# Stock Price Forecasting Project Report

## Executive Summary

This project implements and compares two time series forecasting approaches for stock price prediction: **ARIMA (AutoRegressive Integrated Moving Average)** and **LSTM (Long Short-Term Memory Neural Network)**. The analysis uses Apple Inc. (AAPL) stock data from January 2020 to September 2024.

**Key Finding**: ARIMA significantly outperformed LSTM with 66.62% lower prediction error.

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## 1. Dataset and Methodology

### Data Acquisition

- **Source**: Yahoo Finance API
- **Ticker**: AAPL (Apple Inc.)
- **Period**: January 1, 2020 - September 30, 2024
- **Total Observations**: 1,194 daily closing prices
- **Train/Test Split**: 80/20 (955 training, 239 test observations)

### Data Preprocessing

- **Missing Values**: None detected
- **Feature Engineering**:
  - Moving averages (7, 21, 50-day)
  - Volatility (21-day rolling standard deviation)
  - Returns (daily percentage change)
  - Lagged features (1-5 days)
- **Scaling**: MinMaxScaler [0,1] for LSTM only

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## 2. Model Implementation

### 2.1 ARIMA Model

**Parameter Selection**:

- Grid search over $p \in [0,2]$, $d \in [0,1]$, $q \in [0,2]$
- Selection criterion: Minimum AIC (Akaike Information Criterion)
- Optimal parameters determined through automated search

**Training Approach**:

- Rolling window evaluation (walk-forward validation)
- Model refitted for each prediction with expanding window
- Captures most recent market dynamics

**Advantages**:

- Interpretable parameters
- Fast training and inference
- Well-suited for linear trends
- Low computational requirements

### 2.2 LSTM Model

**Training Configuration**:

- Sequence length: 60 days
- Epochs: 100 (early stopping with patience=10)
- Batch size: 32
- Optimizer: Adam
- Loss function: Mean Squared Error
- Validation split: 10%

**Training Results**:

- Training sequences: 907
- Test sequences: 227
- Best validation loss: 0.0011 (achieved at epoch 13)
- Total parameters: 50,851

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## 3. Performance Comparison

### Performance Metrics Table

| Model | RMSE ($) | MAPE (%) | Accuracy (%) | Training Time | Inference Speed |
|---|---|---|---|---|---|
| **ARIMA** | 2.81 | 1.05 | 98.95 | ~5 minutes | 100ms/prediction |
| **LSTM** | 8.42 | 3.35 | 96.65 | ~15 minutes | 50ms/prediction |

### Key Findings

1. **ARIMA achieved 66.62% lower RMSE** than LSTM
2. **ARIMA's MAPE of 1.05%** is exceptional for stock price forecasting
3. **ARIMA predictions** closely tracked actual values throughout test period
4. **LSTM underperformed** despite sophisticated architecture

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# 4. Model Generalization Analysis

## Winner: ARIMA

**Why ARIMA Generalizes Better for This Dataset**:

**1. Market Characteristics Match ARIMA Strengths**

The test period (October 2023 - September 2024) exhibited:

- **Relatively linear growth trends** - AAPL stock showed stable upward movement
- **Low to moderate volatility** - Fewer extreme market swings
- **Strong short-term autocorrelations -** Yesterday's price strongly predicts today's

ARIMA excels in these conditions because it:

- Captures linear relationships efficiently
- Adapts quickly to recent trends via rolling window
- Focuses on short-term dependencies (AR and MA components)

**2. LSTM's Limitations in This Context**

**Insufficient Training Data**:

- LSTM had only 907 training sequences (~3.6 years of daily data)
- Deep learning typically requires 5-10+ years for optimal stock prediction
- Limited data prevents LSTM from learning complex temporal patterns effectively

**Overfitting Evidence**:

- **Training loss**: 0.0022 (very low)
- **Validation loss**: 0.0011-0.0038 (fluctuating but low)
- **Test RMSE**: 8.42 (much higher than validation suggested)
- This gap indicates the model memorized training patterns rather than learning generalizable features

**Unnecessary Complexity**:

- The market dynamics during this period didn't require deep learning's non-linear modeling capability
- 50,851 parameters were excessive for the relatively simple patterns present
- Simpler ARIMA model avoided overfitting to noise

**3. Rolling Window Advantage for ARIMA**

The walk-forward validation approach particularly benefited ARIMA:

- **Continuous adaptation**: Model updated with each new observation
- **Responsive to regime changes**: Quickly incorporated new market information
- **Recent data emphasis**: Weighted recent observations more heavily
- **Computational efficiency**: Fast enough to retrain continuously

LSTM, by contrast:

- Required full retraining (computationally expensive)
- Fixed 60-day lookback window (less adaptive)
- Slower to respond to market shifts

**4. Model Complexity vs. Data Complexity Mismatch**

**Occam's Razor Principle**: The simplest model that explains the data is preferable

- AAPL stock exhibited patterns explainable by short-term autocorrelations (AR terms) and moving averages (MA terms)
- LSTM's deep neural architecture was "overqualified" for the task
- Added complexity without added predictive power = worse generalization

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# 5. Practical Implications

## When to Use ARIMA:

**Recommended for**:

- Markets showing linear trends
- Limited historical data (2-5 years)
- Need for model interpretability
- Fast deployment requirements
- Short-term forecasting (1-7 days)
- Computational constraints

## When to Use LSTM:

**Recommended for**:

- Complex, non-linear market patterns
- 5-10+ years of quality data
- High volatility periods
- Multiple feature integration
- Longer-term forecasting
- Abundant computational resources

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# 6. Conclusions

## Main Findings

1. **ARIMA significantly outperformed LSTM** with 66.62% lower prediction error
2. **Model complexity doesn't guarantee better performance** - validate with your specific data

3. **Market characteristics determine optimal model choice -** linear trends favor ARIMA
4. **1.05% MAPE is exceptional** for financial time series forecasting

## Scientific Value

This analysis demonstrates:

- **Importance of empirical validation** over theoretical assumptions
- **Value of classical statistical methods** in appropriate contexts
- **Dangers of "deep learning for everything"** mentality
- **Context-dependent model selection** is crucial

## Recommendation

**Deploy ARIMA model** based on:

- Superior accuracy (RMSE: $2.81 vs $8.42)
- Better generalization to test data
- Faster inference and retraining
- Higher interpretability for stakeholders
- Lower computational costs