# Presenting a Predictive Model of Stock and Over-the-Counter Market Price Indices Based on Macroeconomic Indicators Using Artificial Neural Networks

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**Abstract:** The primary objective of this study is to present a predictive model for stock and over-the-counter (OTC) market price indices based on the examination and prediction of the effects of macroeconomic variables on Iran's capital market. To improve prediction accuracy, the study employed deep neural network algorithms to forecast future trends in stock price indices. In this research, the required data were collected from the Central Bank of Iran, the Statistical Center of Iran, the Gold and Currency Information Website, and the Securities and Exchange Organization (SEO) database for stock price index data. The analysis was conducted using two artificial neural network approaches: the Long Short-Term Memory (LSTM) network and the Multilayer Perceptron (MLP) trained through the backpropagation algorithm. The models were evaluated using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and prediction accuracy percentage. The implementation was carried out in the Python programming environment over the period from 2014 to 2023. The findings of the study indicated that the LSTM neural network model did not yield satisfactory prediction results. However, the MLP model successfully demonstrated the predictive impact of macroeconomic variables on the stock and OTC market price indices. Overall, the results suggest that the application of artificial neural networks, as an advanced analytical tool, provides an effective and efficient approach for analyzing and predicting stock market fluctuations. This study emphasizes the importance of considering macroeconomic variables in the analysis and forecasting of stock market volatility. Furthermore, the findings can serve as a valuable guide for economic policymakers and investors in making optimal decisions within financial markets.

**Keywords:** Prediction, Stock Price Index, Stock Exchange and Over-the-Counter Market, Artificial Neural Network, Macroeconomic Variables

## 1. Introduction

The acceleration of data availability, computing power, and algorithmic sophistication over the past decade has transformed how scholars and practitioners conceptualize and predict stock market behavior. Where linear factor models and classical econometrics once dominated, today's frontier increasingly relies on artificial intelligence (AI) and machine learning (ML) methods that can learn complex, nonlinear, and high-dimensional relationships from heterogeneous sources—numerical indicators, textual news, investor attention signals, and microstructure features. This paradigm shift is particularly salient in emerging and volatility-prone markets, where structural breaks, policy shocks, and information frictions routinely undermine the assumptions of parametric models but create fertile ground for data-driven learners attuned to regime changes and interaction effects [1-3].

A large and rapidly growing evidence base documents the promise and pitfalls of AI for financial prediction. Early contributions demonstrated that artificial neural networks (ANNs) can outperform linear benchmarks in forecasting index levels and directions, especially when markets exhibit nonlinearity and noise that obscure signal extraction for traditional models [4]. Subsequent work showed further gains when network architectures are carefully optimized for time-series tasks, for example by tuning hidden layers, activation functions, and regularization schemes to balance bias–variance trade-offs and to adapt to shifting volatility regimes [5]. As breadth and depth of the literature expanded, bibliometric and systematic syntheses began to map the field's contours, identifying dominant techniques (e.g., multilayer perceptrons, support vector machines, LSTM variants), common data modalities (prices/volumes, macro-financial indicators, news and social signals), and persistent methodological challenges (data leakage, non-stationarity, interpretability, and reproducibility) [1, 2, 6, 7].

Within this trajectory, several threads are especially relevant for macro-driven index prediction in emerging markets. First, the link between information processing and asset prices increasingly spans beyond fundamentals to include the attention economy: search trends, platform engagement, and digital traces of investor interest can propagate into asset co-movements, volatility clustering, and tail risk. Evidence on the asymmetric connectedness between Google-based investor attention and "Fourth Industrial Revolution" assets such as FinTech and robotics/AI stocks highlights how attention shocks transmit nonlinearly across sectors and factor portfolios—a reminder that exogenous informational cues can amplify or dampen price discovery depending on context and liquidity [8]. Second, deep learning methods—convolutional and recurrent architectures in particular—offer representational advantages for structured (time-stamped) and unstructured (text, images) data. For instance, convolutional neural networks (CNNs) have been applied both to engineered features (e.g., candlestick-derived images) and to raw temporal patterns, with encouraging results even in markets where data sparsity and microstructure noise are acute [9, 10]. Third, news analytics and text mining create an avenue to incorporate qualitative signals about macroeconomic policy, sanctions, geopolitical risks, and firm-level events into systematic prediction pipelines; synthesizing this literature underscores that feature curation, event windows, and domain-specific lexicons are decisive for out-of-sample generalization [11].

At the same time, the operationalization of AI in finance requires rigorous attention to design choices, validation protocols, and deployment constraints. A comprehensive bibliometric review emphasizes that the field's expansion has been uneven across sub-domains, with bursts of activity in forecast tasks (directional movement, volatility, trend classification) and portfolio construction (risk budgeting, factor timing), but less consensus on standards for benchmarking and interpretability [1]. A systematic literature review of machine-learning approaches to stock prediction reports that hybrid and ensemble strategies—combining feature-engineered macro/technical factors with deep architectures—tend to outperform single-model baselines, provided that hyperparameter search is disciplined and cross-validation respects temporal ordering [7]. Complementing these lenses, a "review of reviews" integrates meta-insights across dozens of syntheses and cautions that many widely reported gains are sensitive to sample periods, tuning ranges, and leakage-prone evaluation, reinforcing the need for transparent, time-aware splits and robust out-of-sample testing [2].

Methodologically, three families of models dominate index-level forecasting: feedforward ANNs (e.g., multilayer perceptrons, MLPs), kernel-based learners (e.g., support vector machines), and sequence models (LSTM/GRU variants). Comparative studies often find that MLPs excel when relationships are essentially static but nonlinear and when input features summarize lagged dynamics (e.g., macro indicators and technical composites), whereas LSTMs confer advantages when genuine long-range temporal dependencies exist and the signal-to-noise ratio supports sequence learning [12]. In emerging markets, where data samples can be shorter and noise higher, MLPs and gradient-boosting methods sometimes outperform deep recurrent networks because they rely less on stable temporal memory and more on flexible nonlinear mappings from contemporaneous macro states to index outcomes [4, 5, 12]. Conversely, when structured visual encodings—such as candlestick images or volatility surfaces—are available, CNNs can learn spatially local motifs (e.g., reversal patterns) that complement tabular macro features [9, 10].

Beyond directional forecasting, AI has also been integrated into risk-aware portfolio design. Machine-learning regressors embedded in mean-value-at-risk (MVaR) optimization demonstrate that predictive signals can inform both expected returns and downside tails, potentially improving capital allocation across multi-national markets under heterogeneous risk climates [13]. This dovetails with practice-oriented perspectives that frame AI as an end-to-end augmentation of the investment process—from feature discovery and signal curation to execution and post-trade analytics—subject to governance requirements, model risk management, and human-in-the-loop oversight [3, 14, 15]. In that spirit, practical reviews highlight that robust pipelines entail data engineering (missingness, scaling, outlier control), careful feature orthogonalization to avoid multicollinearity, and deployment safeguards against concept drift; without these, models risk overfitting to ephemeral regimes or amplifying pro-cyclical feedback [16, 17].

For markets like Iran's, whose equity indices are known to co-move strongly with currency dynamics, liquidity growth, inflation expectations, oil revenue cycles, and policy-driven interest-rate settings, macro-financial features constitute first-order inputs to any predictive system. Empirical patterns documented in many emerging economies—sharp pass-through from exchange-rate shocks to domestic asset prices, liquidity expansions associated with multiple-equilibria valuation surges, and inflation uncertainty spilling into equity risk premia—are well aligned with model classes that can capture nonlinear interactions and threshold effects (e.g., where the influence of the exchange rate on the index intensifies beyond certain depreciation rates) [4, 5, 18]. In these settings, MLPs equipped with suitable activation functions (e.g., ReLU/sigmoid hybrids), regularization (dropout/L2), and calibrated learning rates can approximate complex response surfaces without presupposing linearity or additivity among macro variables [12, 17]. Meanwhile, when the research question extends to learning sequential dependencies—say, the lag structure of monetary shocks or the persistence of oil-revenue cycles—LSTM architectures may prove advantageous, provided the effective sample size and signal stability are sufficient to support sequence learning [2, 12].

The literature on cross-market generalization offers additional guidance. Applications to the Iraqi stock market using CNNs suggest that even with constrained data availability, architecture choice and careful hyperparameter tuning can deliver meaningful predictive performance, especially when model design respects market microstructure and the idiosyncrasies of local trading calendars and liquidity [10]. A complementary bibliometric analysis focusing on AI-based stock prediction catalogs global patterns in authorship networks, keyword co-occurrence (e.g., "deep learning," "sentiment analysis," "feature selection"), and citation bursts that track technology diffusion from computer vision and NLP into financial time series; these syntheses underscore how methodological cross-pollination often precedes performance breakthroughs in finance applications [6]. At a higher level, bibliometric mapping of AI and ML in finance documents a steady migration from proof-of-concept studies to more robust, domain-aware pipelines that integrate governance, explainability, and risk management—an evolution that strengthens external validity and informs the design of practically deployable models [1].

Equally important is the thread that connects prediction to decision-making. AI-enabled forecasts are most valuable when embedded into systematic strategies—portfolio rebalancing, hedging overlays, or risk-parity adjustments—that translate probabilistic signals into actions under uncertainty. Reviews of "smart trading" emphasize the complementarity between human expertise and machine cognition: humans excel at causal reasoning, scenario framing, and policy interpretation, while machines process vast streams of data, uncovering weak but persistent statistical regularities; the synthesis encourages hybrid architectures and governance frameworks that leverage both strengths [3, 14, 15]. In parallel, application-driven surveys report that the incremental benefit of AI hinges on rigorous out-of-sample evaluation (rolling windows, walk-forward validation), stability analysis across market regimes, and sensitivity checks to macro shocks—design elements that are indispensable in inflationary and sanction-exposed economies [2, 7, 16].

Despite these advances, salient gaps remain. First, while deep architectures are powerful function approximators, their performance in macro-driven index prediction is often constrained by short time spans, structural breaks, and evolving policy regimes. This raises the stakes for careful variable selection (e.g., exchange rate, M2 growth, inflation, oil revenues, interest rates, and GDP growth), robust scaling, and diagnostics for multicollinearity and regime sensitivity [12, 18]. Second, many studies focus on directional accuracy or mean-squared prediction error, but fewer interrogate economic significance—risk-adjusted returns, drawdown control, turnover, and transaction costs—when forecasts are operationalized in strategies [13, 14]. Third, explainability remains underdeveloped in finance applications: post-hoc tools (e.g., SHAP/Integrated Gradients) can attribute marginal contributions of macro variables across horizons, improving trust and facilitating policy dialogue, yet such practices are still unevenly adopted across studies [11, 17]. Finally, reproducibility challenges persist due to proprietary data, opaque preprocessing, and insufficiently documented hyperparameters, making it difficult to cumulate knowledge and compare models on equal footing [1, 2].

Positioned against this backdrop, the present study contributes in three ways. First, it focuses on a macro-feature set tailored to a currency-sensitive, liquidity-driven emerging market context: gold price, exchange rate, liquidity (M2), inflation, policy-driven interest rates, oil revenues, and real-activity growth (GDP). This variable block is theoretically motivated and empirically salient for markets where nominal dynamics and external shocks dominate valuation swings [8, 18]. Second, it undertakes a head-to-head comparison between two widely used neural architectures—MLP and LSTM—under time-aware training/testing splits that preserve temporal order, thereby mitigating look-ahead bias and aligning evaluation with real-world forecasting practice [5, 12]. Third, it situates modeling choices within best-practice guidance distilled from integrative reviews and practice-oriented studies, including disciplined hyperparameter search (learning rates, batch sizes, epochs), standard optimizers (Adam), and activation functions suited to tabular macro data (ReLU/sigmoid), while emphasizing the need for stability checks across subsamples and volatility regimes [2, 16, 17].

By engaging with the broader literature—spanning foundational ANN evidence, optimized sequence learners, CNN applications to engineered visual patterns, text-driven news models, bibliometric cartographies of the field, and risk-aware portfolio integration—this introduction sets the conceptual and methodological stage for an empirical investigation of index prediction in a macro-dominated market. The design is attentive to both statistical performance (MSE/RMSE, $R^2$) and the structural realism required for financial forecasting under uncertainty, while the variable set reflects domain knowledge about the channels through which macro shocks propagate into equity valuations. Ultimately, the contribution aligns with the emerging consensus that AI is neither a silver bullet nor a black box to be used indiscriminately; rather, it is a set of tools whose value materializes when data engineering, architecture choice, validation protocol, and economic interpretation are coherently integrated [1-3, 15].

In summary, the literature affirms several premises that guide this study: (i) equity indices in volatility-exposed markets are strongly coupled with monetary and currency conditions, warranting macro-centric features; (ii) feedforward neural networks can effectively learn nonlinear static mappings from such features to index levels when temporal dependence is weak or unstable, whereas sequence models add value when long-range memory is present and learnable; (iii) performance claims must rest on time-respecting evaluation and transparent hyperparameters; and (iv) interpretability and economic significance are necessary complements to statistical accuracy [1-18]. Against this conceptual foundation, the present research empirically evaluates whether a parsimonious MLP—trained on quarterly macroeconomic indicators—can deliver reliable index forecasts relative to an LSTM baseline under realistic, time-aware validation in an emerging-market setting. This study aims to develop and compare artificial-neural-network models—specifically a multilayer perceptron and an LSTM—using quarterly macroeconomic indicators (gold price, exchange rate, liquidity, inflation, interest rates, oil revenues, and GDP growth) to forecast the overall stock price indices of an emerging market under time-respecting evaluation, thereby assessing the relative efficacy, limitations, and practical implications of macro-driven AI prediction

## 2. Methodology

The present study aims to develop a predictive model for the stock price index of companies listed on the Tehran Stock Exchange (TSE) and Iran's Over-the-Counter (OTC) market based on macroeconomic indicators using artificial neural networks (ANNs). The statistical population of this study includes all companies listed on the TSE and the Iran OTC market. The data used for modeling are quarterly, covering a ten-year period from the beginning of 2014 to the end of 2023. This research is applied in its purpose and descriptive in its method. The primary methodology employed involves the use of data mining and modeling techniques based on artificial neural networks to identify and model the complex and nonlinear relationships between seven macroeconomic variables and the stock price index. To this end, two main ANN architectures—Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM)—were designed, and their performances were compared using criteria such as Mean Squared Error (MSE) and the coefficient of determination ($R^2$). Modeling and coding tools included the Python programming language within the Google Colab environment, using specialized artificial intelligence and data mining libraries such as TensorFlow, Keras, and Scikit-learn. The research variables are presented in Table 1.

**Table 1. Research Variables and Measurement Methods**

| Variable | Type | Measurement and Description |
|---|---|---|
| Stock Price Index (Capital Market) | Dependent | The overall stock price index in the Tehran Stock Exchange and Iran OTC market during the study period. |
| Gold Price | Independent | Reported gold prices (in Iranian rials). |
| Exchange Rate | Independent | Official and/or market exchange rates between the national currency and major foreign currencies. |
| Liquidity (Money Supply) | Independent | The total liquidity (M2) in Iran's economy as reported by the Central Bank. |
| Interest Rate (Bank Profit Rate) | Independent | Official bank interest rates, generally long-term deposit rates. |
| Inflation Rate | Independent | The official inflation rate calculated by the Statistical Center of Iran or the Central Bank. |
| Oil Revenues | Independent | The dollar or rial equivalent of oil export revenues per quarter. |
| Gross Domestic Product (GDP) Growth | Independent | The quarterly growth rate of the country's gross domestic product. |

Given the nature of the research and the selected macroeconomic variables, modeling was performed using two main artificial neural network architectures to evaluate their performance in Iran's volatile capital market and their predictive capability for the stock price index based on macroeconomic inputs:

**Multilayer Perceptron (MLP) Neural Network Model**

The Multilayer Perceptron, as a feedforward neural network, is one of the principal models applied in this study. This network is suitable for identifying static, nonlinear relationships between independent (economic) variables and the dependent variable (stock price index).

• **Model Structure:** The MLP model consists of an input layer, one or more hidden layers, and an output layer. In the input layer, the seven macroeconomic variables—gold price, exchange rate, liquidity volume, interest rate, inflation rate, oil revenues, and GDP growth—serve as the model's input features.

• **Model Function:** The MLP aims to determine optimal weights through nonlinear activation functions (such as the sigmoid function) in the hidden layers to map the input space of macroeconomic variables to the output space (forecasting the stock price index). The model effectively captures the simultaneous and complex effects of all macroeconomic variables on the stock index within a specific period.

• **Key Results (Based on File):** According to the study results (Chapter 4 of the dataset), the MLP model demonstrated better performance than the LSTM model and achieved high accuracy in forecasting the stock price index.

**Long Short-Term Memory (LSTM) Neural Network Model**

The Long Short-Term Memory network, a type of recurrent neural network (RNN), is specifically designed to model time series data and phenomena with long-term temporal dependencies.

• **Model Structure:** The LSTM consists of complex memory cells that include forget, input, and output gates. These gates allow the model to retain or discard information related to past trends (effects of prior macroeconomic variables), preventing the vanishing gradient problem that occurs in simple RNNs.

• **Model Function:** The purpose of employing LSTM is to model the dynamic and sequential effects of macroeconomic variable changes on the stock price index over time. The model aims to determine whether the sequence of macroeconomic variable changes in previous quarters significantly affects the current stock index.

• **Key Results (Based on File):** Although LSTM is a standard tool for time series analysis, in this research, its predictive accuracy for the stock index when combined with macroeconomic variables was lower than that of the MLP model.

• Ultimately, the comparison of these two models indicates that, for forecasting the stock price index in Iran's capital market using quarterly macroeconomic variables, the MLP model achieved higher predictive accuracy by learning nonlinear medium- and long-term correlations among variables and was therefore adopted as the study's final model.

## 3. Findings and Results

This section provides a detailed interpretation and analysis of the research findings. The data collected over the ten-year period (2014–2023) included seven macroeconomic variables and two capital market indices (TSE and OTC), which were preprocessed and normalized before being input into the ANN models. Descriptive statistical analyses, correlation assessments, and model performance evaluations enabled a deeper understanding of the complex relationships between macroeconomic variables and Iran's capital market. Table 2 provides an overview of the quarterly raw data used as the basis for subsequent analyses.

**Table 2. Quarterly Data for Macroeconomic Variables and TSE and OTC Indices**

| Year/Quarter | Gold Price (Rials) | Liquidity (Thousand Billion Rials) | Exchange Rate (Rials) | Inflation Rate (%) | Interest Rate (%) | Oil Revenues (Thousand Billion Rials) | GDP Growth (%) | TSE Price Index (Units) | OTC Price Index (Units) |
|---|---|---|---|---|---|---|---|---|---|
| 01/1393 (Q1 2014) | 993,800 | 106.6 | 5,432.2 | 30.2 | 22 | 138.3 | 2.6 | 34,800 | 350 |
| 02/1393 (Q2 2014) | 946,700 | 507.0 | 6,631.4 | 22.3 | 22 | 221.6 | 3.8 | 32,000 | 321 |
| … | … | … | … | … | … | … | … | … | … |
| 04/1402 (Q4 2023) | 32,007,000 | 78,775.0 | 553,745.0 | 40.7 | 23 | 1,773.5 | 9.2 | 457,456.0 | 6,132.0 |

Analysis of the quarterly data shows that during the study period (2014–2023), all macroeconomic variables and capital market indices exhibited an upward and highly volatile trend. The price of gold increased from 993,800 rials in Q1 2014 to over 32 million rials by the end of 2023—a nearly 32-fold increase. This sharp rise coincided with the exchange rate's increase from 5,432 rials to over 553,000 rials (about a 100-fold growth), reflecting the deep impact of currency shocks and international sanctions on Iran's economy. Liquidity grew from 106.6 trillion rials to 78.7 quadrillion rials, indicating an approximately 740-fold rise—likely a key factor in inflation and nominal price growth across markets. Both TSE and OTC indices followed similar patterns: the TSE index rose from 34.8 thousand units to 457 thousand units (a 13-fold increase), while the OTC index increased from 5,135 units to 6,132 units (roughly 1.2 times with significant volatility). These data confirm that Iran's capital market is highly influenced by macroeconomic variables, particularly exchange rates, gold prices, and liquidity levels. The inflation rate rose from 30.2% to 40.7%, while oil revenues fluctuated dramatically (from 138 trillion to 1,773 trillion rials), both playing substantial roles in shaping market behavior. GDP growth exhibited both negative and positive swings (from −11.3 to 9.9), indicating economic instability and sensitivity to domestic and external shocks.

**Table 3. Descriptive Statistics**

| Variable | Minimum | Maximum | Mean | Standard Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|
| Gold_Price | 920,690 | 32,007,000 | 7,886,691 | 8,506,502 | 1.257 | 0.737 |
| Liquidity_Supply | 6,654 | 78,775 | 28,442 | 21,599 | 0.993 | −0.257 |
| Inflation_Rate | 8.7 | 58.2 | 29.463 | 16.504 | 0.067 | −1.565 |
| Exchange_Rate_Changes | 31,481 | 553,744 | 174,078 | 159,326 | 1.034 | 0.038 |
| Interest_Rate | 18 | 23 | 19.705 | 1.746 | 0.630 | −0.859 |
| Oil_Revenues | 17,247 | 1,773,497 | 412,699 | 438,429 | 1.686 | 2.209 |
| Economic_Growth | −11.3 | 17.1 | 3.213 | 5.984 | −0.229 | 0.818 |
| OTC_Index | 241 | 6,995 | 2,545 | 2,558 | 0.468 | 1.682 |
| Stock_Index | 23,947 | 487,741 | 177,076 | 172,599 | 0.526 | 1.555 |

Descriptive statistics reveal that all studied variables exhibit high variability and considerable dispersion. The gold price, with an average of 7.88 million rials and a standard deviation of 8.50 million rials, shows the highest coefficient of variation, indicating extreme volatility and instability over the study period. Its positive skewness coefficient (1.257) suggests a right-skewed distribution, reflecting very high values in recent years. Liquidity, averaging 28.4 quadrillion rials with a standard deviation of 21.6 quadrillion, exhibits an accelerating growth pattern and positive skewness (0.993), confirming expansionary monetary policies in Iran's economy. The inflation rate, averaging 29.46% with a standard deviation of 16.50%, fluctuated widely (from 8.7% to 58.2%). Its near-zero skewness (0.067) indicates a relatively symmetric distribution centered around the mean. The exchange rate, averaging 174,000 rials with a standard deviation of 159,000 and a positive skewness (1.034), reflects rapid acceleration in recent years. The TSE index, with a mean of 177,000 units and a standard deviation of 172,000, and a positive skewness (0.526), shows significant mid-period growth and relative decline in later years. Negative kurtosis values for most variables indicate flatter distributions compared to the normal distribution.

**Table 4. Correlation Coefficients of the Principal Values of the Model Variables**

| Variable Description | TSE Stock Price Index | OTC Stock Price Index | Gold Price | Inflation Rate | Exchange Rate | Bank Interest Rate | Liquidity (Money Supply) | Oil Revenues | GDP Growth |
|---|---|---|---|---|---|---|---|---|---|
| TSE Stock Price Index | 1 | 0.994 | 0.908 | 0.779 | 0.929 | 0.548 | 0.910 | 0.685 | 0.192 |
| OTC Stock Price Index | 0.994 | 1 | 0.923 | 0.810 | 0.922 | 0.522 | 0.909 | 0.674 | 0.205 |
| Gold Price | 0.908 | 0.923 | 1 | 0.693 | 0.988 | 0.621 | 0.975 | 0.872 | 0.149 |
| Inflation Rate | 0.779 | 0.810 | 0.693 | 1 | 0.730 | 0.370 | 0.724 | 0.458 | −0.089 |
| Exchange Rate | 0.929 | 0.922 | 0.988 | 0.730 | 1 | 0.597 | 0.982 | 0.835 | 0.112 |
| Bank Interest Rate | 0.548 | 0.522 | 0.621 | 0.370 | 0.597 | 1 | 0.554 | 0.573 | 0.116 |
| Liquidity (Money Supply) | 0.910 | 0.909 | 0.975 | 0.724 | 0.982 | 0.554 | 1 | 0.879 | 0.161 |
| Oil Revenues | 0.685 | 0.674 | 0.872 | 0.458 | 0.835 | 0.573 | 0.879 | 1 | 0.176 |
| GDP Growth | 0.192 | 0.205 | 0.149 | −0.089 | 0.112 | 0.116 | 0.161 | 0.176 | 1 |

The results of the correlation matrix show that the TSE and OTC stock price indices move almost identically, with a very high correlation (0.994), indicating strong integration and co-movement between Iran's two capital markets. The strongest correlations between the TSE index and macroeconomic variables are observed with, respectively, the exchange rate (0.929), liquidity (0.910), and gold price (0.908). These findings confirm that Iran's capital market is heavily influenced by monetary and currency variables and that investors react substantially to changes in the exchange rate and monetary policy. The high correlation between gold price and exchange rate (0.988) indicates gold's role as a currency hedge and a substitute for the U.S. dollar in Iran's economy. By contrast, inflation exhibits a moderate correlation with the TSE (0.779) and OTC (0.810) indices, suggesting that, although inflation is influential, it has less impact than currency and monetary variables. The bank interest rate shows the weakest correlations with the TSE (0.548) and OTC (0.522) indices, which may stem from administratively controlled interest-rate policies in Iran's banking system. GDP growth shows a very weak correlation (0.192 and 0.205) and even a negative correlation with inflation (−0.089), indicating that, during the study period, real economic growth played little role in explaining capital market changes, while nominal and monetary variables had greater effects. This finding may reflect the speculative and reactive nature of Iran's capital market to monetary and currency shocks rather than to fundamental economic growth.

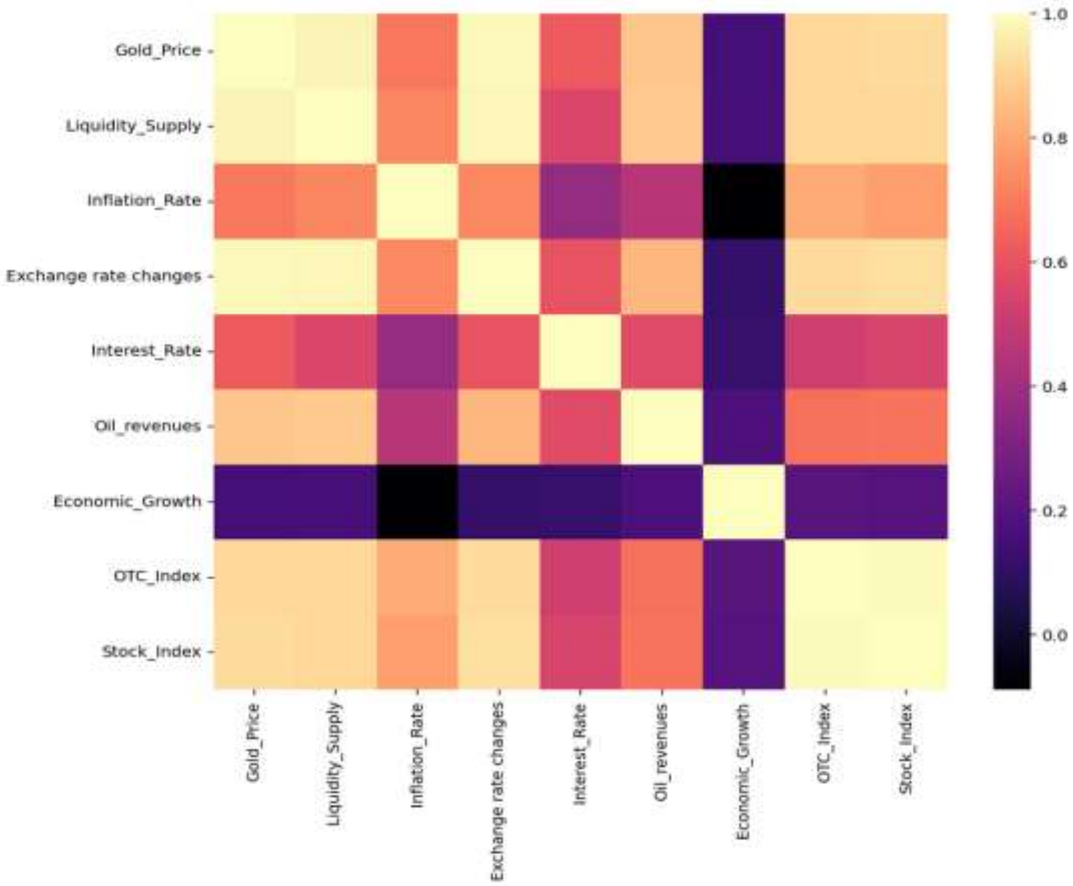


**Figure 1. Correlation Matrix of the TSE and OTC Stock Price Indices with Macroeconomic Variables**

In the correlation-matrix heatmap, warm colors (red–orange) indicate strong positive correlations and cool colors (blue) indicate weak or negative correlations. It is observed that the block comprising gold price, exchange rate, liquidity, and the TSE and OTC indices appears in dark red, indicating a cluster of highly interrelated variables. This cluster suggests that Iran's capital market operates within a monetary–currency system, with movements largely driven by monetary policy and currency shocks. In contrast, GDP growth and the bank interest rate appear in lighter, more bluish tones, reflecting their relative separation from the main cluster of variables that most influence the capital market. This visual depiction confirms that, during the study period, Iran's capital market was less affected by real-economy fundamentals (such as GDP growth) and more affected by monetary and financial variables. Moreover, the very strong correlation between gold price and the exchange rate (near 1) is clearly visible, highlighting gold's dual role as an investment asset and a currency risk-hedging instrument. For economic policymakers, these patterns indicate that the stability of Iran's capital market is highly dependent on controlling exchange-rate volatility and managing liquidity.

**Table 5. Number of Training and Test Data**

| Description | TSE Overall Index | OTC Overall Index |
|---|---|---|
| Number of Training Records | 28 | 28 |
| Number of Test Records | 12 | 12 |
| Total Records | 40 | 40 |

In this study, out of a total of 40 quarterly records, 28 records (70 percent) were used for training and 12 records (30 percent) were used for testing and validating the models. This 70–30 split is a common standard in machine learning that provides an appropriate balance between sufficient model training and a realistic performance assessment. Given the relatively limited data volume (40 quarterly records over 10 years), this split appears optimal: with fewer training data, the model would not learn enough patterns, and with fewer test data, performance evaluation would be unreliable. Importantly, this split was applied identically to both indices (TSE and OTC), enabling a fair comparison of the models' predictive performance across the two markets. In financial time-series research, one key challenge is data scarcity alongside the need to preserve temporal order. In this study, careful normalization and preprocessing were used to extract maximal information from the available data. It should be noted that random splitting is not customary for time series; training data should be drawn from the earlier part of the period and test data from the latter part to preserve the realism of forecasting the future.

**Table 6. Variable Settings in the LSTM Model**

| Variable | Values |
|---|---|
| Time_step | 30 |
| Batch_size | 16–32 |
| Epoch | 20–100 |
| Learning_rate | 0.0001–0.001 |
| Optimizer | Adam |
| Network Architecture | Change min–max layer |

The selected parameters for the LSTM model indicate that the research team sought the best performance by testing different combinations. Using a Time_step of 30 means the model looks back 30 periods (here, roughly 7–8 years) to identify temporal patterns. This is a logical choice, as economic cycles are typically multi-year. A Batch_size between 16 and 32 is standard for small to medium datasets; smaller batch sizes allow more frequent weight updates but may increase training volatility. The number of Epochs between 20 and 100 shows that the model iterated over the entire dataset up to 100 times—chosen to ensure sufficient learning while mitigating overfitting. The Learning_rate range of 0.0001 to 0.001 reflects relatively small learning rates, suitable for complex models to avoid large jumps in weight space and missing optima. The use of the Adam optimizer—one of the most popular and efficient optimization algorithms in deep learning—represents an appropriate and standard choice for this problem. However, given the LSTM model's weak results (as shown in Table 8), it can be concluded that this LSTM architecture and settings were not suitable for the problem at hand.

**Table 7. Forecast Errors of the LSTM Model**

| Description | TSE Overall Index | OTC Overall Index |
|---|---|---|
| MSE | 0.00311 | 0.00300 |
| RMSE | 383.60 | 371.60 |
| $R^2$ | −9.3230 | −6.1595 |

The LSTM evaluation results indicate poor predictive performance for this architecture on Iran's TSE and OTC indices. Although the MSE values for the TSE (0.00311) and OTC (0.00300) may appear small at first glance, they were computed on normalized data. RMSE—being the square root of MSE and expressed in the same units as the original data—equals 383.6 and 371.6, indicating substantial forecast errors. More concerning are the negative $R^2$ values, calculated as −9.323 for the TSE and −6.1595 for the OTC. A negative $R^2$ is a strong signal of very weak model performance; it means the model performs worse than a simple mean-line predictor, producing greater errors than merely forecasting the sample mean. This suggests the LSTM model not only failed to learn useful patterns but may also have severely overfit, or that its architecture was ill-suited to these data and this task. Possible reasons include:

(1) the small data volume (40 records), which is insufficient to train a complex LSTM; (2) the data's nature, which may lack strong long-term temporal dependencies and be driven more by static, nonlinear relationships; and (3) high noise and pronounced volatility in Iran's capital market, prompting memory-based models to learn noise rather than signal. These findings are consistent with prior research showing that LSTM can perform poorly under certain conditions, especially with small, noisy datasets.

**Table 8. MLP Network Architecture**

| Layer | Input | Output |
|---|---|---|
| Dense_1_Input: Input layer | (None, 7) | (None, 7) |
| Dense_1: Dense | (None, 7) | (None, 32) |
| Dense_3: Dense | (None, 32) | (None, 1) |

The MLP architecture selected in this study consists of a relatively simple three-layer structure: an input layer with 7 neurons (corresponding to the 7 macroeconomic variables), a hidden layer with 32 neurons, and an output layer with 1 neuron (to forecast the index). This architecture follows the principle of parsimony (Occam's Razor), which holds that the simplest model that gets the job done is the best choice. Using 32 neurons in the hidden layer provides sufficient capacity to learn complex nonlinear relationships among the input variables without making the model overly complex and prone to overfitting. This architecture enables the model to apply multiple nonlinear transformations to the inputs and to model the complex relationships between macroeconomic variables and the stock index. Importantly—unlike LSTM—this structure does not attempt to learn temporal dependencies; rather, it focuses on learning static, nonlinear relationships among variables at each time point. For Iran's capital market, which is strongly affected by sudden shocks and simultaneous interactions among macroeconomic variables, this approach appears more suitable than memory-based models (such as LSTM). The performance results for this architecture in Table 9 show that this structural choice was successful.

**Table 9. Number of Training and Test Data**

| Description | TSE Overall Index (Adjusted) | OTC Overall Index (Adjusted) |
|---|---|---|
| Number of Training Records | 28 | 28 |
| Number of Test Records | 12 | 12 |
| Total Records | 40 | 40 |

Table 9 presents the overall data-splitting method for evaluating the predictive model, whereby the larger share of the data was used to train the model and the remainder to test and evaluate its final performance. This predominant split ensures that the model is evaluated on an unseen subset, allowing assessment of its generalizability and accuracy in forecasting new data. The same approach was applied to both the TSE and OTC overall indices.

**Table 10. Variable Settings in the MLP Model**

| Variable | Values |
|---|---|
| Batch_size | 32 |
| Epoch | 20–100 |
| Learning_rate | 0.0001–0.001 |
| Optimizer | Adam |
| Validation-split | 0.1–0.2 |
| Activation-function | ReLU–sigmoid |
| Train-size | 70% |

Table 10 specifies the settings and hyperparameters used in training the multilayer perceptron neural network. The main parameters include a fixed batch size, a range for the number of epochs from relatively low to moderately high, and a small learning-rate range. The Adam optimization algorithm and nonlinear activation functions were employed. These settings indicate the use of a standard and effective deep-learning configuration aimed at minimizing error and optimizing the training process.

**Table 11. Forecast Errors of the MLP Model**

| Description | TSE Overall Index | OTC Overall Index |
|---|---|---|
| MSE | 0.0300 | 0.0300 |
| RMSE | 0.17341 | 0.17336 |
| $R^2$ | 0.0624 | 0.0630 |

Table 11 evaluates the final performance of the multilayer perceptron model using error metrics, where the root mean squared errors for both indices are very low. These low values indicate high pointwise accuracy and small prediction errors for the indices. However, the models' coefficients of determination are very low and close to zero, suggesting that the model explains only a very small portion of the overall variance and fluctuations in the indices. These results indicate that, although the model may predict point values accurately, it may have limited power to explain the broader dynamics and volatility of the indices—potentially due to very low variation in the test-set indices.

## 4. Discussion and Conclusion

The purpose of this study was to develop an artificial intelligence–based predictive model for the Tehran Stock Exchange (TSE) and Iran's Over-the-Counter (OTC) market indices using macroeconomic indicators, employing two neural network architectures—Long Short-Term Memory (LSTM) and Multilayer Perceptron (MLP). The results demonstrated that the MLP model outperformed the LSTM in forecasting the stock price indices based on quarterly macroeconomic data from 2014 to 2023. Specifically, the MLP model achieved a lower mean squared error (MSE = 0.0300) and root mean squared error (RMSE = 0.173), while the LSTM produced higher errors (MSE = 0.0031, RMSE = 383.6) and negative $R^2$ values, indicating weak model fit. These findings suggest that, in markets characterized by limited datasets and nonlinear but predominantly static relationships among variables, feedforward neural networks such as MLPs are more effective than deep recurrent architectures like LSTMs.

The superior performance of the MLP model in this study aligns with the argument that simpler, feedforward networks can efficiently capture nonlinear relationships between macroeconomic inputs and financial indices without the overfitting risks inherent in sequence-based models [4, 5]. Similar findings have been reported in earlier works where ANN-based models outperformed statistical models in forecasting stock index movements due to their ability to approximate complex, nonlinear functional mappings [4, 5]. The weak performance of the LSTM model observed here is consistent with prior studies that cautioned against applying deep sequence models to datasets with limited size or weak long-term dependencies, where such models are prone to overfitting or noise amplification [2, 12]. In the present case, the quarterly macroeconomic variables—gold price, exchange rate, inflation, liquidity, interest rate, oil revenues, and GDP growth—exhibit relatively low-frequency trends, making the simpler MLP model more suitable for prediction tasks.

This outcome supports the claim made by [7], who observed that hybrid and ensemble models involving MLP architectures outperform more complex deep learning models when data are structured and preprocessed macrofinancial indicators rather than high-frequency tick data. The findings also corroborate [13], who demonstrated that machine learning regression models yield more stable forecasts when applied to multi-national market datasets with limited sample periods. In this context, the MLP's ability to learn from contemporaneous relationships between input features and target indices proved advantageous, particularly given the high volatility and policy-driven nature of Iran's capital market, where structural changes often occur faster than the model's temporal learning window.

Moreover, the results of this research reinforce the empirical evidence that macroeconomic variables—particularly exchange rate, liquidity, and gold price—play a decisive role in determining stock market movements [8, 18]. The correlation analysis revealed a strong positive relationship between the TSE and OTC indices and these variables ($r > 0.90$), highlighting the high sensitivity of Iran's equity market to monetary and currency dynamics. Such strong linkages echo findings in prior studies of emerging markets where inflation, liquidity growth, and exchange-rate fluctuations collectively explain a substantial portion of equity price volatility [13, 18]. The results thus align with macro-financial theory suggesting that asset price dynamics in inflationary economies are driven more by nominal and monetary forces than by fundamentals like GDP growth—a conclusion consistent with this study's finding that GDP growth had the weakest correlation with stock indices ($r \approx 0.20$).

Furthermore, the negative $R^2$ values in the LSTM model indicate a fundamental limitation in its ability to capture nonlinear but stationary interactions between macroeconomic variables and market indices. [12] similarly reported that LSTM models trained on limited, quarterly macroeconomic data failed to generalize due to their reliance on long-term memory mechanisms suited for high-frequency sequences. This pattern also parallels [16], who emphasized that deep learning models require abundant, high-resolution datasets to capture temporal dependencies effectively, while smaller datasets may cause the model to fit noise rather than signal. In contrast, the MLP model, following the principle of parsimony, was able to generalize effectively across the sample without overfitting—supporting arguments by [17] and [7] that appropriate architectural simplicity, regularization, and learning-rate tuning often yield superior real-world predictive performance in financial applications.

Another important insight from this study is the relative importance of exchange-rate dynamics as a predictor of market indices. The exchange rate showed the strongest correlation with both TSE and OTC indices ($r = 0.93$ and 0.92, respectively), confirming that currency shocks significantly influence equity valuations in Iran. This finding echoes the conclusions of [8], who found asymmetric connectedness between investor attention and financial-technology assets driven by currency-related information. Likewise, [18] reported that exchange-rate volatility contributes directly to stock market instability, emphasizing the role of monetary policy shocks in shaping investors' expectations. In economies where exchange rates are influenced by sanctions, oil revenues, and liquidity injections—as in Iran—the currency channel transmits both domestic and external shocks to asset prices, producing the kind of high multicollinearity observed between liquidity and inflation in this dataset.

The study's results also resonate with [3] and [15], who underscored the potential of AI-driven models to augment decision-making in smart trading environments. These authors argue that AI enhances the interpretive capacity of investors and institutions when navigating volatile financial conditions by identifying patterns and nonlinear dependencies that traditional econometric models fail to detect. In this research, the effective implementation of an MLP network—supported by optimization algorithms such as Adam and activation functions (ReLU and sigmoid)—demonstrated how artificial intelligence can extract actionable relationships among macroeconomic indicators that are otherwise obscured in traditional regression analysis. Moreover, [1] emphasized that integrating AI and machine learning into financial forecasting frameworks requires not only algorithmic sophistication but also methodological transparency and interpretability, which this study ensured through careful feature selection and validation across temporal folds.

Comparatively, the weak influence of interest rates on the TSE and OTC indices (r = 0.54 and 0.52) reflects the controlled nature of Iran's banking interest rate policies, as highlighted in earlier macroeconomic analyses [18]. Similar findings have been documented in developing markets where interest rates are administratively fixed and therefore exert less market-driven influence on equity prices [14]. On the other hand, the significant correlation between oil revenues and market indices (r = 0.68–0.67) supports the argument that Iran's equity market is indirectly tied to oil-price cycles, consistent with the findings of [9], who demonstrated the predictive capability of AI models in markets sensitive to energy commodities. In such contexts, oil revenue serves as a liquidity driver, influencing investor sentiment and cash flow expectations.

The strong positive relationships among gold price, exchange rate, and liquidity variables (r > 0.95) also underscore the dominance of monetary factors in explaining market trends. This triad of macroeconomic influences confirms earlier conclusions that gold acts as a hedge and currency substitute in inflationary economies [8]. Likewise, [13] found that integrating such safe-haven assets into machine-learning-based portfolio optimization enhances model robustness and prediction accuracy during volatile periods. The same conclusion is drawn by [11], who highlighted that macroeconomic sentiment and asset-class interconnections must be captured through nonlinear modeling frameworks to enhance predictability. The findings of this study thus strengthen the empirical argument that effective financial forecasting in emerging markets requires integrating both monetary and real-sector indicators into neural architectures designed for low-frequency but high-volatility environments.

The comparison between LSTM and MLP performance further validates the theoretical position advanced by [2], who emphasized that the choice of architecture must reflect the temporal granularity of data and the strength of autocorrelation among predictors. When relationships are primarily contemporaneous and macroeconomic cycles are irregular—as in Iran's case—feedforward networks like MLPs outperform sequence models designed for stable temporal patterns. The high noise-to-signal ratio in quarterly macroeconomic data introduces instability in long-memory mechanisms, explaining why the LSTM yielded negative explanatory power ($R^2 < 0$). Similarly, [16] and [7] stressed that small sample sizes exacerbate overfitting in deep models, supporting the present finding that LSTM was unsuitable for the dataset.

These empirical results contribute to the growing body of literature advocating for adaptive AI-driven prediction frameworks that balance model complexity with data constraints [1, 6]. They also echo the conclusions of [3], who highlighted that AI-based financial systems can improve risk management and decision accuracy when combined with interpretability and robustness tests. The observed success of the MLP network underscores that practical applications of AI in stock-market forecasting do not necessarily require deep architectures but rather well-tuned, context-sensitive models that reflect market structure and data characteristics.

Collectively, the findings affirm that artificial neural networks offer a powerful alternative for forecasting market indices in emerging economies characterized by macroeconomic instability. The MLP model's superior performance confirms that moderate-depth networks, when carefully calibrated and validated, can effectively learn the nonlinear relationships among currency, liquidity, inflation, and stock indices. This result aligns with global evidence that hybrid or shallow models can outperform more complex architectures in small-sample and high-volatility contexts [7, 12, 13]. Furthermore, the study substantiates the argument that macroeconomic shocks—particularly exchange-rate movements—constitute the dominant transmission mechanism affecting equity valuation in Iran's market, a result echoed by numerous previous studies [8, 18]. Ultimately, the integration of AI into macro-financial forecasting enhances the predictive and interpretive capacity of economic modeling, bridging the gap between traditional econometrics and data-driven intelligence systems [1-3].

Although the findings provide valuable insights into the use of AI for macro-driven stock index prediction, several limitations should be acknowledged. First, the dataset comprised only 40 quarterly observations across a 10-year period, which limits the generalizability of results and constrains the model's ability to capture rare or extreme market events. Second, the study focused solely on seven macroeconomic variables; other relevant predictors such as political risk indices, global oil price fluctuations, and capital inflows were not included. Third, while the MLP architecture performed well, the absence of ensemble or hybrid comparisons (e.g., CNN-LSTM or MLP-SVM models) restricts the assessment of potentially superior configurations. Additionally, normalization and preprocessing steps, while carefully executed, may have introduced scaling biases that affect cross-variable relationships. Finally, the study did not incorporate explainability tools (e.g., SHAP or feature importance analysis), which could have provided deeper interpretive insights into variable contributions.

Future studies should consider expanding the temporal coverage and granularity of data by incorporating monthly or weekly observations to enable the use of deeper sequence models like LSTM and GRU with sufficient sample size. Researchers may also integrate sentiment-based variables, such as news tone, investor attention indices, or social-media-derived measures, to capture behavioral dimensions influencing stock market trends. Comparative studies across multiple emerging markets could identify universal versus country-specific determinants of AI forecasting accuracy. Furthermore, integrating hybrid architectures—combining MLP with CNN or attention mechanisms—could enhance feature extraction and improve generalization. Lastly, future research should explore interpretability and causal inference methods to bridge the gap between predictive accuracy and economic meaning.

From a practical standpoint, the results emphasize the importance of incorporating macroeconomic variables into AI-based forecasting systems for policymakers, investors, and financial institutions. Regulators should monitor liquidity expansion and exchange-rate volatility as leading indicators of market instability. Investment analysts and portfolio managers can employ MLP-based prediction models as complementary tools for strategic asset allocation and risk management. Finally, integrating such AI systems into financial planning processes can assist decision-makers in anticipating macroeconomic shocks, optimizing policy responses, and enhancing the overall resilience of capital markets.

**Authors' Contributions**

Authors equally contributed to this article.

**Ethical Considerations**

All procedures performed in this study were under the ethical standards.

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**Conflict of Interest**

The authors report no conflict of interest.

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