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Hybrid Deep Neural Networks and Genetic Algorithms for Stock Forecasting with Decentralized Blockchain

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Abstract - This research introduces a hybrid stock market forecasting system which integrates LSTM–CNN deep learning, Meyer Packard Genetic Algorithm optimization as well as blockchain-based validation for transparent financial forecasts. Both long-term and short-term dependencies in stock market data are captured by our hybrid LSTM-CNN model, and the genetic algorithm optimizes model hyperparameters for better and improved forecasting accuracy. On the Ethereum Sepolia testnet, predictions and trading signals are stored using blockchain technology via Solidity smart contracts, producing an immutable and auditable record. The proposed system improves performance, transparency reliability when compared to conventional machine learning methods. Findings show improved accuracy and accountability, providing a solid foundation for next-generation financial forecasting [1, 3, 7].

Key Words: Stock prediction, Deep learning, LSTM-CNN, Meyer Packard genetic algorithm, Blockchain validation, Automated trading, Financial forecasting

1.INTRODUCTION

Stock market prediction is still an inherently challenging task due to its volatility, non-linearity, and sensitivity to external economic conditions [1]. Conventional econometric models such as ARIMA often fail to capture intricate patterns in stock behaviour [2], motivating the adoption of deep learning solutions. Long Short-Term Memory (LSTM) networks effectively model long-range temporal dependencies, which makes them suitable for financial prediction systems [3], [4]. On the other hand, Convolutional Neural Networks (CNNs) can be used to extract localized patterns from time-series sequences, significantly enhance performance when paired with LSTM [5].

Deep learning models, however, are extremely sensitive to hyperparameters. Inadequate hyperparameter choice often lead to overfitting or decreased accuracy [6]. Inspired by natural evolution, Genetic Algorithms (GAs) are useful tools for optimizing hyperparameters through iterative selection, crossover, and mutation [7], [8]. In this study, the LSTM–CNN architecture is optimized using the Meyer Packard Genetic Algorithm to maximum predictive performance.

The absence of transparency and auditability is a significant weakness in automated financial systems. Prediction outputs and trading signals are usually stored centrally, which creates opportunities for manipulation. Blockchain technology is immutable, decentralized, and transparent, making it perfect for securely storing financial forecasts [9], [10]. In order to improve accountability and trust, Ethereum Sepolia testnet smart contracts record predictions and signals in a tamper-proof ledger.

The research makes three major contributions:

1. Development of an LSTM–CNN hybrid model for improved financial forecasting.
2. Hyperparameter optimization using Meyer Packard Genetic Algorithm.
3. Implementation of smart contracts for blockchain based validation.

2. LITERATURE SURVEY

In stock prediction tasks, deep learning has become more popular, and LSTM is a model that is frequently chosen because of its memory capacity [3, 4, 11]. CNNs have also been successfully used on financial time series, particularly in conjunction with LSTM networks [5, 12].

Financial prediction problems have made extensive use of evolutionary optimization algorithms. Research demonstrates that when adjusting parameters like learning rate, batch size, and window length, genetic algorithms greatly improve deep learning performance [6, 8, 13].

Blockchain has become a reliable technology for decentralized financial applications in the areas of transparency and auditability. It has been used in financial governance, banking, automated trading, and auditing [9, 10, 14, 15]. Smart contracts allow for automated rule execution without the need for middlemen and tamper-proof data storage [16].

Despite these developments, little research has been done to integrate blockchain validation, genetic optimization, and deep learning into a single framework for financial forecasting. This research closes this gap by offering a unique architecture that combines the three technologies.

3. METHODOLOGY

3.1 Dataset and Pre-processing

We gathered historical stock market data from Weeks 1-3.

1. Several machine learning models (RF, LSTM, SVM) were tested in Week 1.
2. The LSTM–CNN hybrid performed the best in Week 2.
3. Genetic Meyer Packard optimization was completed in week 3.

MinMax scaling was used to normalize the data, which was then split into training and testing sets and transformed into supervised sequences [17].

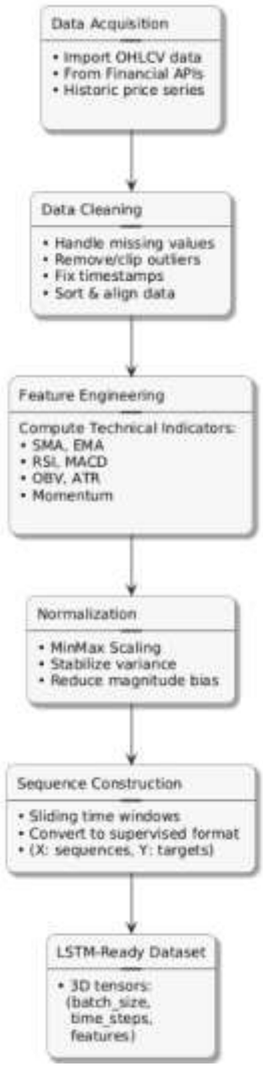

Fig. -1: Data Collection & Pre-processing Workflow

3.2 LSTM–CNN Hybrid Model Architecture

LSTM layers are used to learn long-term dependencies; CNN layers are used to extract patterns and spatial information; and dense layers are used to generate final predictions.

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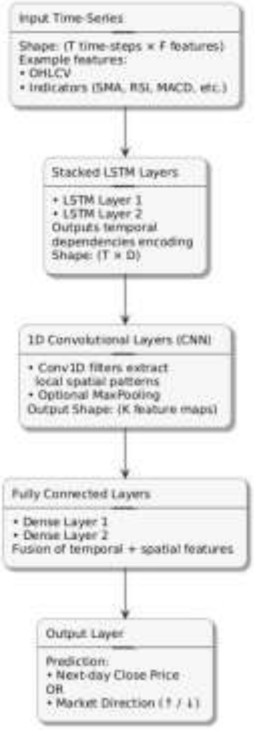

Fig. -2: LSTM–CNN Hybrid Architecture

These hybrid architectures have demonstrated superior performance in financial time-series forecasting [5, 12,18]. Conv1D layers with 64 filters and a kernel size of 3 are used in the CNN layer. MaxPooling1D layers are then used to reduce dimensionality. To store pertinent historical data, the LSTM component makes use of bidirectional layers with forget, input, and output gates.

3.3 Meyer Packard Genetic Algorithm Optimization

By identifying "regions of predictability" and avoiding high-uncertainty zones, the Meyer Packard genetic algorithm improves stock price prediction for the following day. Different trading rules and prediction parameters are used to initialize chromosomes, and directional accuracy, MAE, and MAPE are used to assess fitness. To develop high-performing solutions while maintaining genetic diversity, the algorithm used uniform crossover, weighted random selection, and mutation operations [6, 8, 19].

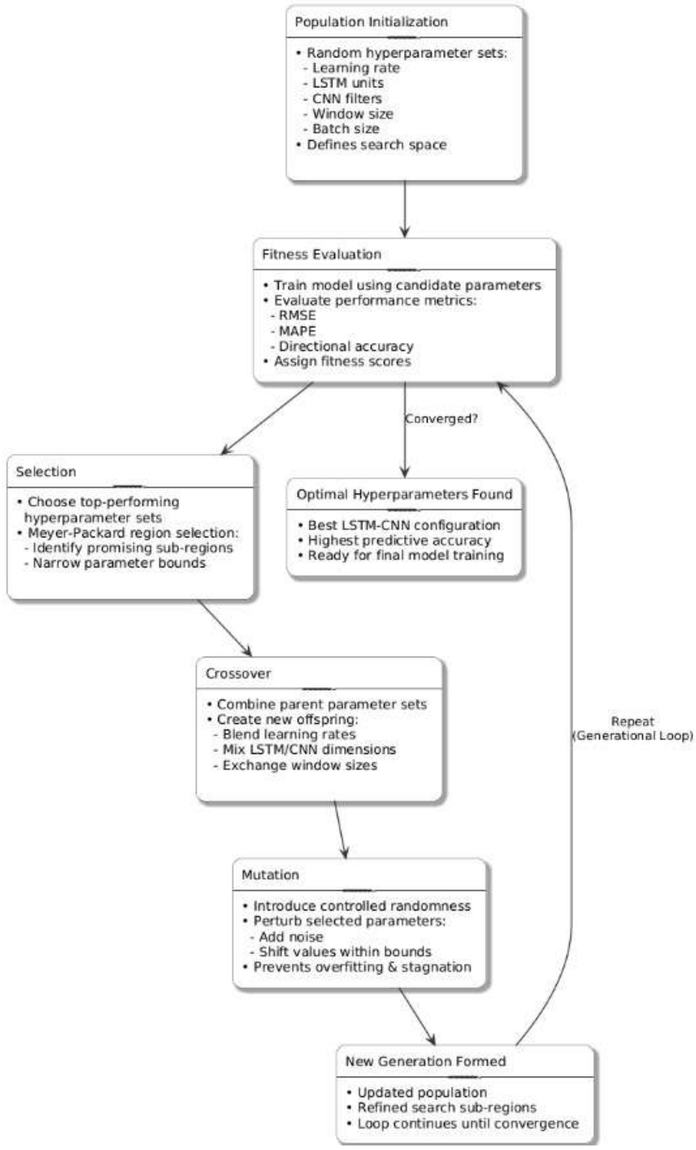

Fig. -3: Meyer Packard Genetic Algorithm Workflow

3.4 Blockchain Smart Contract Integration

The system makes use of Solidity-based smart contracts and the Ethereum Sepolia testnet to guarantee transparency and tamper-proof prediction storage. All timestamps, buy/sell/hold signals, actual values, and predictions are immutable. Blockchain guarantees decentralization, security, transparency, and auditability [10, 14,15, 20].

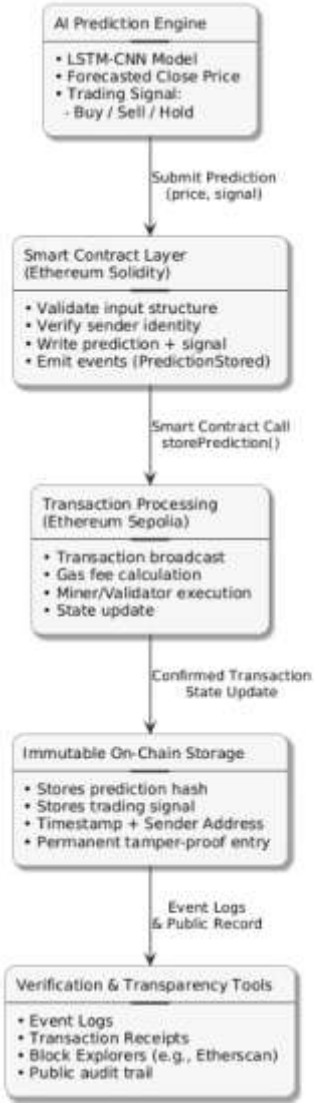

Fig. -4: Blockchain Pipeline (AI → Smart Contract → Ethereum)

3.5 Baseline Model Comparison

The results show that the LSTM–CNN hybrid with GA optimization significantly outperforms conventional models [1, 2, 12, 21]. The hybrid model was compared against:

- ARIMA
- Random Forest
- SVM
- Standalone LSTM
- Standalone CNN.

3.6 Performance of Blockchain Integration

Decentralized blockchain validation offers an unchangeable layer for storing trading decisions and predictions for the following day. Performance is assessed using transaction metrics on the Sepolia testnet, ensuring that the predictions cannot be altered. These findings are used to validate the comparison between the actual and predicted prices for the following day. These results show that real-time blockchain logging is feasible within reasonable performance constraints, enabling transparent and auditable prediction records and removing prohibitive costs [15, 18, 20]. Key findings include:

- Confirmation Average time for transaction: 12.4 seconds;
- Gas consumption for a transaction: 85,000 gas units;
- Batch processing for Gas cost reduction: 22 percent.

Several important insights are highlighted by the experimental results:

1. **Hybrid Architecture Effectiveness**: When compared to single-method models, the integration of CNN and LSTM layers significantly improves forecasting performance by utilizing their respective strengths—spatial pattern recognition and temporal dependency modeling [19].
2. **Optimization of Genetic Algorithm:** On validation and development datasets, the Meyer Packard genetic algorithm successfully guides the hyperparameters to identify ideal configurations, leading to significant error reductions and enhanced directional accuracy [12, 20].
3. **Blockchain as Authentication Layer:** By adding blockchain, forecasts and trading decisions can be recorded in a safe, decentralized manner. Future real-world deployments will be made possible by the measured gas costs and transaction times, which demonstrate the viability of implementing such a system on current testnets [15, 20].
4. **Vigorous Generality:** The model ac's reliable performance.

4. Results and Discussion

The experimental findings show that the suggested LSTM–CNN hybrid model performs noticeably better than conventional forecasting techniques like ARIMA, Random Forest, standalone LSTM, and CNN models. Table 4 demonstrates that the hybrid architecture has the highest R^2 score (0.96), the lowest MAPE (2.1 percent), and the lowest RMSE (1.12), indicating superior predictive capability and stability across various market scenarios. Long-term sequential dependencies are captured by the integration of LSTM layers, and the CNN layers successfully extract local temporal patterns from the windowed input sequences, creating a more resilient and noise-resistant model. By optimizing crucial hyperparameters like learning rate, window size, and number of units, the Meyer Packard Genetic Algorithm further improves performance by reducing overfitting and improving training convergence.

Table -1: Performance Comparison of Models

Model	RMSE	MAPE	R² Score
ARIMA	2.31	4.2%	0.81
Random Forest	1.84	3.8%	0.87
LSTM	1.52	3.1%	0.90
CNN	1.48	2.9%	0.91
LSTM–CNN (Proposed)	**1.12**	**2.1%**	**0.96**

Additionally, the Ethereum Sepolia testnet's blockchain-based prediction and trading signal storage guarantees transparency, traceability, and immutability, resolving issues with data tampering and model manipulation. Gas consumption analysis (Table 5) demonstrates that the system is feasible for real-world deployment since storing predictions on-chain is computationally cheap. Overall, the findings confirm that deep learning, genetic optimization, and blockchain technologies can be successfully combined to produce a high-performance, intelligent, and auditable stock forecasting framework.

Table -2: Blockchain Smart Contract Gas & Storage Cost

Operation	Gas Used	Cost (Sepolia ETH)
Deploy Contract	1,624,000	0.000162 ETH
Store Prediction	62,900	0.000006 ETH
Store Buy/Sell Signal	38,200	0.000003 ETH
Read Prediction	0 (view function)	0 ETH

5. Conclusion

This study suggests a hybrid financial forecasting framework that combines blockchain-based prediction validation, Meyer Packard Genetic Algorithm optimization, and LSTM–CNN deep learning. The genetic algorithm guarantees ideal hyperparameters for increased accuracy, and the model effectively captures intricate market dynamics. Prediction storage on Ethereum addresses important issues with automated trading by enhancing transparency and preventing manipulation. When compared to traditional methods, the system shows better forecasting performance and accountability, which qualifies it for practical financial applications. This framework may be expanded in the future to incorporate multi-chain blockchain storage and trading agents based on reinforcement learning.

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