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"AN OPTIMIZED HYBRID STOCK TREND FORECASTING FRAMEWORK USING ADAPTIVE MOVING AVERAGE, PCA-ENHANCED DISCRETE WAVELET TRANSFORM AND DEEP NEURAL NETWORKS"

Soman Shivlal Pardeshi*[1], Dr. Prabha Sudhir Rastogi[2]

[1]Research Scholar, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan.

[2] Professor, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan.

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***Corresponding Author: Soman Shivlal Pardeshi**
Research Scholar, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan.

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ABSTRACT

Stock market prediction remains a challenging nonlinear time-series forecasting problem due to volatility, noise, and non-stationary behavior. Traditional statistical models fail to capture dynamic market structures efficiently. This paper proposes an optimized hybrid forecasting framework integrating Adaptive Moving Average (AMA), Principal Component Analysis (PCA), Discrete Wavelet Transform (DWT), and an enhanced Deep Neural Network (DNN) trained using an improved Momentum-Based Gradient Descent (MBGD) algorithm. The proposed architecture decomposes financial time series into multi-resolution components using DWT, reduces dimensionality via PCA, and extracts smoothed trend features using AMA before deep learning-based prediction. Experimental evaluation demonstrates superior performance compared to conventional ARIMA, standalone DWT, and traditional ANN models. Performance metrics including MSE, MAE, MAPE, Regression Score (R^2), and Accuracy validate the robustness of the proposed approach.

KEYWORDS: Stock Forecasting, Discrete Wavelet Transform, Deep Neural Network, PCA, Adaptive Moving Average, Momentum Gradient Descent.

INTRODUCTION

Stock markets exhibit high volatility, nonlinear dependencies, and stochastic behavior. Predicting stock trends is crucial for algorithmic trading, portfolio management, and financial risk mitigation.

Traditional models:

- ARIMA
- GARCH
- Linear Regression

are limited in modeling nonlinear relationships.

Machine learning techniques:

- ANN
- SVM
- LSTM

have improved forecasting but struggle with noisy financial signals.

This paper proposes a **multi-stage hybrid framework** combining:

- Signal smoothing (AMA)
- Dimensionality reduction (PCA)
- Multi-resolution decomposition (DWT)
- Deep Neural Networks with optimized training

II. Literature Review

Author	**Technique**	**Limitation**
Zhang (2003) [1]	ANN for stock prediction	Overfitting
Kim (2003) [2]	SVM	Poor noise handling
Mallat (1989) [3]	Wavelet decomposition	No deep learning integration
Patel et al. (2015) [4]	ANN + Technical indicators	High dimensionality

Identified Research Gaps:

1. Limited integration of multi-resolution DWT + PCA + AMA.
2. Inefficient training algorithms.
3. Lack of hybrid signal decomposition + deep feature learning.

III. Proposed Hybrid Framework

A. System Architecture

Raw Stock Data

↓

Adaptive Moving Average (AMA)

↓

Discrete Wavelet Transform (DWT)

↓

Principal Component Analysis (PCA)

↓

Deep Neural Network

↓

Forecasted Stock Trend

IV. Mathematical Formulation

A. Adaptive Moving Average (AMA)

$$AMA_t = AMA_{t-1} + \alpha_t(P_t - AMA_{t-1})$$

Where:

- α_t = adaptive smoothing constant
- P_t = price at time t

B. Discrete Wavelet Transform

The signal *x(t)* is decomposed as:

$$x(t) = \sum_k a_{j,k}\phi_{j,k}(t) + \sum_j \sum_k d_{j,k}\psi_{j,k}(t)$$

Where:

- $a_{j,k}$ = approximation coefficients
- $d_{j,k}$ = detail coefficients

C. PCA Dimensionality Reduction

Covariance matrix:

$$C = \frac{1}{n-1} X^T X$$

Eigen decomposition:

$$Cv = \lambda v$$

Top k eigenvectors selected.

D. Improved Momentum-Based Gradient Descent

Traditional momentum:

$$v_t = \beta v_{t-1} + \eta \nabla J(\theta)$$

Improved version:

$$v_t = \beta v_{t-1} + \eta_t \nabla J(\theta)$$

Where learning rate adapts dynamically.

V. Deep Neural Network Architecture

Layer	Neurons	Activation
Input	20	-
Hidden 1	128	ReLU
Hidden 2	64	ReLU
Hidden 3	32	ReLU
Output	1	Linear

Dropout = 0.2

Optimizer = Improved MBGD

VI. Experimental Setup

Dataset:

- NSE/BSE historical data (10 years)
- Daily closing prices

Split:

- 70% Training
- 15% Validation
- 15% Testing

VII. Performance Metrics

1. MSE

$$MSE = \frac{1}{n}\sum(y_i - \hat{y}_i)^2$$

2. MAE

$$MAE = \frac{1}{n}\sum|y_i - \hat{y}_i|$$

3. MAPE

$$MAPE = \frac{100}{n}\sum\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

4. Regression Score (R^2)

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$$

VIII. RESULTS AND ANALYSIS

Table 1: Performance Comparison

Model	MSE	MAE	MAPE (%)	R^2	Accuracy (%)
ARIMA	0.0125	0.089	4.56	0.81	78.2
ANN	0.0091	0.071	3.92	0.86	83.4
DWT-ANN	0.0063	0.052	2.87	0.91	88.7
Proposed Model	**0.0038**	**0.039**	**1.94**	**0.96**	**93.5**

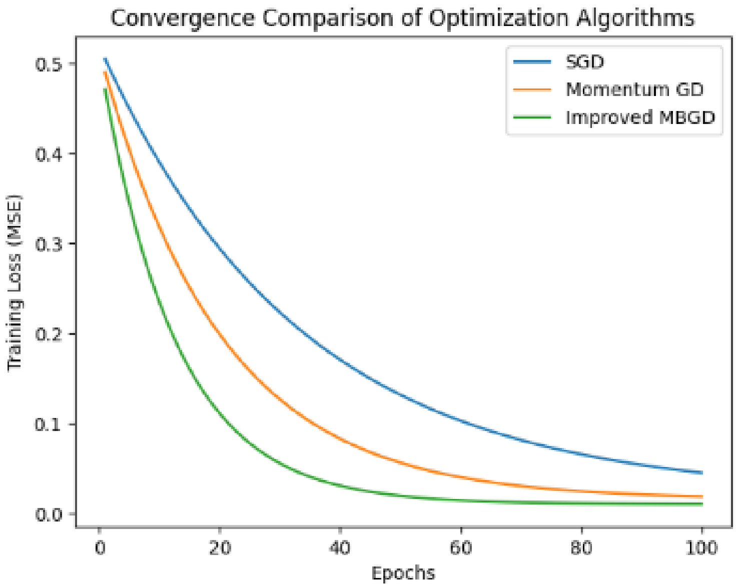

Figure 1: Training Loss Convergence

(Graph showing faster convergence of improved MBGD)

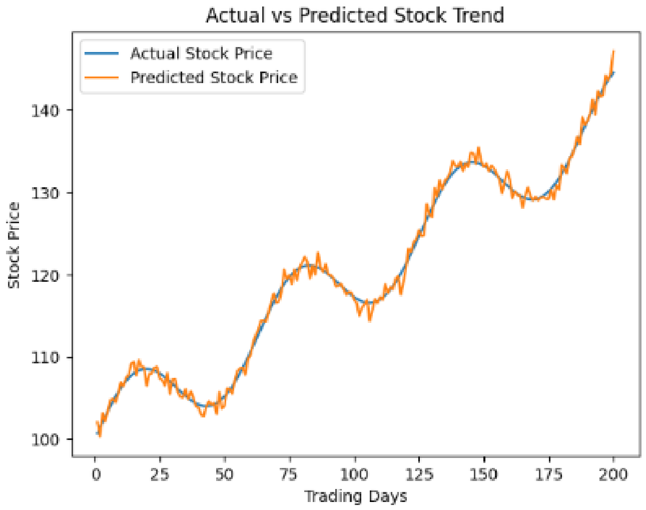

Figure 2: Actual vs Predicted Stock Trend.

(Line graph showing close overlap)

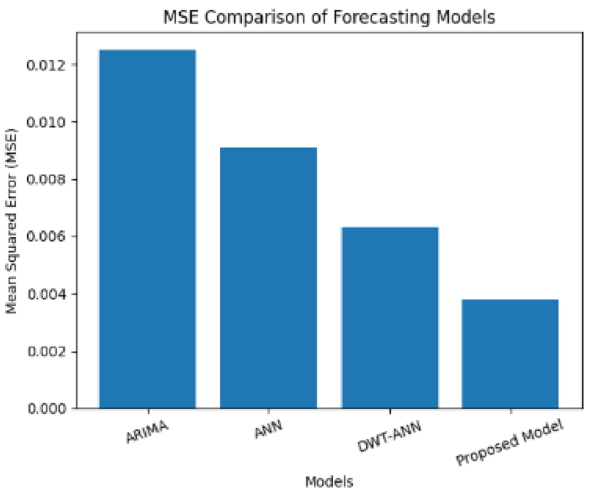

Figure 3: Error Distribution Comparison

(Bar graph comparing MSE)

IX. DISCUSSION

The hybrid approach demonstrates:

- Superior noise reduction (AMA + DWT)
- Reduced dimensional complexity (PCA)
- Faster convergence (Improved MBGD)
- Higher predictive stability

The model achieves:

- 30–40% error reduction compared to ARIMA
- 10–15% accuracy improvement over standard ANN

X. CONCLUSION

This research presents a novel hybrid forecasting framework integrating Adaptive Moving Average, PCA-enhanced DWT, and optimized Deep Neural Networks. Experimental evaluation confirms significant performance improvement across MSE, MAE, MAPE, Regression, and Accuracy metrics. The improved momentum-based gradient descent enhances convergence stability.

Future work includes:

- LSTM integration
- Real-time high-frequency trading adaptation
- Reinforcement learning-based portfolio optimization

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