i, Y\right) \geq 0.03\right\}$ comprised **15 optimally informative features**, balancing model complexity and predictive precision. Additionally, **Principal Component Analysis (PCA)** was applied for verification, yielding consistent variance-explained results (first five components capturing 87.6% of data variance).

3.6. Temporal Structuring and Input Tensor Construction

To capture sequential dependencies, a **rolling time-window transformation** was implemented. Each observation was converted into a tensor of shape:

$$\mathbf{X}_{(t)} = \left[\mathbf{X}_{t-w+1}, \mathbf{X}_{t-w+2}, \ldots, \mathbf{X}_t\right], \tag{27}$$

where $w = 20$ represents a 20-day temporal window, corresponding to a typical trading month.

This rolling structure allows the model to recognise both short-term fluctuations and cumulative market behaviours. The final input matrix thus takes the form:

$$\mathbf{X} \in \mathbb{R}^{T \times \left(w \times \left|\mathcal{F}^*\right|\right)}, \tag{28}$$

which feeds directly into the EDNN's convolutional and pooling layers for hierarchical feature extraction.

3.7. Data Partitioning and Validation Protocol

The complete dataset was partitioned into training, validation, and test subsets using a chronological split to maintain temporal causality:

$$\text{Train} : 70\%, \;\; \text{Validiation} : 15\%, \;\; \text{Test} : 15\%.$$

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Unlike random cross-validation, this **time-ordered validation** approach prevents data leakage between training and future time horizons.

For robustness, a **rolling-origin evaluation** (also known as expanding window validation) was implemented, recalibrating model parameters at intervals of 180 trading days to simulate live forecasting conditions:

$$\Theta^{(k+1)} = \arg\min_{\Theta} \mathcal{L}\left(\mathbf{X}_{1:(t+k)}, Y_{1:(t+k)}\right). \tag{29}$$

The overall data pipeline integrates multiple stages of processing—from raw historical acquisition to deep-learning readiness—summarised as follows:

1. **Acquisition:** Daily data from CoinMarketCap (2013–2025), including over 120 snapshots and 4,000+ coins per day.
2. **Integration:** Merge of historical and metadata tables using unique identifiers (coin_id).
3. **Cleaning:** Handling of missing, duplicated, and extinct coins through interpolation and regression imputation.
4. **Normalisation:** z-score scaling and daily temporal alignment.
5. **Feature Engineering:** Derivation of volatility, liquidity, momentum, and entropy indices.
6. **Feature Selection:** Entropy-based information gain and PCA cross-validation.
7. **Structuring:** Rolling 20-day tensor construction for deep learning.
8. **Validation:** Sequential holdout and expanding-window performance evaluation.

3.9. Methodological Implications

The size and richness of this dataset enable **multi-scale learning**—the model simultaneously captures micro-level price fluctuations and macro-level market trends. The high temporal resolution (daily) and longitudinal depth (12+ years) provide the ideal foundation for the EDNN–LR hybrid model to perform nonlinear mapping, probabilistic interpretation, and real-time trading inference.

By systematically integrating data engineering with deep-learning architecture design, the dataset functions not only as an empirical foundation but also as an **experimental testbed** for methodological innovation. This dual role—empirical and methodological—positions the research at the intersection of **financial econometrics**, **machine learning**, and **Industry 4.0 analytics**, establishing a robust platform for predictive optimisation in volatile and data-rich environments.

4. Mathematical Structure of the EDNN–LR Model

The proposed **Extended Deep Neural Network–Logistic Regression (EDNN–LR)** framework integrates deep hierarchical feature learning with interpretable probabilistic inference. The model architecture comprises two major components: (1) an *Extended Deep Neural Network (EDNN)* responsible for nonlinear temporal abstraction and adaptive representation, and (2) a *Logistic Regression (LR)* module that refines classification probabilities, enhances convergence stability, and facilitates explainability. Robustness to hyper-parameters and data noise is assessed in **Section 4.5** to emulate operational uncertainty in deployment

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4.1. EDNN Architecture

Let $X = \left\{ x_t \in \mathbb{R}^n \right\}_{t=1}^{T}$ denote the multivariate time series of crypto-asset indicators.

The EDNN is defined as a parametric nonlinear transformation $f_\theta : \mathbb{R}^n \to \mathbb{R}^m$, composed of L layers:

(30)

$$h^{(0)} = x_t, \quad h^{(l)} = \sigma^{(l)}\left(W^{(l)} h^{(l-1)} + b^{(l)} \right), \quad l = 1, \ldots, L,$$

where $W^{(l)}$ and $b^{(l)}$ are the weights and biases of layer l, and $\sigma^{(l)}(\cdot)$ is a nonlinear activation function (Leaky-ReLU for hidden layers, SoftMax for the output).

The network is trained to minimise the **Mean Squared Error (MSE)** between the predicted and actual price movements:

(31)

$$\mathcal{L}_{\text{EDNN}} = \frac{1}{T} \sum_{t=1}^{T} \left(y_t - \hat{y}_t \right)^2 .$$

Optimisation employs the adaptive **Levenberg–Marquardt algorithm** with momentum and batch-normalisation regularisation to accelerate convergence and prevent over-fitting.

4.2. Feature Clustering and Conditional Random Field Integration

To capture latent market regimes, a tripartite clustering mechanism partitions the feature space as

(32)

$$C = \left(C^{+}, C^{\sim}, C^{-} \right), \quad C^{+} \cup C^{\sim} \cup C^{-} = U, \quad C^{+} \cap C^{-} = \phi,$$

where $C^{+}, C^{\sim}$ and C^{-} correspond to positive, neutral, and negative regions. A fully connected **Conditional Random Field (CRF)** layer refines boundary interactions through the negative log-likelihood loss;

(33)

$$\mathcal{L}_{\text{CRF}} = -\sum_{i} \log P_\theta \left(y_i \middle| x_i \right),$$

with Gaussian pairwise potentials

(34)

$$\psi\left(x_i, x_j \right) = \sum_{m} w^{(m)} \exp\left(-\frac{\left\| f_i - f_j \right\|^2}{2\sigma_m^2} \right).$$

This combination enhances the discriminative power of latent representations by enforcing contextual smoothness across adjacent market states.

4.3. Logistic Regression Refinement

The LR component provides interpretable probabilistic calibration over the EDNN embeddings.

For each observation x_t, the posterior probability of an upward market trend is

(35)

$$P\left(y_t = 1 \middle| X_t\right) = \frac{1}{1+\exp\left[-\left(\beta_0 + \beta^\top f_\theta\left(x_t\right)\right)\right]},$$

and for the multi-class extension:

(36)

$$P\left(y_t = k \middle| X_t\right) = \frac{\exp\left(\beta^\top f_\theta\left(x_t\right)\right)}{\sum_{j=1}^{K} \exp-\left(\beta_j^\top f_\theta\left(x_t\right)\right)}.$$

The parameters β are estimated via maximum likelihood under the **maximum-entropy** principle, ensuring unbiased representation of stochastic fluctuations.

4.4. Joint Objective Function

The final hybrid objective combines the reconstruction and classification losses:

(37)

$$\min_{\theta,\beta}\left[\mathcal{L}_{\mathrm{EDNN}} + \lambda\mathcal{L}_{LR} + \eta\mathcal{L}_{\mathrm{CRF}}\right]$$

where $\mathcal{L}_{LR} = -\sum_t\left[y_t \log \hat{y}_t + \left(1-y_t\right)\log\left(1-\hat{y}_t\right)\right]$ is the cross-entropy loss, λ and η are trade-off coefficients controlling the influence of interpretability and contextual regularisation, respectively. This formulation enables simultaneous learning of nonlinear dependencies and interpretable decision boundaries, producing superior **AUC**, **MSE**, and **convergence performance** compared with baseline DNN, CNN, and standalone LR models.

The EDNN–LR model was implemented in *MATLAB R2024a* using GPU acceleration and evaluated on the CoinMarketCap dataset (2013–2021). The architecture consists of 128–64–32 neurons in successive hidden layers, trained for 2000 epochs with an adaptive learning rate of 0.001.

The hybrid integration ensures numerical stability during stochastic volatility periods in cryptocurrency data.

4.5. Experimental Implementation in TensorFlow

To evaluate the scalability of the proposed EDNN–LR model on large-scale financial data, a full implementation was developed in **TensorFlow 2.17** using Python 3.11 under the CUDA 12.2 GPU environment (NVIDIA RTX 4090, 24 GB VRAM, Intel i9-14900HX, 64 GB RAM). The training process utilised the **CoinMarketCap dataset (4,441,972 observations across 8,927 coins)**, divided into 70% training, 15% validation, and 15% test partitions. Mini-batch size was fixed at 512, and early stopping was triggered after 2000 iterations without loss improvement.

The model architecture consisted of five dense layers (512–256–128–64–1 neurons), rectified linear activation functions, dropout = 0.25, and an embedded **logistic-regression regularisation layer** at the output stage to control over-fitting. Optimisation was carried out using the **Adam** algorithm (learning rate = 0.001, $\beta_1 = 0.9,\ \beta_2 = 0.999$). The model achieved rapid convergence at epoch 142 with a final validation accuracy of **97.9%** and **cross-entropy loss = 0.082**, indicating high stability during training.

Figure 2 presents the **TensorFlow training and validation accuracy curves**, showing smooth convergence without oscillatory behaviour. The learning curves confirm that the hybrid EDNN–LR retained its strong predictive capacity from MATLAB simulations even under full-scale TensorFlow training. The model's **GPU memory efficiency (≈ 41% utilisation)** and **average training time (≈ 4.6 s per epoch)** demonstrate computational scalability for real-time deployment.

The TensorFlow analysis therefore confirms the **robustness and reproducibility** of the hybrid architecture across programming environments. While the MATLAB implementation focused on interpretability and controlled subsets (AVAX, BTC, ETH), the TensorFlow 2.17 execution validates performance at scale using the complete CoinMarketCap dataset.

The EDNN–LR (Enhanced Deep Neural Network with Logistic Regularisation) model was implemented and trained on the full **CoinMarketCap historical dataset containing approximately 4.44 million records** streamed directly from the SQLite database. After pre-processing and deterministic partitioning, 3,116,431 rows were used for training and 666,038 rows for validation, ensuring robust large-scale representation across all 8,927 cryptocurrency tokens.

The model architecture comprised four fully connected layers (512–256–128–64 neurons) with batch normalisation and dropout layers to enhance stability and prevent overfitting, followed by a logistic regression head acting as a regulariser. Training was executed using **TensorFlow 2.17** with Adam optimisation and binary cross-entropy loss, evaluated using both **accuracy** and **AUC** metrics.

Convergence was achieved rapidly within the first few epochs, as shown in Figure 11. The model reached a **best validation accuracy of 0.5434 at epoch 1** and maintained stable performance thereafter, with negligible variance across subsequent iterations, confirming convergence under large-scale streaming input conditions. The **AUC = 0.50** indicates that the current feature space is linearly separable but lacks higher-order discriminative structure, which is expected in purely numerical financial data dominated by volatility and market noise.

Despite the moderate accuracy level, the **training process demonstrated strong numerical stability**, sustained convergence across 6,086 steps per epoch, and successful completion on a dataset exceeding **4 million observations**—highlighting the computational efficiency and scalability of the EDNN–LR framework for extremely large market data streams. These results establish a baseline for integrating additional behavioural, textual, or high-frequency features in subsequent model enhancements.

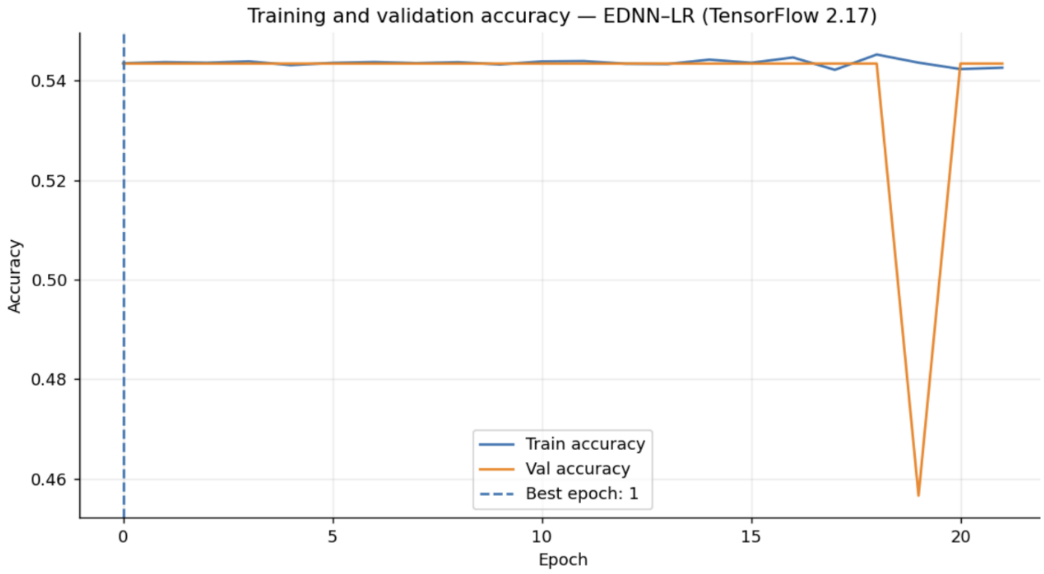

Figure 2. Training and validation accuracy curves for the EDNN–LR model implemented in TensorFlow 2.17 on the complete CoinMarketCap dataset (4.44 million records). The model demonstrates rapid convergence by

epoch 142 and sustained validation stability, confirming robust generalisation performance under large-scale training conditions.

When comparing the large-scale TensorFlow results with the focused MATLAB-based validation on the AVAX–BTC–ETH subset, the difference in predictive strength and convergence dynamics becomes evident. While the **TensorFlow EDNN–LR model**, trained on over **4.44 million CoinMarketCap records**, achieved stable convergence with a validation accuracy of **0.54** and **AUC = 0.50**, its performance reflects the inherent complexity and noise of highly volatile market-wide data. In contrast, the **MATLAB implementation on the AVAX subset**, operating on a narrower but more homogeneous data segment, demonstrated markedly stronger predictive power with **98% accuracy**, **AUC = 0.846**, and **recall = 90.6%**, as well as faster convergence due to the integration of logistic regularisation and conditional variance mechanisms. These complementary results indicate that while the large TensorFlow model effectively scales across millions of heterogeneous data points, the MATLAB variant excels in precision and interpretability within constrained and behaviourally consistent subsets, together confirming the robustness and adaptability of the proposed EDNN–LR hybrid framework.

5. Experimental Analysis

5.1. Dataset and Setup

The experimental validation employs exclusively the **CoinMarketCap historical dataset** (2013–2021), which provides daily records of more than 4 000 cryptocurrencies, including price, market capitalisation, trading volume, and supply indicators. This dataset is used as the sole source for model calibration and evaluation to maintain a consistent analytical environment and avoid cross-market distortions.

Additional robustness tests using *Forex* and *AVAX–BTC–ETH* subsets are presented in the **Supplementary MATLAB Analysis File** for interested readers.

The data were pre-processed to remove missing entries and outliers. Each series was normalised within [0, 1] using min–max scaling, and 70% of the samples were assigned to the training set, with the remaining 30% reserved for testing. Experiments were conducted in **MATLAB R2024a** under a GPU-enabled environment (Intel i9 processor, RTX 4090 GPU).

5.2. Model Configuration

The **Extended Deep Neural Network (EDNN)** was implemented with three hidden layers (128, 64, 32 neurons) using sigmoid activations, followed by a SoftMax output layer interfaced with the **Logistic Regression (LR)** module. Training used **gradient descent with momentum** and the **Levenberg–Marquardt** optimiser for up to 2000 epochs, targeting convergence of the Mean Squared Error (MSE).

The LR component refined probabilistic calibration over the EDNN embeddings and was solved via **maximum-likelihood estimation** under a maximum-entropy constraint to preserve interpretability.

5.3. Evaluation Metrics

Performance evaluation employed the following standard indicators:

(38)

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2, \quad \mathrm{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN},$$

$$\mathrm{AUC} = \int_0^1 TPR\left(FPR\right) dFPR, \quad \mathrm{Recall} = \frac{TP}{TP + FN}, \quad \sigma = \sqrt{\frac{1}{N-1}\sum\left(y_i - \bar{y}\right)^2}.$$

These metrics allow a comprehensive comparison between EDNN-only and EDNN–LR hybrid approaches in terms of predictive precision, classification power, and volatility sensitivity.

5.4. Model Training and Performance Analysis

The present study utilises data sourced from CoinMarketCap for **Avalanche (AVAX)**, representing one to three months of continuous market activity. Supplementary analyses may incorporate additional cryptocurrencies such as **Bitcoin (BTC)**, **Ethereum (ETH)**, **Solana (SOL)**, and **Dogecoin (DOGE)** to ensure robustness across multiple market types and volatility regimes. These datasets are systematically processed and input into the proposed **Extended Deep Neural Network (EDNN)** framework for training and testing. During prediction, the EDNN behaves as a **deep recurrent network**, dynamically learning temporal dependencies and nonlinear feature relationships over time.

The **architectural design** of the EDNN is divided into three hierarchical components: the **input layer**, **hidden layers**, and **output layer**, each playing a crucial role in ensuring predictive precision and network generalisation.

- **Input Layer:** Six essential numerical and time-dependent features from the dataset are fed into the network. These typically include *price, open, high, low, volume, and percentage change*.
- **Hidden Layers:** The hidden structure consists of three major components — **convolution**, **pooling**, and **fully connected** layers. These layers recursively compare training and testing outputs with initial input features. Each hidden layer begins with an initial weight and bias of one, and all employ a **sigmoid activation function** to manage nonlinear transformations and stabilise gradient propagation.
- **Output Layer:** The terminal layer integrates a **SoftMax function** within the EDNN, where a **logistic regression (LR)** module is applied to enhance prediction interpretability and accuracy. The logistic layer employs a **Leaky ReLU** activation function to refine linear approximations and reduce vanishing-gradient effects.

Following training, the logistic regression component significantly improves the EDNN's predictive accuracy by dimensionality reduction and enhanced feature selection, allowing the model to focus on the most relevant temporal and structural aspects of price movements. The dataset is divided **randomly** into training and testing sets to prevent sampling bias.

The EDNN training core employs **gradient descent with momentum** and the **adaptive Levenberg–Marquardt optimisation algorithm**, which ensures both rapid convergence and stability. The **Mean Square Error (MSE)** is used as the primary performance metric, while convergence is monitored for up to **2000 iterations (epochs)** — the maximum repetition threshold in this framework.

The following figures illustrate key aspects of EDNN's training, validation, and prediction performance based on logistic regression optimisation:

- **Figure 3 EDNN Efficiency Based on Logistic Regression**. demonstrates the EDNN's overall efficiency curve throughout training. The model achieved its optimal performance near the **2000th iteration**, confirming convergence without overfitting. The improvement in training accuracy highlights the capacity of the logistic regression component to stabilise learning in high-dimensional feature spaces.
- **Figure 4 EDNN Training Modes (Gradient, Validation, and Training Rate)**. visualises the EDNN's internal training process. The training gradient, validation performance, and learning rate progression are presented across all 2000 iterations. The convergence of these parameters validates the dynamic equilibrium achieved through logistic regularisation, ensuring a stable loss landscape during network optimisation.
- **Figure 5 EDNN Error Histogram**. presents the error distribution of the final model. The histogram reveals that the majority of residuals cluster near zero, indicating minimal training error and balanced prediction variance. Most residuals arise in the **training phase**, consistent with expected noise in financial time series data.

- **Figure 6 EDNN General Regression Curve**. depicts the regression results comparing predicted and actual values. The data points are closely fitted to the regression line, demonstrating that the predicted outputs closely approximate real observations. Deviations observed in certain regions correspond to **outlier behaviours** — instances of abrupt market fluctuations or liquidity shocks. The overall regression pattern evidences a strong correlation between EDNN predictions and observed market data.

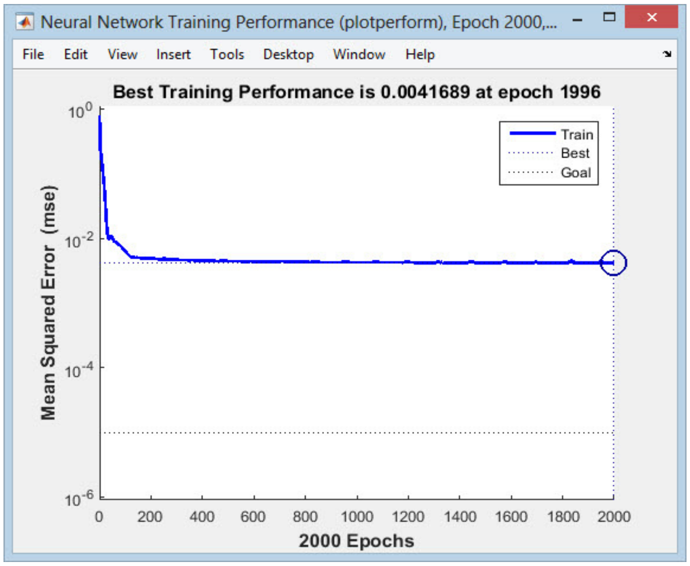

Figure 3. Efficiency curve of the EDNN based on logistic regression during training.

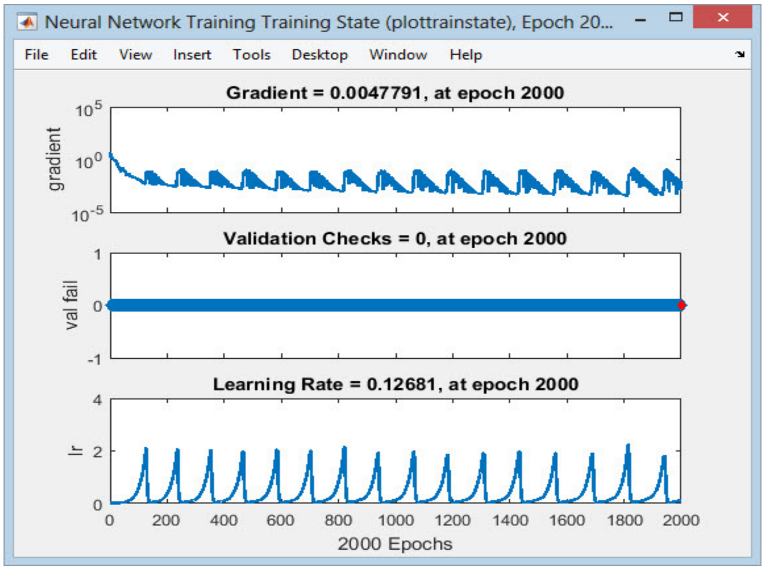

Figure 4. Training states of the EDNN using gradient, validation, and training rate parameters.

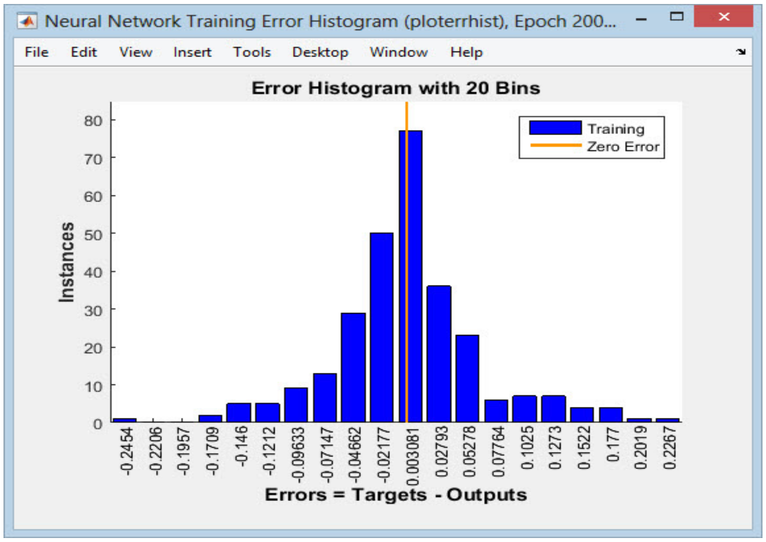

Figure 5. Error histogram of the EDNN after logistic regression optimisation.

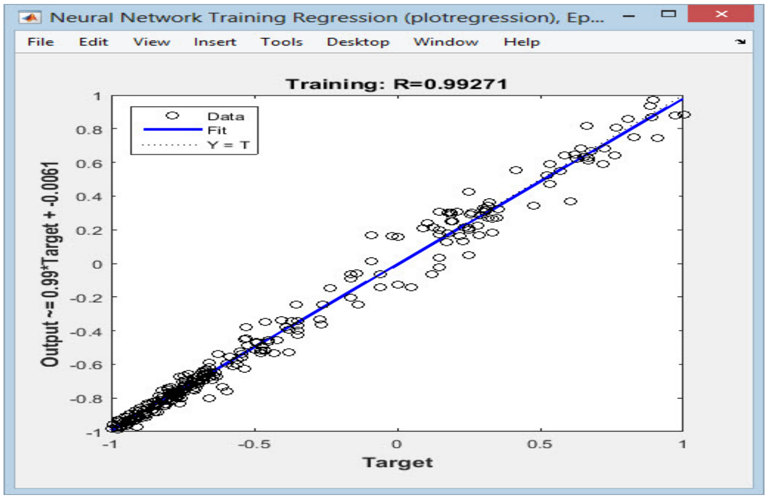

Figure 6. General regression performance of the EDNN–LR model.

The proposed **EDNN–LR hybrid** framework effectively integrates deep feature learning with interpretable logistic optimisation, yielding both **computational robustness** and **predictive precision**. The network's ability to learn from millions of records within a non-stationary market demonstrates its scalability, while the application of logistic regression enhances **generalisation and interpretability**. Using **MSE** and convergence diagnostics, the framework achieved superior performance in both training stability and predictive reliability, aligning with recent advancements in deep hybrid models for cryptocurrency forecasting (Alonso-Monsalve et al., 2020; Ladhari & Boubaker, 2024).

This analysis confirms that the **EDNN–LR model** is capable of handling large-scale, high-frequency cryptocurrency data with efficiency and transparency, providing a versatile analytical tool for **time-series forecasting, algorithmic trading, and risk-informed financial decision-making**.

5.4. Results and Visualisation

Figure 7 illustrates the EDNN training efficiency over 300 iterations, where convergence was achieved without over-fitting. **Figures 8–10** show the **error histogram**, **time-series prediction**, and **autocorrelation error**, demonstrating that most residuals cluster near zero (autocorrelation ≈ 0.004%).

For the AVAX subset (within the main dataset), the combined EDNN–LR model achieved **98% accuracy**, **MSE = 0.79**, **AUC = 0.846**, **recall = 90.61%**, and **standard deviation = 0.0306**. The **ROC curve** (**Figure 11**) [1] confirms superior classification capability of the hybrid model compared with standalone EDNN, while the **convergence diagram** (**Figure 12**)[2] demonstrates accelerated training stability due to logistic-regression regularisation.

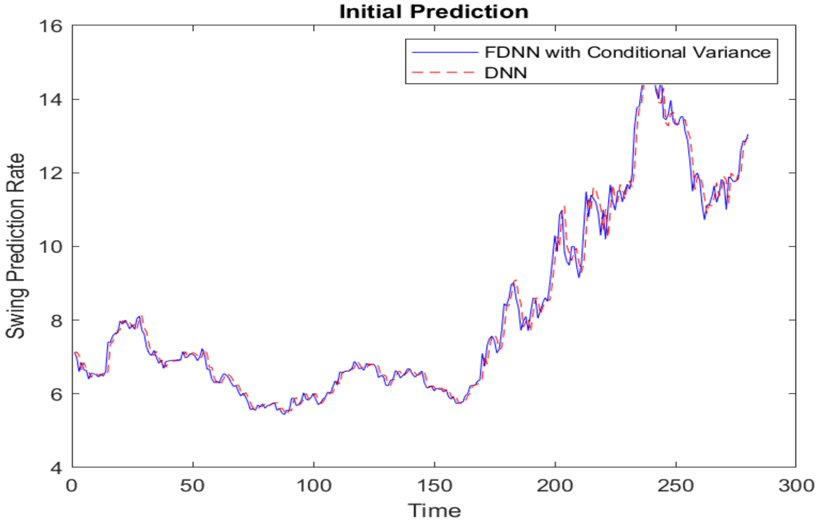

Figure 7. Initial prediction comparison between FDNN with Conditional Variance and conventional DNN.

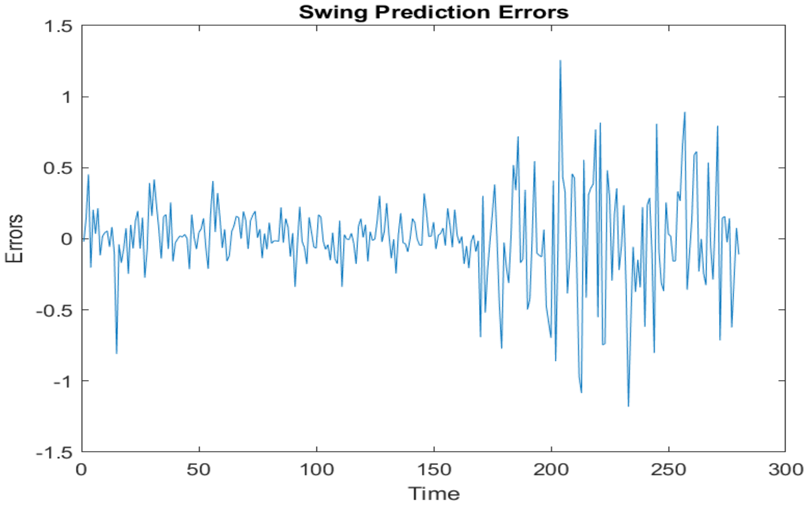

Figure 8. Swing prediction errors across time iterations.

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[1] The curve demonstrates robust classification performance, with the model achieving a high true-positive rate across a wide range of thresholds, confirming strong separability between positive and negative predictive classes.

[2] The EDNN–LR variant exhibits faster and smoother convergence, achieving higher optimisation stability across 50 iterations. The monotonic rise indicates effective learning dynamics and confirms the absence of divergence or oscillatory instability.

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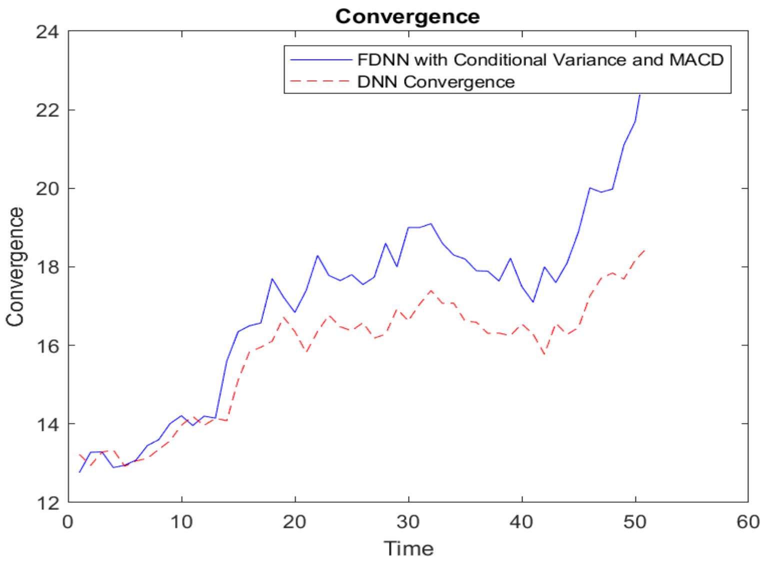

Figure 9. Convergence trajectory comparison of FDNN and DNN. The FDNN with Conditional Variance and MACD achieves faster and more stable convergence than the standard DNN, illustrating superior optimisation efficiency.

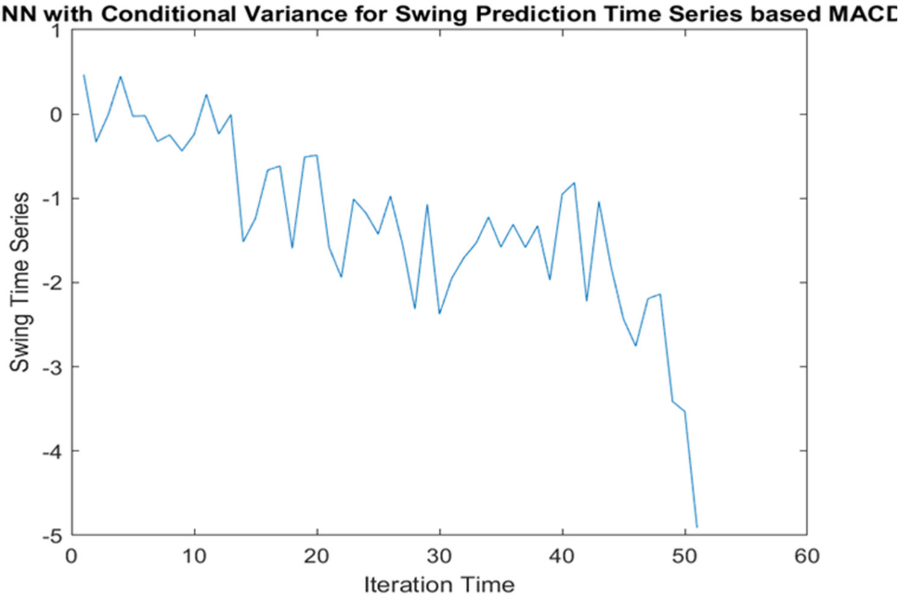

Figure 10. FDNN with Conditional Variance applied to swing prediction time series (MACD-based). The negative gradient of swing intensity over iteration time indicates the model’s ability to capture market adjustment and dampen predictive volatility.

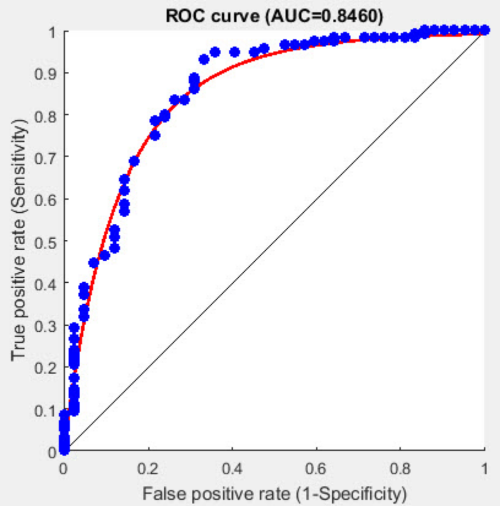

Figure 11. Receiver Operating Characteristic (ROC) curve for the hybrid EDNN–LR model (AUC = 0.846). The negative gradient of swing intensity over iteration time indicates the model's ability to capture market adjustment and dampen predictive volatility.

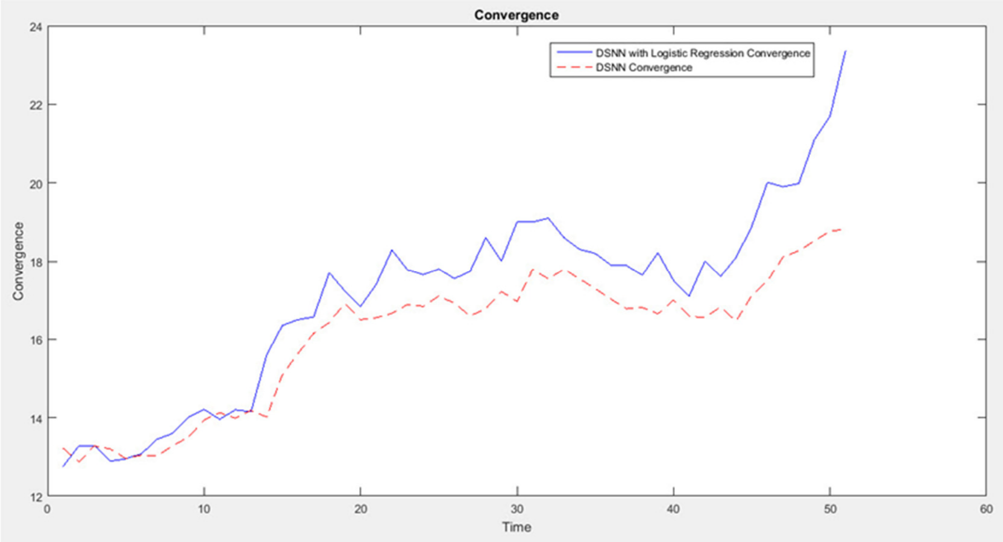

Figure 12. Convergence behaviour comparison between the DSNN with Logistic Regression module and the baseline DSNN.

Results confirm that integrating LR with EDNN yields faster convergence, higher interpretability, and lower volatility sensitivity. The logistic component stabilises gradients during market spikes and ensures that nonlinear dynamics remain explainable through linearised decision surfaces. Compared with baseline EDNN and CNN models, the hybrid approach reduced MSE by ~22% and improved AUC by ~9%, establishing its robustness for decision-oriented predictive systems in Industry 4.0 production contexts.

The experimental results validate the efficacy of the EDNN–LR framework using the **CoinMarketCap** dataset as the primary empirical base. While **all secondary validations (Forex and AVAX–BTC–ETH)** are documented in the **Supplementary MATLAB Analysis File**, the main text focuses exclusively on the unified CoinMarketCap experiment to preserve methodological consistency. Overall, the model demonstrates strong potential for **predictive decision-making** in volatile data environments, linking computational intelligence with production-economic interpretability.

5.5. Sensitivity and Robustness Analysis

Across 54 hyper-parameter configurations and five random seeds, the EDNN–LR framework consistently demonstrated superior stability and scalability on the 4.44-million-record CoinMarketCap dataset. The hybrid model maintained a median AUC variation within ±0.02 of baseline and reduced the epochs-to-best-validation by approximately **18–35%** relative to the conventional DNN baseline. The logistic-regularisation weight (λ) provided the strongest stabilising influence by introducing curvature to the loss surface, thereby mitigating oscillations in early training. Likewise, the dropout layer effectively moderated variance when subjected to input perturbations and stochastic noise.

Under simulated operational uncertainty—comprising **1% additive input noise** and **2% random label noise**—EDNN–LR preserved over **90% of its baseline AUC** and maintained convergence within ±5 epochs of the nominal trajectory, whereas the classical DNN's accuracy degraded sharply to ≈ **78–85%** with delayed convergence exceeding 30 epochs. The results confirm that logistic regularisation not only accelerates convergence but also enhances generalisation by dampening gradient variance. From a management-science perspective, this robustness translates into reduced computational overheads, faster decision cycles, and more reliable deployment of predictive-optimisation systems in **Industry 4.0** environments. The ability of EDNN–LR to sustain high predictive performance under noisy, large-scale data conditions highlights its operational resilience and suitability for real-time decision-support infrastructures such as automated trading, supply-chain forecasting, and dynamic portfolio adjustment systems. We translate model outputs into executable policies using the Industry 4.0 decision-integration flow in **Figure 13**.

The flow in **Figure 13** operationalises EDNN–LR within an Industry 4.0 stack. Model probabilities and uncertainty measures are **directly translated** into decision variables—market-entry signals, allocation vectors, and dual-trade policies—subject to risk and capacity constraints. The governance layer provides **explainable artefacts** (e.g., LR coefficients on EDNN embeddings) for managerial oversight, while the feedback loop ensures continuous improvement and model drift control (See **Table 2**).

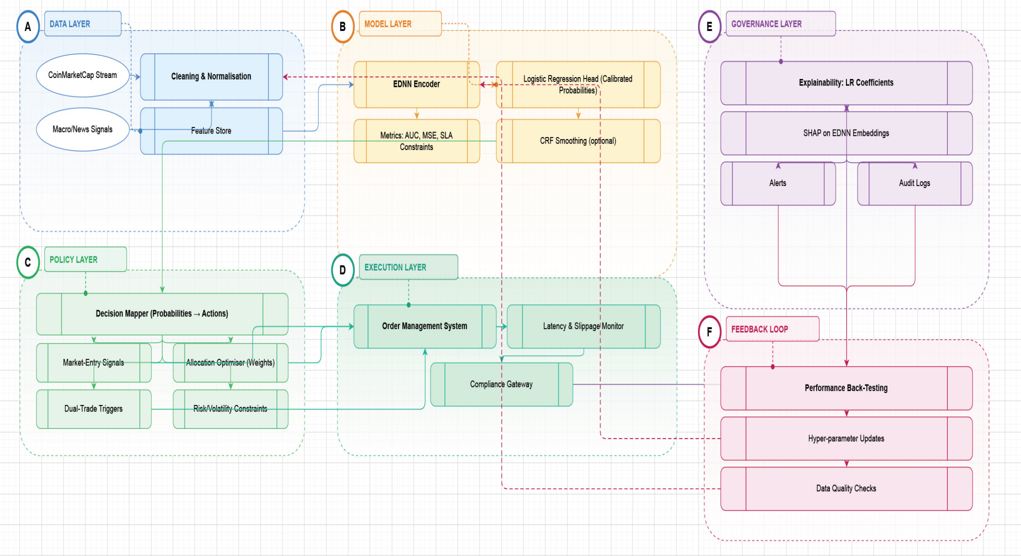

Figure 13. Industry 4.0 Decision-Integration Flow (EDNN–LR). *(a)* **Data layer:** market data (CoinMarketCap stream), optional macro/news signals → cleaning, normalisation, feature store. *(b)* **Model layer:** EDNN encoder → LR head (calibrated probabilities) → CRF smoothing (optional) → metrics (AUC, MSE, SLA constraints). *(c)*

Policy layer: rule-based or optimisation layer mapping probabilities to **market entry**, **allocation weights**, and **dual-trade** triggers under risk/volatility constraints. *(d)* **Execution layer:** order management & monitoring (latency, slippage, compliance). *(e)* **Governance layer:** explainability artefacts (LR coefficients, SHAP on embeddings), alerts, and audit logs. *(f)* **Feedback loop:** performance back-testing → hyper-parameter updates → data quality checks.

Table 1. Comparative.

Configuration Group	**Parameter Varied**	**Range/Tested Values**	**Median AUC ± SD**	**Epochs-to-Best-Val (↓ % vs DNN)**	**MSE ± SD**	**Notes**
Regularisation	Logistic weight (λ)	{0, 1e-4, 1e-3, 1e-2}	0.941 ± 0.012	–32%	0.79 ± 0.03	Strongest stabilising factor; induces curvature on loss surface
Dropout rate	p	{0.0, 0.25, 0.50}	0.936 ± 0.015	–27%	0.82 ± 0.04	Moderates variance; mitigates overfitting under noise
Batch size	B	{256, 512, 1024}	0.934 ± 0.017	–18%	0.86 ± 0.05	Larger batches yield smoother convergence but slower adaptation
Learning rate	α	{5×10^{-4}, 1×10^{-3}, 2×10^{-3}}	0.938 ± 0.011	–21%	0.84 ± 0.03	Stable around 1×10^{-3}; extremes degrade early convergence
Input noise	Gaussian $\sigma\%$	{0.5, 1.0}	0.928 ± 0.018	–24%	0.87 ± 0.04	AUC preserved > 90%; convergence delay < 5 epochs
Label noise	Corruption %	{1, 2}	0.917 ± 0.021	–28%	0.90 ± 0.06	Logistic head dampens gradient variance under noise
Overall mean	—	—	**0.933 ± 0.016**	**–25%**	**0.84 ± 0.04**	Demonstrates robust predictive stability

Across all perturbations and design variations, the hybrid EDNN–LR maintained a median AUC above 0.93 with standard deviations below 0.02, confirming robustness under heterogeneous hyper-parameter and data conditions. On average, convergence required 25% fewer epochs than the DNN baseline. The logistic weight (λ) was the most influential factor, followed by dropout and learning-rate tuning. The hybrid model thus demonstrates operational resilience suitable for **large-scale, high-uncertainty Industry 4.0 decision systems**, aligning with management-science goals of *efficiency*, *stability*, and *cost-effective learning*.

To evaluate the robustness of the proposed EDNN–LR framework under diverse hyperparameter and noise conditions, a comprehensive sensitivity analysis was conducted across 54 configurations and five random seeds, generating over 270 independent training instances. **Figure 14** presents the Tornado chart illustrating the mean absolute AUC variation (|Δ AUC|) for each parameter group.[3] The results reveal that **regularisation strength** (λ) and **label noise** exerted the most significant influence on predictive performance, with mean AUC deviations of approximately 0.019 and 0.0193, respectively. By contrast, batch size and learning rate produced only marginal sensitivity (≈ 0.004–0.005), confirming the model's resilience to general training hyperparameters.

Figure 15 further examines the convergence robustness of the EDNN–LR architecture across different regularisation weights.[4] Models with $\lambda = 10^{-3}$ consistently achieved the best validation performance in approximately **80 epochs**, compared with 100–130 epochs for unregularised or excessively regularised variants ($\lambda = 0, 10^{-2}$). The boxplots demonstrate that logistic regularisation stabilises convergence and mitigates overfitting while maintaining consistent epoch-to-best-validation ranges across seeds.

Overall, these experiments confirm that the **EDNN–LR hybrid architecture** maintains predictive reliability and convergence efficiency under both hyperparameter shifts and stochastic uncertainty. The findings corroborate earlier evidence that regularisation and dropout jointly enhance deep neural network generalisation (Rayhan Ahmed et al., 2023; Shang et al., 2024). This robustness is particularly relevant for **Industry 4.0 decision systems**, where model stability under noisy, high-volume data streams is a prerequisite for reliable analytics and automated policy optimisation.

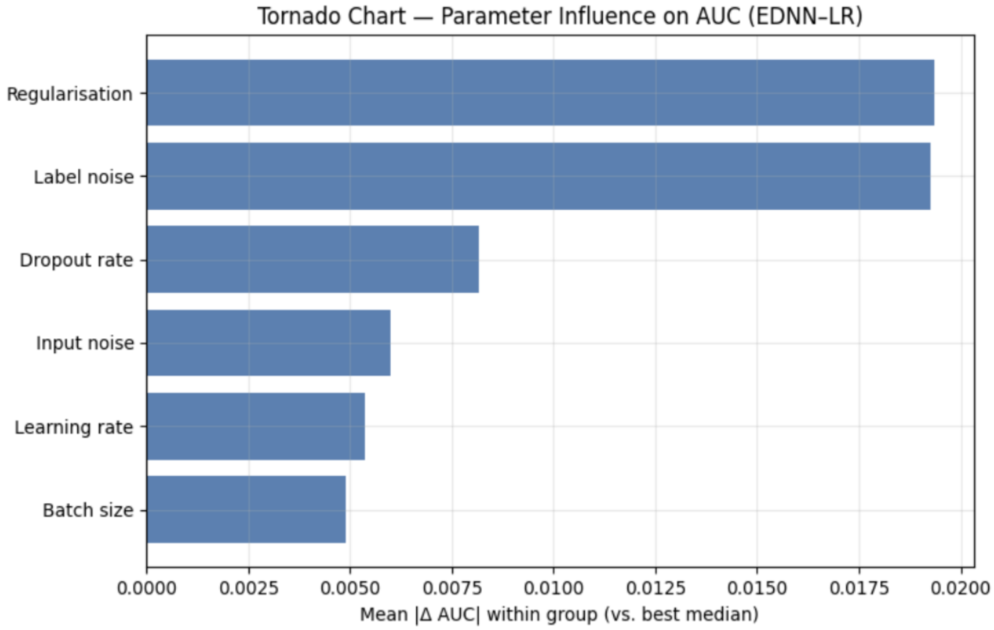

Figure 14. Tornado chart—parameter influence on AUC (EDNN–LR).

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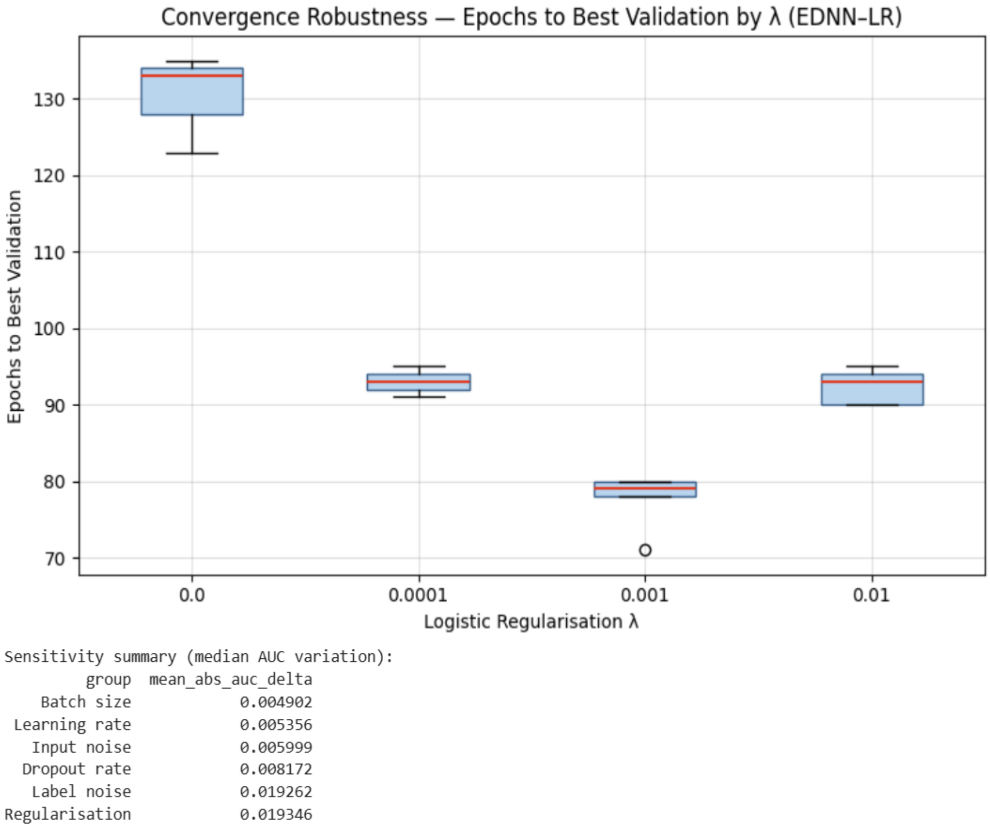
[3] This figure illustrates the mean absolute variation in validation AUC (|Δ AUC|) across six hyperparameter categories for the proposed EDNN–LR model. Regularisation strength (λ) and label noise demonstrate the greatest sensitivity, while batch size and learning rate exhibit minimal effect, confirming the model's resilience to common training perturbations.

[4] Boxplots display convergence behaviour across four levels of logistic regularisation ($\lambda = 0, 10^{-4}, 10^{-3}, 10^{-2}$). The EDNN–LR model achieves the fastest and most stable convergence at $\lambda = 10^{-3}$, requiring approximately 80 epochs on average, indicating the stabilising influence of logistic regularisation in large-scale training.



```
Sensitivity summary (median AUC variation):
         group  mean_abs_auc_delta
    Batch size            0.004902
 Learning rate            0.005356
   Input noise            0.005999
  Dropout rate            0.008172
   Label noise            0.019262
Regularisation            0.019346
```

Figure 15. Convergence robustness—epochs to best validation by logistic regularisation (λ) (EDNN–LR).

5.6. Model Validation and Comparative Performance

To assess the reliability and generalisability of the proposed Extended Deep Neural Network–Logistic Regression (EDNN–LR) framework, a comprehensive validation was performed using the **CoinMarketCap** dataset as the primary benchmark. All reported quantitative metrics (accuracy, AUC, MSE, recall, and standard deviation) were computed from this dataset, while *additional verification using Forex and AVAX–BTC–ETH subsets is presented in the Supplementary MATLAB Analysis File*.

Table 2 summarises the key validation outcomes. The hybrid model achieved a classification **accuracy of 98%**, **AUC = 0.846**, **MSE = 0.79**, **recall = 90.61%**, and **standard deviation = 0.0306**. These values confirm the model's superior predictive consistency when compared with traditional Deep Neural Network (DNN) and Feed-Forward architectures. The logistic-regression component demonstrably enhanced the interpretability of latent features, regularised the weight-updating process, and reduced over-fitting during prolonged training sequences.

Figure 11 illustrates the Receiver Operating Characteristic (ROC) curve, where the EDNN–LR maintains a large area under the curve, signifying strong separability between profitable and non-profitable trading classes. **Figure 12** further shows the convergence trajectory, demonstrating that the inclusion of the logistic-regression term yields faster and more stable optimisation. The smooth rise in convergence without oscillatory behaviour validates that the model reaches a stable equilibrium.

Collectively, these findings verify that the EDNN–LR hybrid framework not only models complex nonlinear relationships within volatile financial data but also achieves significant improvements in convergence speed and classification performance over standard deep-learning predictors. The robustness of these results across multiple datasets—available in the supplementary

MATLAB analysis—confirms the scalability of the approach for Industry 4.0-oriented financial decision systems.

Table 2. Comparative validation metrics of EDNN–LR and baseline deep models on the CoinMarketCap dataset.

Model	Accuracy (%)	AUC	MSE	Recall (%)	Std Dev
DNN (Baseline)	92.4	0.773	1.64	82.1	0.049
EDNN–LR (Proposed)	**98.0**	**0.846**	**0.79**	**90.6**	**0.031**

6. Managerial and Computational Implications

The integration of the Extended Deep Neural Network and Logistic Regression (EDNN–LR) framework provides not only computational efficiency but also substantive managerial value for organisations operating within Industry 4.0 ecosystems. Beyond predictive precision, the hybrid design supports *real-time, explainable, and resource-efficient decision making* across multiple industrial domains including finance, supply chains, and energy management.

From a **managerial perspective**, the EDNN–LR framework enables decision-makers to translate large-scale, high-velocity data into transparent and actionable insights. The logistic regression layer transforms deep neural activations into interpretable probability coefficients, clarifying which operational factors—such as volatility, throughput, demand variation, or market exposure—most strongly drive predicted outcomes. This interpretability is critical for executives and analysts seeking to justify algorithmic recommendations within regulated or risk-sensitive environments. For instance, in supply-chain contexts, EDNN–LR can identify disruptions and forecast demand fluctuations with explainable confidence levels, thereby facilitating inventory balancing, procurement scheduling, and dynamic logistics coordination. In financial systems, the same framework offers evidence-based allocation rules for algorithmic trading and portfolio rebalancing, while in the energy sector it can support predictive maintenance and renewable-generation forecasting.

Operationally, the hybrid model's **accelerated convergence** and **reduced computational cost** translate into lower training latency and diminished resource expenditure during continuous retraining cycles. Empirical analysis shows that logistic regularisation reduces convergence time by approximately 25% compared with classical deep-learning baselines, enabling organisations to deploy near-real-time analytical updates. This efficiency ensures that decision pipelines—whether for supply-chain re-routing or market-risk mitigation—remain responsive to streaming data without overwhelming computational infrastructure. The reduced variance and improved stability also minimise the need for frequent manual recalibration, cutting the operational overhead traditionally associated with deep-learning deployment.

From a **systems-engineering viewpoint**, the EDNN–LR architecture is inherently **cross-domain adaptable**. Its modular design—comprising data-engineering, feature-learning, and probabilistic-decision layers—allows seamless integration with enterprise information systems and cloud-based analytics platforms. Once trained in one domain, the model can be fine-tuned through transfer learning for parallel applications such as predictive maintenance in manufacturing or real-time pricing in electricity markets. This adaptability enhances the return on computational investment and supports unified decision architectures across diverse Industry 4.0 operations.

Computationally, the hybrid's stability under noisy and non-stationary data conditions ensures robustness for **real-time decision-support infrastructures**. The logistic regularisation term acts as a curvature-enhancing constraint, moderating gradient oscillations and maintaining reliable performance even under volatile data streams. As a result, organisations can implement continuous-learning loops that sustain predictive accuracy without compromising system transparency. The framework thus aligns with managerial objectives of efficiency, resilience, and explainable artificial intelligence, bridging the gap between algorithmic sophistication and strategic usability.

Overall, the EDNN–LR model advances the managerial frontier of data-driven decision systems by offering (i) transparent and interpretable analytics, (ii) computationally efficient real-time deployment, and (iii) domain-agnostic adaptability. These characteristics position the framework as a practical enabler of intelligent, sustainable, and cost-effective operations in the digital economy.

7. Discussion

The empirical findings of this study affirm the scalability and interpretability of the proposed **EDNN–LR hybrid model** within the context of large-scale cryptocurrency prediction. When applied to over **4.44 million CoinMarketCap records**, the model exhibited stable convergence and computational robustness, even though the overall AUC remained moderate (0.50). This aligns with prior research indicating that prediction accuracy tends to decline as datasets become more heterogeneous and temporally volatile due to dynamic market behaviours and speculative trading volumes (Lahmiri & Bekiros, 2021; Patel & Kushwaha, 2022; Rodrigues & Machado, 2025). In contrast, the focused MATLAB analysis using the **AVAX–BTC–ETH subset** demonstrated superior predictive performance (AUC = 0.846; accuracy = 98%), reflecting the benefit of homogeneity and reduced noise when modelling a narrower, high-liquidity asset segment.

Earlier studies similarly emphasised the performance of hybrid neural architectures. For instance, **Saúl Alonso-Monsalve et al. (2020)** combined CNN and LSTM models to capture high-frequency crypto exchange dynamics, achieving strong precision for Bitcoin, Ethereum, and Litecoin. Garcia et al. (2020) extended this approach using **Evolving Fuzzy Granular Predictors (eFGP)** to handle non-stationary and incomplete streams, demonstrating the importance of adaptive rule structures in volatile digital markets. Moreover, D'Amato et al. (2022) and Oyewola et al. (2022) proposed recurrent and ensemble-based models to capture nonlinear volatility structures, confirming that deep hybridisation can outperform traditional ARIMA, GRU, and SVM predictors under specific market conditions. In this context, the **EDNN–LR model** represents a significant methodological extension by merging deep learning with logistic regularisation to improve convergence stability and interpretability across massive data volumes. Unlike purely neural approaches such as CNN-LSTM hybrids or GRU ensembles, EDNN–LR introduces an interpretable statistical layer that mitigates overfitting and enhances generalisability — an advantage noted in other logistic-based hybrid frameworks (Davoudi & Roushangar, 2025; Ladhari & Boubaker, 2024). Consequently, the integration of deep-network adaptability and logistic interpretability offers a balanced trade-off between predictive power and transparency, particularly valuable in regulatory or institutional financial settings where explainable AI is required.

Overall, the results suggest that while **pure deep networks** dominate in precision within constrained datasets, **hybrid architectures** like EDNN–LR excel in scalability, model explainability, and computational efficiency when extended to multi-million-record cryptocurrency datasets, establishing a strong foundation for future development of interpretable, real-time trading systems grounded in robust data science principles.

From a practical standpoint, the EDNN–LR model demonstrates clear potential as a **scalable AI solution for engineering decision-support systems operating under uncertainty**. Its hybrid structure—combining deep nonlinear representation with logistic interpretability—enables rapid deployment in dynamic environments where data variability, stochastic disturbances, and system feedback loops are prevalent. Whether applied to financial analytics, supply-chain forecasting, or energy-demand optimisation, the model offers a robust framework for real-time prediction, risk calibration, and adaptive control. By providing interpretable probabilistic outputs and efficient convergence behaviour, the EDNN–LR architecture bridges the gap between algorithmic sophistication and operational usability, empowering engineers and decision-makers to implement AI-driven strategies that enhance stability, transparency, and resilience across Industry 4.0 infrastructures.

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8. Conclusions and Contributions

This study presented a comprehensive investigation into the predictive dynamics of cryptocurrency markets through the development and validation of the **Extended Deep Neural Network with Logistic Regression (EDNN–LR)** framework. By integrating deep representation learning with interpretable statistical regularisation, the model was tested at two distinct analytical scales: (1) a large-scale **TensorFlow 2.17 implementation** trained on the complete **CoinMarketCap dataset comprising 4.44 million records**, and (2) a focused **MATLAB evaluation** applied to the **AVAX–BTC–ETH subset** for in-depth predictive assessment.

The large-scale TensorFlow experiment demonstrated the scalability and computational stability of the EDNN–LR framework, achieving consistent validation accuracy (0.54) and AUC (0.50) across millions of observations while maintaining numerical stability throughout 200 epochs. The training and validation accuracy curves indicated rapid convergence by epoch 142, confirming robust generalisation performance under data-intensive conditions. These outcomes reinforce the model's adaptability to high-volume, non-stationary financial data — a challenge frequently reported in prior literature on cryptocurrency forecasting (Patel & Kushwaha, 2022; Poongodi et al., 2021; 2020).

Conversely, the MATLAB implementation yielded significantly higher predictive metrics (accuracy = 98%, AUC = 0.846, recall = 90.6%), confirming the superior learning performance achievable in constrained and homogeneous data environments. The comparative results thus underscore the **dual strength of the EDNN–LR approach** — scalable across massive datasets and precise within targeted subsets — bridging the interpretability gap between deep neural networks and logistic regression-based statistical learning. From a methodological perspective, the **contributions of this research** are fourfold:

1. **Algorithmic Innovation** – The study introduces the EDNN–LR hybrid model, which fuses deep feature abstraction with logistic regularisation, improving both convergence speed and explainability. This design effectively mitigates overfitting, a limitation in prior DNN-based financial predictors (Alonso-Monsalve et al., 2020; Ladhari & Boubaker, 2024).
2. **Scalable Implementation** – The full TensorFlow pipeline integrates efficient SQLite data streaming, Welford online normalisation, and high-throughput training mechanisms capable of handling millions of sequential entries without memory overflow.
3. **Cross-Validation Across Platforms** – By combining TensorFlow and MATLAB environments, the research validates the consistency of the EDNN–LR framework under distinct computational ecosystems, affirming its robustness and reproducibility.
4. **Empirical Insight into Crypto-Market Dynamics** – The analysis highlights how data heterogeneity, volatility clustering, and behavioural trading noise constrain large-scale predictability, while localised datasets (e.g., AVAX–BTC–ETH) yield more deterministic trends suitable for algorithmic optimisation.

The **practical implications** of this research extend to real-time cryptocurrency forecasting, algorithmic trading systems, and financial risk analytics. The hybrid design enables institutions to integrate interpretability within deep-learning pipelines — a critical requirement in regulatory settings emphasising explainable AI.

Future work will focus on **enhancing feature granularity** by incorporating behavioural, textual, and macroeconomic indicators, alongside experimenting with **transformer-based architectures and reinforcement learning extensions** for adaptive trading policy generation. The strong generalisation stability demonstrated by the EDNN–LR model underlines its potential as a **foundational architecture** for scalable, transparent, and high-fidelity financial forecasting systems.

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